Ecological and biological modeling for natural resource management: Applications to wetland classification and evaluation

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Submitted in fulfillment of the requirements of the degree of Doctor of Philosophy

July 2014

Abstract

The goal of wetland assessment is to identify and quantify the condition of wetlands, taking into account the presences of threats likely to impact the services and functions the wetlands provide. There are a wide variety of methods available for undertaking wetland assessment; most rely on data collection across a broad range of attributes at wetland sites to gauge wetland condition. This thesis examines the practice of wetland assessment in West Gippsland, south-eastern Australia and it investigates the contribution, and potencies, of component biological, chemical, hydrological and physical data inputs, individually and collectively, to the identification of high social, economic and environmental value wetlands in the region. A systematic analysis using statistics and data-mining techniques was undertaken of the inventory data for 163 representative wetlands to discover pertinent relationships between the values of different site characteristics and the classification of high-value wetlands. Binary logistic regression and neural networks were used to build models mimicking the wetland assessment process, and an assessment of their abilities to do so was conducted. The influences of two wetland classification schemes: Corrick and Norman (1980) scheme, and Ecological Vegetation Classes (EVCs), on the naming of high-value wetlands were also investigated.

Results showed that binary logistic regression models and neural networks were capable of correctly classifying over 90% high-value wetland assessments using absence/presence data for a minimal set of inputs. The major contributions of this research are the identification of the most suitable inputs for assessments of wetland economic, social and environmental values in West Gippsland and support for the use of neural networks to predict wetland assessments. Additionally, this research found little evidence that either classification scheme impacted significantly the case study assessments. The research has demonstrated possible reductions in effort and expenditure in undertaking wetland assessments through the identification of salient input features with high predictive potency. Cognisant of these benefits, management can streamline future inventory collections and better target assessment and monitoring efforts.

Student Declaration

I, Anne Therese Venables, declare that the PhD thesis entitled Ecological and biological modeling for natural resource management: Applications to wetland classification and evaluation is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

[redacted]

Anne Therese Venables

7 July 2014

Acknowledgements

First, and foremost, my heartfelt thanks go to my supervisor, Professor Paul Boon for his continual encouragement and eternal patience. Throughout my research, his friendly guidance and thought-provoking suggestions have always been delivered enthusiastically and in good humour.

My thanks go to Michelle Dickson of the West Gippsland Catchment Management Authority for her friendly and professional assistance with descriptions of wetlands assessment and in providing access to the dataset upon this research is based.

Additionally, I wish to thank my friends Grace Tan and Iwona Miliszewska for their encouragement in my research efforts.

Finally, the backing of my family has been paramount in my seeing this thesis through to completion. Thank you to Gary, my husband of thirty-nine years, for his unerring support of all my academic pursuits during our time together.

Anne

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Dowd Morass, Victoria, July 2010.
Image courtesy of Paul Boon

Chapter 1

Objectives and scope

This research is concerned with the identification of high-value wetlands, and how they are classified and evaluated, through the process of wetlands assessment. The task of wetland assessment is to make a measure of wetland condition and take account of threats likely to negatively affect the services and functions that a wetland provides. Wetlands assessment is one of three important steps designated by Contracting Parties to the Ramsar Convention in their advice on how to protect and manage wetlands (Ramsar, 2005). As illustrated in Figure 1.1, the wetlands assessment task is preceded, and informed by, the collection of a wetlands inventory, which involves the collection of data to be collated and synthesized during the assessment process. The outcome of assessment process is the identification of wetlands to be considered higher in value. These high-value wetlands are further monitored so that they can be adaptively managed into the future for "sustainable development" and "wise use' as described by the Ramsar Convention (2005). Each of the processes of Figure 1.1 is defined and explained further in the next chapter of this thesis.

The objective of the research outlined in this thesis is to increase the understanding of the process of wetland assessments by examining its practice in Gippsland, south-eastern Australia through:

- A statistical exploration of the relationships between the values of different input factors and the classification of high-value wetlands;
- An investigation of the impact of two wetland classification schemes in evaluating and ranking of wetland sites; and,
- The application of data-mining techniques designed to mimic the wetland assessment process.

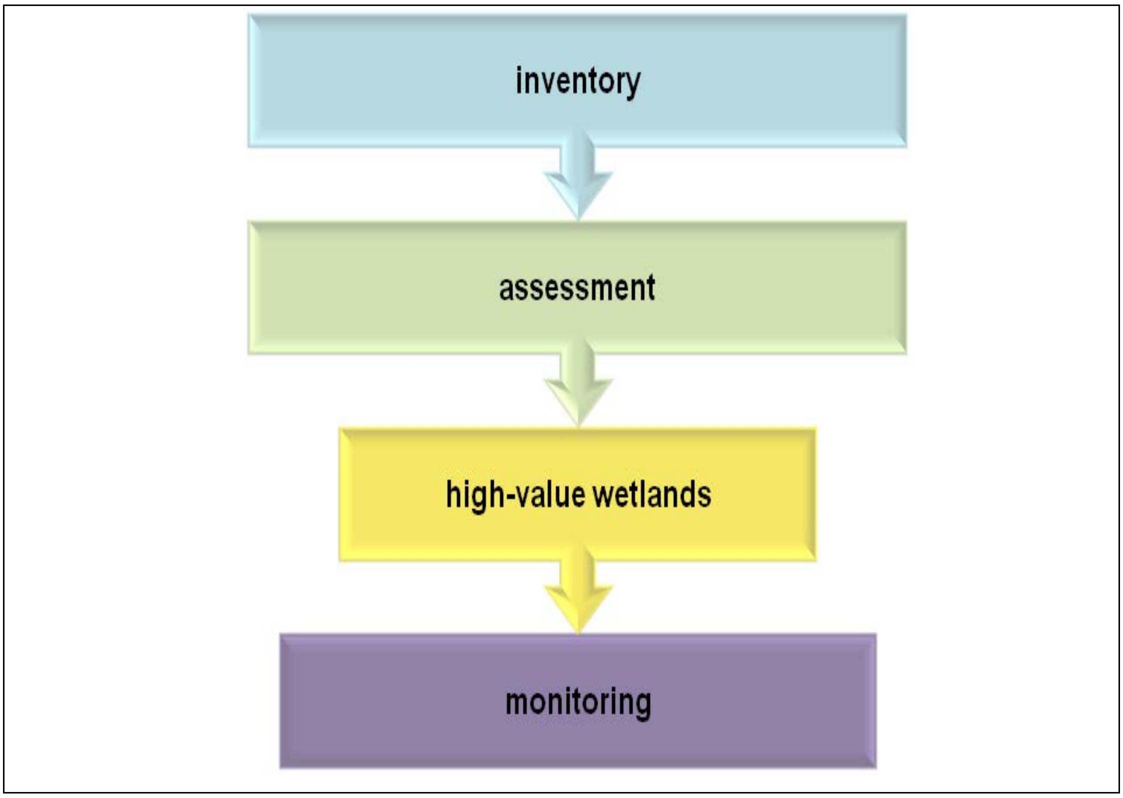


Figure 1.1: **Major component processes and their interactions for protecting and managing wetlands.** The processes were specified by the 2005 Conference of Contracting Parties to the Ramsar Convention on Wetlands in advice on how to protect and manage wetlands, particularly those of high-value (Ramsar, 2005).

1.1 Outline of thesis

Wetlands assessments need to account for all of the interacting biological, hydrological and physical components that are used in determining wetland condition and threat influence. Thus, most wetland assessments rely on inventory data collection across a broad range of attributes at wetland sites, where data values of the attributes are indicators used to gauge and classify wetland condition and threat status, as shown in Figure 1.2. Typically, the assessment process decides that wetlands are high in value for their economic or social or environmental worth. Details on how wetland assessment is undertaken are given in Chapter 2, where, background information on the Australian and Victorian contexts of wetland assessments is described. The chapter concludes with the aims of the research.

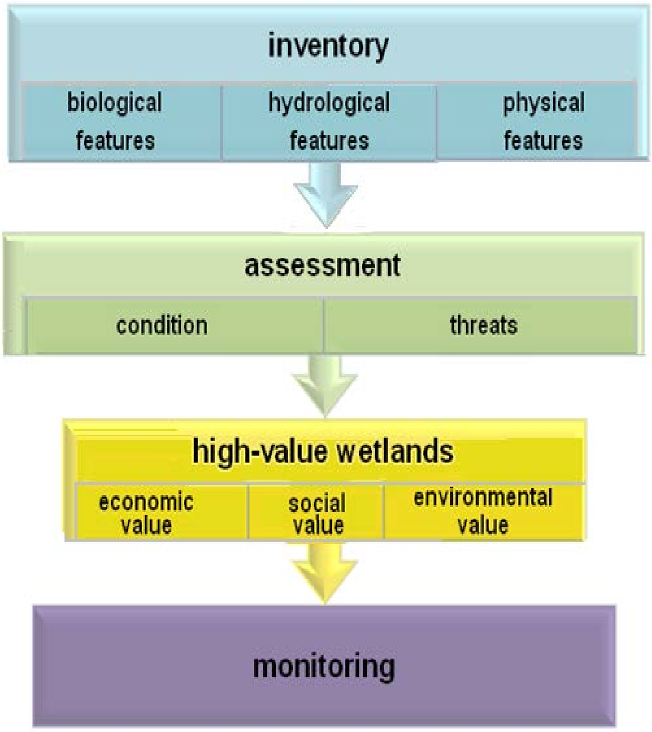


Figure 1.2: Breakdown of the major component processes and their interactions for protecting and managing wetlands. Shown are the stages of inventory and assessment used to identify high economic, social and environmental value wetlands.

A case study description of wetland inventory and assessment carried out during 2006 in south-eastern Australia by the West Gippsland Catchment Management Authority (WGCMA) to classify and evaluate high-value wetlands within their region follows in Chapter 3. The wetland assessment was a major part of an overarching regional Wetlands Plan needed to "help ensure that future investment in significant wetlands is targeted towards the highest priority activities and wetland assets over the next five years" (West Gippsland Catchment Management Authority [WGCMA], 2006b, p.6). The inventory stage of the WGCMA Wetlands Plan amassed a large collection of data, which was stored in the WGCMA Wetland Inventory Database (7.61 Megabytes). Throughout the assessment process, the Database was accessed for input values on a wetland by wetland basis. As an instance of best practice, the WGCMA case study illustrates the complexity of the wetland assessment task and the amount of effort required to undertake it. As noted in Chapter 3, the only reported analyses undertaken on the Database were frequency statistics for different wetland types and the prevalence of various inputs recorded during inventory per catchment and across the region (Greening Australia, 2006). The wealth of data stored in the Database was largely untapped and ripe for more thorough analyses. Such analyses would shed light on the contribution, and potencies, of component biological, chemical, hydrological and physical data inputs, individually and collectively, to the identification of high social, economic and environmental value wetlands in the region. As a first step, the inventory dataset collected for the WGCMA case study is explored using traditional univariate statistics in a preliminary search for relationships between inputs and high-value wetland assessments. The results of the investigation are reported in Chapter 4 and compared to wetland assessments observed during the original WGCMA assessment.

There has been a steady rise in the number of powerful statistical techniques, novel computer algorithms and search methods being applied in ecology over the past decade (Fernandes et al., 2006; Guisan & Thuiller; 2005; Guisan & Zimmermann 2000; Kelly, Guo et al., 2007; Khanna, 2007; Ticehurst et al., 2007). Such methods hold particular promise in being able to extract useful information from large datasets in order to find novel and useful patterns that otherwise would remain undiscovered, and although computationally expensive, data-mining techniques have progressively become cheaper and more readily accessible (Chen, Jakeman et al., 2008; Negnevitsky, 2011; Tan et al., 2006). In Chapter 5, the application of multivariate statistical techniques to wetland assessments is explored where models are constructed and examined for their abilities in identifying the most suitable inputs associated with high-value wetlands, and for their overall predictive powers in making wetland assessments. Further in Chapter 6, a novel approach using neural networks is undertaken. Neural networks provide a non-linear mechanism to data mine inventory data and recognize factors which predict high-value wetlands assessments.

Previously, others have noted that various classification schemes together with condition and threat assessment protocols influence the assessment process and these, along with their underlying assumptions, sway the naming of high-value wetlands (e.g. Frankiewicz & Wainwright, 2009; Ling & Jacobs, 2003; Stevens, 2009). The analyses of Chapter 5, and later in Chapter 6, include an examination of the influence of these schemes in identifying high economic, social and environment value wetlands in the West Gippsland region.

Neural networks are increasing being applied to environmental assessment and management problems, including water-resource problems (Maier &Dandy, 2000b; Maier et al., 2010). Their popularity is in part due to their ability to cope well with non-traditional datasets, where other approaches may fail, and in part due to their ability to be trained to learn patterns within datasets and to recognize these patterns in unseen data (Brosse et al., 2001; Findlay & Zheng, 1999; Lek & Guegan, 1999; Olden et al., 2006; Zhang, 2000). This research evaluates the predictive abilities and reports on the suitability of neural networks in mimicking wetland assessments decision making on unseen data in Chapter 6. Finally, Chapter 7 summarizes the results of research and it discusses the findings of the investigation and the implications for future wetland assessments in West Gippsland.

1.2 Overview of thesis

The application of multivariate statistics and neural networks on the WGCMA dataset provides two major opportunities. First for each technique, it is possible to examine the relationship between data values collected during inventory for their individual, and collective, strengths in classifying high-value wetlands. In turn, this examination leads to the identification of a minimal set of biological, hydrological and physical indicators for inventory collection and an understanding of these strengths and relationships can be used to better comprehend the complexity of wetland systems and inform future inventory and monitoring efforts. Second, the two techniques can be compared and evaluated for their efficacy in tackling wetland assessments. The strengths and weaknesses of each approach are also discussed in Chapters 5, 6 and 7.

It has been well argued that Australian wetlands are more typical of the rest of the world's wetlands than those of Western Europe and North America found documented in the literature (Boulton & Brock, 1999; Williams, 1988). Therefore the significance of this research goes beyond the context of the WGCMA case study. Chapter 7 discusses the findings of this research and recommends how lessons learnt in the case study can be applied elsewhere in Australia, and indeed, further afield.

Latrobe River estuary, Victoria, December 2010.
Image courtesy of Paul Boon

Chapter 2

Literature review and background information

Until the last quarter of the 20th century, there was little recognition of the substantial worldwide loss of wetlands due to human activity. In 1971 the Convention on Wetlands of International Importance at Ramsar highlighted the need for all nations to manage and conserve wetlands through "sustainable development" and "wise use". The Convention put in place Articles to define wetlands and it outlined the first necessary steps towards wetland conservation as being inventory, assessment and monitoring of existing wetlands.

Australia, an early signatory to the Convention, has seen large-scale losses of wetland habitat since European occupation. In complying with its Ramsar obligations, representative data have been collected to identify, and ultimately, assess and rank wetlands according to their economic, social and environmental values. The wetland assessment process results in large data collections and it consumes many hours through consultation with experts, database interrogation, literature reviews and workshop discussions.

This chapter details the importance of wetlands and the impact of the Ramsar Convention towards their protection. It introduces the Australian and Victorian context of wetland valuations and it describes the complex task of wetland assessment. With the aim of finding efficiencies to streamline wetland assessments, the chapter outlines the application of statistical and data-mining approaches to the process so that the most important input variables, and the salient relationships amongst them, can be identified within the inventory data. Finally, the aims of this research are detailed and conclude the chapter.

2.1 An introduction to wetlands and their place in human society

Wetlands are, and always have been, of importance to humankind. Early civilizations recognized wetlands for their natural abundance and productivity. Archaeological evidence in New Guinea indicates that the peoples of Kuk swamp undertook several episodes of wetland agriculture from 9,000 through to 2500 b.p. At roughly the same time, the earliest farmers in ancient Greece established civilizations using the natural irrigation of river and lake floodplains of Thessaly plain (Bayliss-Smith, 1996; van Andel & Runnels, 1995). In medieval England, agriculture relied upon the flooding of low-lying meadows to improve the early spring growth of grass, thereby increasing overall annual stock rates (Cook et al., 2003). Similarly other peoples, like the "marsh" Arabs of the Tigris-Euphrates wetlands, the west Africans of the Niger Valley and the inhabitants of the Mekong delta, have for centuries continued to reap and modify their wetland areas (Madaley, 2002; Williams, 1994). A detailed description of the biological, hydrological, social and economic services which wetlands provide is found in Appendix A.

Historically, wetlands have been often viewed as a resource for the taking and to be modified for human needs. The increased mechanization of the industrial revolution provided the means whereby wetlands could be drained, dyked and built upon (Williams, 1994). In the Middle Ages, people in the Netherlands systematically drained wetlands for agriculture and built the Rotterdam port on reclaimed land to become one of the major agricultural exporters in Europe (Dugan, 1990; Gedan et al., 2009; Knottnerus, 2005). Wetland reclamation was encouraged by early medical theories which associated diseases, such as cholera and the Black Death, with miasmata or the "bad air" of mires, marshes and bogs (Gardiner, 1994) further contributing to losses of wetland habitat, particularly in Europe. There over time, it has been estimated that 40% of Brittany's coastal wetlands have vanished, 60% of the United Kingdom's wetlands have been destroyed and 70% of Portugal's Algarve region has been drained (Williams, 1994). In Australia, European settlement has gravitated to coastal regions, which has impacted significantly coastal marshes and mangroves, particularly in Queensland and New South Wales where losses since the

World War 2 have been reported as up to 70% (Harty & Cheng, 2003; Saintilan & Williams, 2000; Sinclair & Boon, 2012).

Finlayson and Spiers (1999) spotlight agriculture as the principal cause of global wetlands loss. They estimate that in Europe and North America 56-65% of available wetlands had been drained by 1985, along with 27% losses of wetlands in Asia, 6% in South America and 2% in Africa. However, as Finlayson and Spiers (1999) point out, global losses are difficult to quantify due to differences in comparing timeframes and scales of analyses, the various techniques used to collect and interpret basic data, and what is considered to be a wetland. For instance, many wetland types such as salt marshes, coastal flats, seagrass meadows, karsts and vaces, reservoirs and artificial wetlands, such as rice paddies in Asia, may not be included in the inventories under comparison. Finlayson and Spiers (1999, p.8) concluded that "The loss of wetlands worldwide has been estimated at 50% of those that existed in 1900 – a figure that includes inland wetlands and possibly mangroves, but not large estuaries and marine wetlands such as reefs and seagrasses". In the earlier part of the 20th century significant wetland losses occurred in the northern temperate zones due to land-claim for agriculture. Later in the 20th century, losses of tropical and subtropical wetlands, particularly swamp forests and mangroves, were due mainly to aquaculture and coastal developments (Boon et al., 2011; Gedan et al., 2009). Given that originally wetlands represented only 6% of the earth's surface, the disappearance of over half that means "wetlands are probably even more endangered than tropical forests" (Meadows et al., 1992, p.64).

With the awakening of the environmental movement in the late 1960s, the shrinking of the world's wetlands and the losses of other natural habitats did not go unnoticed. In 1972 the United Nations' Stockholm conference penned the Declaration on the Human Environment. The Declaration spelt out the right of each state to exploit their own resources for economic and social development together with a state's associated responsibilities to make resources available for the preservation and improvement of the environment so that it may be protected for future generations (Aplin, 2002). As a result of this conference, the United Nations Environment Programme (UNEP) became established in 1974 to "provide leadership and encourage partnership in caring for the environment by inspiring, informing and enabling nations and peoples to improve their quality of life without compromising that of future generations" (UNEP, 2013). By 1980, a World Conservation Strategy (WCS) was formulated by the International Union for the Conservation of Nature and Natural Resources (IUCN)[1], in conjunction with the World Wildlife Fund, other experts from around the world, government bodies and non-government bodies (NGOs). The Strategy's emphasis was on strengthening of national capacity to undertake conservation activities in a cross-sectoral and interdisciplinary manner, with a focus on the underlying causes, as well as the symptoms of the problems (Aplin, 2002).

In 1983, the United Nations established the independent World Commission on the Environment and Development (WCED) to deal with environmental concerns at the international level and to formulate long-term strategies for sustainable development (United Nations, 1983). Subsequently, the 1992 United Nations' Conference on the Environment and Development (UNCED) in Rio de Janeiro produced two significant documents: the Rio Declaration; and Agenda 21. The Rio Declaration set out "27 principles to govern economic and environmental behaviour of both nations and individuals" and the Agenda 21 listed the most important environmental principles and concerns that were agreed to by 178 world governments (Aplin, 2002; United Nations, 2009). These commitments were reviewed in 1997 and subsequently reaffirmed at the World Summit on Sustainable Development in 2002.

Against this backdrop of growing global environmental commitment, the first and most significant step in halting worldwide wetland losses came during 1971 in the small Iranian town of Ramsar, where The Convention on Wetlands of International Importance was signed (Dugan, 1990). The Ramsar Convention, as it is now commonly known, was the first modern inter-governmental treaty between states aimed at conserving natural resources through wise use and management (Department of Sustainability, Environment, Water, Population and Communities [DSEWPC], 2013b; MacDonald, 1997). Its major objectives are the prevention of wetland losses and conservation of existing wetlands (Kruchek, 2003). As the first signatory in

[1] Founded in 1948, the IUCN is a global conservation network of over 1,000 member organizations, inclusive of government and non-governmental organizations (NGOs), research institutions, and conservation agencies with representation in over 160 countries (IUCN, 2009).

1974, Australia took on a key role in identifying Ramsar sites and listed the first in 1974 with Cobourg Peninsula, Northern Territory (DSEWPC, 2013a; Yeend, 2004). Today Australia has 64 Ramsar sites covering 8.1 million hectares, of which 14 are located in Victoria. Worldwide there are 159 Contracting Parties to the Convention committed to the protection of 2,098 separately listed Wetlands of International Importance which cover collectively 205 million hectares (Ramsar, 2013).

Signatories to the Ramsar Convention take seriously their obligations under the treaty (Verschuuren, 2008; Vriesinga, 2008). The current Mission Statement of the Ramsar Convention Parties states unambiguously “The Convention’s mission is the conservation and wise use of all wetlands through local and national actions and international cooperation, as a contribution towards achieving sustainable development throughout the world” (Ramsar, 2013). The focus of the Mission Statement is twofold; the conservation and “wise use” of all wetlands under the Convention on the one hand, and, the striving for continued development on the other. The juxtaposition of these two aims points to possible contrasting positions that signatories make take in meeting their obligations under the Convention. As noted by Adam (1997), a signatory has considerable latitude in the interpretation of the “sustainable development” and “wise use” terms. This has broader implications for wetland managers attempting to resolve any inherent contradictions or tensions in meeting the two aims at a local level (Kruchek, 2003; Vriesinga, 2008).

2.2 Wetland definitions and their application to the Australian situation

2.2.1 International definitions

Before any wetland can be conserved or its “wise use” implemented, a crucial decision as to what specifically constitutes a wetland needs to be made. This is not a simple task as there are several wetland definitions in active use and they vary considerably in breadth, context, and application (Phinn et al., 1999; Whitten & Bennet, 2005). For some authors, wetlands are simply “inland, standing (lentic), shallow bodies of water” (Williams, 1997, p.10) or “Areas of seasonally, intermittently, or permanently waterlogged soils, of inundated land, whether natural or otherwise, fresh or saline, e.g. waterlogged soils, ponds, billabongs, lakes, swamps, tidal flats, estuaries, rivers and their tributaries" (National Parks Association of New South Wales, 1988, p.1). Others describe wetlands as "Land permanently or temporarily under water or waterlogged. Temporary wetlands must have surface water or waterlogging of sufficient frequency and/or duration to affect the biota. Thus, the occurrences, at least sometimes, of hydrophytic vegetation or use by waterbirds are necessary attributes" (Paijmans et al., 1985 as used by Finlayson, 1999b, p.119). The often referenced U.S. Fish and Wildlife Service definition states that wetlands are "lands transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is covered by shallow water" (Cowardin et al., 1979). By excluding temporary waters and salt lakes, the application of Cowardin's definition to Australian wetlands is particularly problematic since it ignores the most abundant types (Boulton & Brock, 1999; Pressey & Adam, 1995).

As seen above, wetland definitions vary in their descriptions to include, to some degree or not, the permanence of water, the presence of specific biota, and reference to certain chemical processes. Broadly speaking, Whitten and Bennet (2005) note that wetlands can be described in four different ways: by using their biophysical characteristics; by the combination of resources employed; by the processes the wetlands perform; and by the outputs (benefits and harms) the wetlands produce. In their survey of currently used wetland definitions by government and non-government organizations in Australia and the United States, Whitten and Bennett (2005) found a variety of definitions including those of: Ramsar (2012); Commonwealth Wetlands Policy, Australia (Environment Australia, 1997); United States Environmental Protection Agency (2012); Ducks Unlimited (2001); and the Sierra Club (2001). Whilst Phinn et al. (1999) additionally document the U.S. Fish and Wildlife Service (Cowardin et al., 1979) and Paijmans et al. (1985) definitions they advocate, as do many others, the use of the Ramsar Convention definition as the most suitable for making global comparisons of international inventories (Finlayson & Spiers, 1999; Pressey & Adam, 1995).

The Ramsar Convention uses two Articles to define wetlands. Article 1.1 specifies that

> *"For the purpose of this Convention wetlands are areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six metres".*

Article 2.1 which allows that wetlands

> "*may incorporate riparian and coastal zones adjacent to the wetlands, and islands or bodies of marine water deeper than six metres at low tide lying within the wetlands".* (Ramsar, 2012).

Associated with these articles are groupings of defined wetland types that are broadly divided into natural or human-made sets. Natural wetlands encompass both Marine/Coastal Wetlands, consisting of 12 subtypes, and Inland Wetlands, including 20 subtypes. Additionally, there are 10 Human-made subtypes listed (Ramsar, 2012). Classification of types is predominantly based on geomorphic types and water regimes (Robertson & Fitzsimons, 2004). See Appendix B for a more complete listing of wetland subtypes.

The Ramsar Convention's definitions of wetlands and subtypes are necessarily broad so that they can encompass the wide spectrum of wetland types found throughout the world. This latitude allows for a situation where "countries have discretion in what they declare a wetland and (in) subsequent land use decisions" (Vriesinga, 2008, p.180). It is often necessary for an adaptation of the Ramsar wetland definition to be made to account for local circumstances (for an example, see Department of Environment and Resource Management, 2011). For practical purposes, Dugan (1990) suggests that a reduction of the Ramsar subtype groupings should be made to give seven landscape units: estuaries; open coasts; floodplains; freshwater marshes; lakes; peatlands; and, swamp forests, which are indeed wetlands or locations where wetlands form an important component. Williams (1997) argues that the Ramsar definition covering all inland wetlands, lentic and lotic, as well as shallow coastal waters is too broad. Based on a definition given by Bunn, Boon, Brock and Schofield (1997), Williams suggests that a restricted version of the Ramsar definition, including both permanent and temporary bodies of standing water, is more relevant to the Australian context particularly when taking an ecological view that accounts both the wet and dry phases of these ecosystems.

In his review of classification schemes, Williams (1997) categorized all wetlands, including Australian, into a number of groups including: permanent fresh waters; permanent saline waters; temporary freshwaters; and, temporary saline waters. Importantly, the majority of what is known about wetlands, their ecology and their management comes from studies of the well-watered regions of eastern North America and western Europe, where inland wetlands are typically of the permanent freshwater type. In a seminal opinion paper, Williams (1988) lamented the historical accident that saw much limnological research undertaken on permanent freshwater wetlands as it skewed wetland perspectives and decision-making worldwide and it lead to the neglect of saline and ephemeral systems. Assumptions made of wetland ecological processes and energy flows are particularly problematic when such knowledge is used to inform Australian wetlands management (Boulton & Brock, 1999). As an illustration, many accepted energy-flow models reference the importance of shredders (small chewing invertebrates) in providing nutrients and energy flows for further downstream. These models are applicable for wetlands in Northern Hemisphere deciduous forests but do not easily transpose to Australian streams with highly variable hydrology, notably less predictable leaf-fall, and far fewer shredders. Likewise, thermally dimictic lakes are rare in Australia, yet many accepted concepts concerning sediment chemistry, nutrients and hydro-dynamics are based on dimictic thermal models derived from the northern hemisphere (Boulton & Brock, 1999; Williams, 1988). Faunal distinctiveness aside, the reality is Australian wetlands are far more representative of the majority of the rest of the world's wetlands than are the permanent freshwater wetlands of western Europe and Williams (1988, p.410) notes that "The River Murray is more like the Nile than the Thames is!"

2.2.2 An Australian perspective on wetlands

Australia has a rich endowment of wetlands, despite being often described as the "driest inhabited continent" (Boulton & Brock, 1999, p.18). The variety and uniqueness of the Australian wetland types is due to the vastness, flat topography and dryness of most of the continent (McComb & Lake, 1990). Low average rainfall, of less than 500 millimetres rain annually for two-thirds of the continent, coupled with high evaporation rates ensures that temporary wetlands are the norm. Although montane wetlands and permanent lakes exist in Australia, it is far more common to find rivers and streams flowing inland and draining into salt lakes. Usually, flows are intermittent and waterways fill and flow only seasonally, or in other cases after rare rainfall events (Australian Society for Limnology, 2004; Boulton & Brock, 1999).

Human inhabitation on the Australian continent has existed for at least 40,000 years. Aborigines seasonally harvested wetlands for fish, eel, birds and their eggs, turtle, snake, goanna, crab, worms, freshwater mussels, clams, oysters, seeds, and the rhizomes of various plants (Kingsford, 1997; McComb & Lake, 1990). Some 220 years ago Europeans colonized Australia, arriving with a set of agricultural and land-management traditions better suited to their wetter homelands. Over time, poor land-management and water-management practices have resulted in about 50% of wetlands Australia-wide having undergone major modifications (Natural Heritage Trust, 2002) with losses in Victoria for the years between 1830 and 1990 at 33% (Buisson & Bradley, 1994, p.38 quoting data from Dugan, 1993). The effects have been particularly noticeable in the Murray-Darling river basin where altered flow regimes have resulted in 90% loss of floodplain wetlands, further evidenced by dramatic declines in waterbird numbers (Beeton et. al., 2006; Kingsford & Norman, 2002; Schrobback et al., 2011; Spencer et al., 1998).

In the least-settled areas and in more remote regions, particularly in the monsoonal north of Australia, many wetlands remain relatively unaltered and in near-pristine condition. These wetlands are of international significance. Recognizing this, and the importance of protecting and managing all its wetland resources, Australia was the first country to join the Ramsar Convention, by signing in 1971 (Environment Australia, 1997; MacDonald, 1997). Likewise, Australia was an early signatory to the WCS adopting a National Conservation Strategy in 1984, which gave widespread political and public exposure to the concept of sustainable development (Alpin, 2002).

The Ramsar Convention provides a suitable framework for the national protection of wetland resources. As mentioned earlier, Ramsar wetland definitions are broad, allowing for local interpretation and adaptation (Bowman, 2002). In Australia, a revision of the Ramsar Convention classification scheme has been made to account for water regimes, salinity and vegetation. The Australian Directory of Important Wetlands (Environment Australia, 2001, Appendix 1) identifies 40 different wetland types within three categories: marine and coastal zone wetlands; inland wetlands; and, human-made wetlands (Department of Sustainability and Environment [DSE], 2012). Notable additions to the Ramsar scheme include non-tidal freshwater forested wetlands and freshwater springs, oases and rock pools (Australian Society for Limnology, 2004). Each state and territory uses the Directory and its classification scheme as the commencing framework for their own wetland classification schemes. A review of the different State-wide approaches is detailed in Pressey and Adam (1995).

2.2.3 Victorian wetlands and their classification

Located in the south-east of the continent with a temperate, winter-rainfall climate, Victoria is the smallest (227,600 km^2) and most densely populated mainland State of Australia with approximately 5.6 million people (Australian Bureau of Statistics, 2012). Relative to the rest of the mainland, Victoria is comparatively well-watered (Traill & Porter, 2001) and the State holds 159 wetlands recognized as being of national importance (Environment Australia, 2001). Of these wetlands, 11 wetland systems are listed as Ramsar sites of international importance. Recent surveys show that 57 of the 159 nationally important wetlands have threatened water regimes and the remainder are under threat of continual degradation due to salinity, drainage problems and agricultural practices (Beeton et al., 2006; Environment Australia, 2001).

In meeting the Commonwealth's Ramsar obligations, funding over recent years has gone to the setting up of a State-wide wetland inventories (pre-European estimate and current) and to the establishment of specific aquatic protected areas. Amongst the States, Victoria is the recognized leader in developing wetlands conservation policy and its commitments include the State Conservation Strategy, 1987; Biodiversity Strategy, 1997; and, the Healthy Rivers Strategy, 2002-3. Failings in the implementation of these listed Strategies have occurred as pointed out by the

Australian Society for Limnology (2004, p.86 for detail) and an Auditor-General's Report on Environmental Flows during Water Shortages (Victorian Auditor-General, 2010), so much work remains to be done.

In 1992 as part of a process to develop a State-wide inventory, all wetlands larger than 1 ha were mapped and classified by the Department of Conservation and Environment [DCE] (1992b). By 1995, more than 16,000 naturally occurring wetlands (>1 ha) were recorded (DSE, 2013b). During this process, two classification schemes were used to categorize wetlands types: Ecological Vegetation Classes (EVCs) and the Corrick and Norman (1980) scheme. The first scheme classifies on plant assemblages and the later relies primarily on hydrologic characteristics in distinguishing different categories of wetland, then secondly on floristics to discern subcategories.

The EVC scheme categorizes all native vegetation types in Victoria, including wetland types, according to the type(s) of EVC present; it represents distinct and identifiable collections of native floristic communities, which commonly cohabit and interact together with their environment. Thus, an EVC description includes a floristic description with its associated altitude, topography, geology and soils (DSE, 2013a). In an effort to provide a meaningful native vegetation classification system across Victoria, EVCs have been classified into 20 broad groupings and 34 sub-groupings in which relate to a range of attributes including climate, soils, and vegetation (DSE, 2013b; King et al., 2001). Until recently, wetlands were poorly represented within the EVC groupings as conventional floristic analyses, reliant upon species diversity, was used discern separate wetland plant communities (Davies et al., 2002). A revision of this "species-richness" approach to a method that uses individual species' tolerance to inundation within a floristic community has resulted in the identification of 127 wetland EVCs (DSE, 2013a).

In the Corrick and Norman scheme, there are seven categories of naturally occurring wetlands; they have been indexed with numbers from 1 to 7, as shown in Table 2.1 (Corrick & Norman, 1980; Corrick, 1981). Based essentially on hydrologic features, the primary categories are separated by differing characteristics of salinity, depth and period of inundation. Vegetation types form subcategories (DSE, 2012). The number of hectares of each wetland type in Victoria on public and private lands is given in

Table 2.2. In reading Table 2.1 and Table 2.2, it is important to note marine beaches, bed and banks of a stream, creek or river, reservoirs, farm dams, or other dams for the supply of water, land that is periodically irrigated for agriculture, artificial water supply and drainage channels are not considered under this classification scheme.

Table 2.1: The Corrick and Norman (1980) wetland classification scheme for the south-east region Australia. The table has been adapted from Corrick and Norman (1980) and Corrick (1981) as presented by Heron (1989, p.5, Table 2) and Centre for Environmental Management (2005, p.9, Table 2.3).

Category	**Depth**	**Period of Inundation**	**Subcategory**
1. Flooded River Flats	< 2 m		
2. Freshwater Meadows	0.3 m	< 14 days	2.1 Herb-dominated 2.2 Sedge-dominated 2.3 Red gum-dominated 2.4 Lignum-dominated
3. Shallow Freshwater Marshes	0.5 m	6-8 months	3.1 Herb-dominated 3.2 Sedge-dominated 3.3 Cane grass-dominated 3.4 Lignum-dominated 3.5 Red gum-dominated
. Deep Freshwater Marshes	< 2 m	Remain inundated during years of average or above average rainfall	4.1 Shrub-dominated 4.2 Reed-dominated 4.3 Sedge-dominated 4.4 Rush-dominated 4.5 Open water 4.6 Cane grass-dominated 4.7 Lignum-dominated 4.8 Red gum-dominated
5. Permanent Open Freshwater	> 1 m	Permanent	5.1 Shallow (<2m) 5.2 Deep (>2m) 5.3 Impoundments
6. Semipermanent Saline Wetlands	0.5m varies	Varies 3-5 months only during winter	6.1 Salt pan 6.2 Salt meadow 6.3 Salt flats 6.4 Sea rush-dominant
7. Permanent Saline Wetlands	Varies	Varies	7.1 Shallow (<2m) 7.2 Deep (>2m)

Table 2.2: The number of hectares of wetland types using Corrick and Norman (1980) classification scheme on public and private landholdings. Source: Traill and Porter (2001).

Victorian Wetlands Extent		
Wetland category	**Public wetlands (ha)**	**Private wetlands (ha)**
Freshwater meadow	36.465	78,636
Shallow freshwater marsh	20,869	33,523
Deep freshwater marsh	34,164	19,617
Permanent open freshwater	173,689	16,520
Semipermanent saline	49,510	18,366
Permanent saline	145,069	2,938

The use of both classification schemes in Victoria has been considered progressive in other jurisdictions, but neither scheme is without its failings (Davies et al., 2002; Fitzsimmons & Robertson, 2005; Robertson & Fitzsimmons, 2004; Sainty & Jacobs, 2003). As mentioned above, in practice EVC mappings do not represent wetlands well (Traill & Porter, 2001) and, in fact, broad-scale vegetation analyses generally fail to describe freshwater ecosystems (Australian Society for Limnology, 2004), and misrepresentations can occur (Robertson & Fitzsimmons, 2004). In a comparative study undertaken where both EVC mappings and Corrick and Norman classification scheme were used in the Wimmera bioregion, very different conclusions were reached (Fitzsimmons & Robertson, 2003). All wetland types were identified as significantly depleted with less than 20% remaining when the EVC classification was used, whereas the Corrick and Norman classification scheme showed no wetland type as depleted by more than 50% (Robertson & Fitzsimons, 2004, Figure 1). Since the two schemes grade and classify using differing qualities, being floristics versus hydrology, it should not surprise that results differ so widely. It is essential for wetland management to be cognizant of strengths and weaknesses of any classification system being used for decision-making.

2.3 Scale of wetland loss in south-eastern Australia

Although Australia was an early signatory to the Ramsar Convention and the World Conservation Strategy (WCS), historically Australian governments have favoured rural and urban developmental uses of wetlands over those of conservation and environmental stewardship (Alpin, 2002; Kingsford, 2000 & 2003). The 200 years of European-style settlement in Australia has seen wetlands routinely drained and filled for conversion to more intensive agricultural land (Traill & Porter, 2001). In 1990, 60% of Australia's land surface was being used for grazing domestic livestock with livestock managers viewing wetlands simply as available watering points (Wilson, 1990). Consequently, poor grazing practices are one of the major causes of long-term modification of Australian wetlands (Robertson, 1997) and Yencken and Wilkinson (2001, p.360) note that "Some of our most pressing problems are the loss of biodiversity, land degradation and disturbances to inland water regimes".

Aside from agricultural development, wetlands have been drained in Australia for urban growth and industrial expansion, land-claim, recreational development, river regulation for irrigation, and hydroelectricity (Boon et al., 2011; Buisson & Bradley, 1994; Gedan et al., 2009; Saintilan & Williams, 2000; Sinclair & Boon, 2012). The full value and ecological importance of wetlands has been largely ignored; they have been seen as waste areas harbouring mosquito infestations, algal blooms, environmental weeds, introduced fish (notably carp), and feral animals (such as pigs, buffalo and wild horses). Where wetlands have been seen as areas ripe for development, Adam (1985, p.5) notes "the popularity of the coast for recreation and retirement makes it inevitable that proposals for canal estates, marinas and holiday resorts continue to appear" and that these developments have impacted upon local biodiversity and cause disruption of ecological pathways (Ticehurst et al., 2007). There is increasing political debate about the continued investment that will become necessary to protect coastal infrastructure and reclaimed agricultural land from rising sea levels (Dugan, 1990). Canal estates built around marinas can have problems with water circulation and the flushing of canals whilst dredging removes reed beds and other habitats. Through the loss of buffer zone functions, hydrological works to prevent flooding come necessary, which in turn often result in accelerated sedimentation accompanied by invasive weed species (Gardiner, 1994).

In Victoria, good arable land rapidly attracted European settlement, which has resulted in the widespread alteration, degradation and fragmentation of land, water, and biodiversity resources (Lindenmayer, 2007; Traill & Porter, 2001). Estimates suggest that since 1860, when land selection began, almost 4,000 natural wetlands, approximately one-third of wetland area (191,000 hectares) have been lost, attributed primarily to drainage for agricultural purposes (DCE 1992a, 1992b; Finlayson, 2000). Victoria's wetlands have shrunk from 725,600 to 531,200 hectares with over 90% loss of wetlands being on private land (Beeton et al., 2006; DCE, 1992a; Spiers & Finlayson, 1999). Remaining are approximately 16,700 non-flowing wetlands, of which 12,800 (covering 432,800 hectares) are natural. These represent a wide diversity of type including: alpine bogs; floodplain billabongs; red river gum forests; coastal tea tree swamps; large open lakes; estuaries; intertidal mudflats; and, inland salt lakes (Department of Natural Resources and Environment [DNRE], 1997; DSE, 2012; Victorian Catchment Management Council, 2007). By number, 79% of wetlands in Victoria are privately owned, and 50 % of Victoria's threatened vegetation types are found almost entirely on private land (Beeton et al., 2006 quoting Davis et al., 2001) as evidenced in Table 2.2 with greater areas of freshwater meadows and shallow freshwater meadows located on private properties (Traill & Porter, 2001).

Against this backdrop, the first steps to arrest continued wetland losses came between 1988 and 1992 with the Victorian government's Wetlands Conservation Program. Building upon earlier surveys, the Program undertook a State-wide wetland inventory and classification with the aim of identifying high-value wetlands and providing wetland management guidelines (DCE, 1992a; Jensen, 1997). At the time, draining of wetlands was identified as the biggest threat and the Program required that wetlands, whether publicly or privately owned, be managed to provide conservation, social and economic values to the Victorian community (Government of Victoria, 1988). The Program raised public awareness of wetland values and issues, but today after several changes in government later, wetland policy is guided essentially by the requirements of international conventions, national strategies and partnerships and State legislations including:

- The Ramsar Convention;

- Japanese Australia Migratory Bird Agreement (JAMBA);
- Chinese Australia Migratory Bird Agreement (CAMBA);
- Republic of Korea on the Protection of Migratory Birds Agreement ROKAMBA 2007;
- National Strategy for the Conservation for the Conservation of Australia's Biodiversity;
- Flora and Fauna Guarantee Act 1988;
- The Catchment and Land Protection Act 1994;
- Coastal Management Act 1995; and,
- Victorian Water Act 1989.

There are a number of programs in Victoria for protection of wetlands through reservation, and rehabilitation activities together with public education and awareness schemes (Natural Heritage Trust, 2002; DSE, 2013b). Underpinning all these activities is the need for reliable data upon which to make scientifically grounded management decisions to achieve "sustainable development" and "wise use" and of all Victorian wetlands.

2.4 Wetland value assessments and ranking approaches

According to the 2005 Conference of Contracting Parties to the Convention on Wetlands, the first necessary steps in the protection of wetlands to be undertaken are inventory, assessment and monitoring. Specifically, the Ramsar Convention (Ramsar, 2005, point 17) defines each as:

Wetland inventory: *The collection and/or collation of core information for wetland management, including the provision of an information base for specific assessment and monitoring activities.*

Wetland assessment: *The identification of the status of, and threats to, wetlands as a basis for the collection of more specific information through monitory activities.*

Wetland monitoring: *The collection of specific information for management purposes in response to hypotheses derived from assessment activities, and the use of these monitoring results for implementing management.*

The primary focus of my research is centred on wetland assessment, which is detailed in a following subsection. Inventory, as the necessary precursor for assessment, is described in the next subsection. Although an important process, monitoring is not detailed further in this chapter since its goal is to inform and guide wetland management after assessment has been conducted. However, the research outcomes will have implications for monitoring programs, and these will be discussed in Chapter 7.

2.4.1 Inventory

Making an inventory of wetlands is the necessary first step upon which to base managerial decisions. Inventory work is needed to identify the number, types and condition of wetlands and to evaluate any threatening processes and management opportunities in protecting them (Claus et al., 2011a; Davidson & Finlayson, 2007; Frankiewicz & Wainwright, 2009; Natural Heritage Trust, 2002; Rebolo et al., 2009; Stevens, 2009). Although it is widely acknowledged that a good inventory is a necessary antecedent to assess wetland resources, historically only parts of North America and Western Europe have adequate past and current inventories upon which decisions are based. In their survey of existing wetland inventories, Finlayson and Spiers (1999, p.6) lamented "of 206 countries or territories for which the state of inventory was assessed, only 7% have adequate or good national inventory coverage. Of the remainder, 69% have only partial coverage, and 24% have little or no national wetland inventory…. Thus we do not yet know globally what wetlands we have and how important they are, even as they are being degraded and lost". Therefore, as recognized by Resolution VII.20 at the 1999 Conference of Ramsar Contracting

Parties, there remains an urgent need for wetland inventories and studies of wetland loss and degradation around much of the world (Ramsar, 1999b; Rebolo et al., 2009).

In Australia, there is a national need for a comprehensive, consistent and up-to-date information base upon which to base planning decisions (Davidson & Finlayson, 2007; Finlayson et al., 2005; Lowry & Finlayson, 2004; Spiers & Finlayson, 1999; Williams, 1997). There two issues associated with the classification and mapping of wetlands that make the task of wetland inventory difficult. Firstly, there is much dispute about what constitutes a wetland, where its boundaries are, and what processes need to be observed. This issue has been discussed earlier in this chapter. Secondly, the choice of classification system used to describe specific wetlands types has a profound impact on the identification and mapping of wetland assets, and thus subsequent conservation decisions based on those identifications (Ling & Jacobs, 2003).

Robertson and Fitzsimons (2004) addressed this second matter by investigating the impact of using the two different Victorian wetland classification systems in deciding conservation status of various Victorian wetlands in geospatial datasets maintained by the Victorian Department of Sustainability and Environment. Their work and analyses highlight the differences of the two schemes in identifying wetlands, their types, extent and overall conditions, as well as recording the general inefficiency of EVCs in delineating wetlands recognized using the Corrick and Norman scheme (1980). Another important issue to consider when undertaking wetland inventory is the often transient nature of wetlands that comes into play when factors, like the amount of inundation, have strikingly varying influences at different times. For instance, the wetlands in the salt lake regions of central Australia only fill episodically and are dry for much of their existence. Additionally, once the nature and size of a wetland is determined, there can be a great deal of uncertainty in trying to quantify its ecological condition and the effects of possible threats may have upon a given wetland, making ecological assessments even more difficult (Pollino et al., 2006; Stevens, 2009).

2.4.2 Assessment

Condition, or more specifically, ecological condition is used to indicate the "state" of a wetland; it encompasses all of the "biological, physical, and chemical components of the wetland ecosystem, and their interactions, which maintain the wetland and its products, functions, and attributes" (Ramsar, 1999a). This definition implies, inadvertently or otherwise, the real-world existence of an ideal benchmark or reference wetland site that can be measured, described and referenced against for wetlands of inferior through to superior conditions (Department of Environment and Conservation [DEC], 2008; Spencer et al., 1998). Not surprisingly, there is little consensus on what constitutes a good reference site; experts cannot agree on the desirable wetland condition qualities, and nor can they agree on how they can be adequately measured (Boon et al., 2011; DSE, 2007 & 2012; Fairweather, 1999; Stoddard et al., 2006). Assessments usually involve a scoring or weighting system of different indicators or variables present during the snapshot of a single site visit (Claus et al., 2011b; Daniel, 2009; DEC, 2008; Spencer et al., 1998). Given the transient nature of most Australian wetlands, it is often difficult to assess alteration of condition as being within normal temporal variation, or otherwise (Boon et al., 2011).

Traditional assessments using indicators

Traditional condition assessments are based upon a set of indicators that can be applied broadly across differing wetland types. The identification of a suitable suite of useful indicators over differing geographic regions has occupied much of the literature (Cowardin & Golet, 1995; Fennessy et al., 2004; Finlayson et al., 2005; Hruby, 1999 & 2001; Ling & Jacobs, 2003; Lu, 1995; Pressey & Adam, 1995; Spencer et al., 1998; Stander & Ehrenfel, 2009; Thiesing, 2001). For instance, Finlayson et al., (2005, Table 2) lists minimum data fields for biophysical and management features of wetlands in northern Australia that use, singularly or in various combinations, hydrology, vegetation structure and floristic components, physical and geomorphic characteristics, and land usages in their wetland assessments. Boon, Raulings, Morris, Roache and Bailey (2005) note for groundwater-dependent ecosystems in Australia, that a national review strongly recommended groundwater hydrology becomes a standard part of wetland assessments and that the threats of salinity, acid sulphate soils, turbidity, and nutrient enrichment should be included. More recently, there has been an effort to measure the performance of protection programs for inland rivers and wetland made under the National Action Plan and the Natural Heritage Trust. Wetlands indicators under discussion include the extent of inundation; dissolved oxygen and temperature; transparency and colour; nutrients (phosphorus and nitrogen); vegetation; phytoplankton; marcoinvertebrate index; macroinvertebrate indicator species; and, macroinvertebrate diversity and community composition (DSE, 2012).

Currently, best practice assessments of ecological condition usually include some analysis of wetland structure including plant (phyla, genus or species) dominance, a measure of ecological function through the measurement of key biological, hydrological and chemical processes, and an incorporation of value humans place upon the wetland (Boon et al., 2011; DEC, 2008; Stevens, 2009). The scale of the assessment prescribes the approach and tools used to conduct the assessment (Finlayson et al., 2005, Figure 2). For instance, landscape level assessment dictates the use Graphical Information Systems (GIS) for collection and processing data (Rebelo et al., 2009), whereas intensive site assessment focuses on the details of an individual site (DEC, 2008). For assessment of conditions at numerous wetland sites, typically across a stream catchment, the use of relatively simple observations and records to assess ecological condition is called rapid assessment (Daniel, 2009; Lui, Frazier et al., 2006). This thesis is primarily concerned with wetland classification and evaluations based on data collected through the process of the rapid assessment over a geographically defined stream catchment area.

Rapid assessments

The Ramsar view is that rapid assessment involves “methods that have been adapted to permit the adequate collection, analysis and presentation of the assessment information when this information is urgently needed. It may also involve the rapid collection of “baseline” wetland inventory information” (Ramsar, 2005, paragraph 52). In describing rapid assessment, the adjective “rapid” is used to indicate the use of techniques that speed the assessment of individual wetlands within a larger group, and some sense of urgency for the outcomes. It does not imply that the process is simplistic or done with unnecessary haste, although in practice it may be constrained within a specific timeframe (DCE, 2008). Rapid assessment is a non-trivial, standardized, repeatable and cost-effective monitoring of ecological conditions of sites over large areas (Finlayson, 2003). Its intent "is to evaluate the complex ecologic condition of a natural ecosystem using a finite set of observable field indicators and to express the relative condition of a particular site in a manner that informs ecosystem management" (Sutula et al., 2006, p.158).

In describing some of the tasks within rapid assessments, paragraph 54 of Resolution IX.1 Annex E lists that "rapid assessment of wetlands include(s):

a. Collecting general biodiversity data in order to inventory and prioritize wetland species, communities and ecosystems, obtaining baseline biodiversity information for a given area;

b. Gathering information on the status of a focus or target species (such as threatened species); collecting data pertaining to the conservation of specific species;

c. Gaining information on the effects of human or natural disturbance (changes) on a given species;

d. Gathering information that is indicative of the general ecosystem health or condition of a specific wetland ecosystem; and,

e. Determining the potential for sustainable use of a biological resources in a particular wetland ecosystem". (Ramsar, 2005).

A necessary precursor to undertake these steps is the identification of the parameters and indicators that will be used to assess the ecological condition of wetlands under study (Claus et al., 2011b; Spencer et al., 1998; Stevens, 2009). Typically, these indicators are incorporated within a scoring system for use in making site comparisons and rankings. Ideally, the scoring system should, in some way, account for the wetland structure, its ecological function, condition and services it supplies; it may include risk assessments of biophysical pressures likely to impact upon ecological function (Daniel, 2009; Finlayson et al., 2005; Gitay et al., 2011; Lynch, 2011). As well, it is important to incorporate some measure of human perceptions of a wetland's value including the social, economic and environmental services afforded by the wetland (Alpin, 2002; Beeton et al., 2006; Finlayson & Weinstein, 2008).

2.4.3 Ranking procedures and decision support tools

For any wetland conservation or management effort, it is important to know the extent, condition and value of the resource as the basis from which to guide protection, investment decisions and monitoring efforts (Claus et al., 2011b; DSE, 2007; Finlayson et al., 2005; Ramsar, 2005). Regardless of whether traditional or rapid assessments are used to quantify these values, inventory data needs to be collected on the range of physical, chemical, hydrological and biological processes during wetland site visits. Once site data has been collated and validated, it is used to supply values for the various components of the scoring system being used to rank the ecological condition of the wetland sites so that individual high-value sites can be identified for conservation investment.

Current approaches

The most common current method of ranking wetlands is the triple-bottom-line approach, and instances of its application abound in the natural resource management literature (Argent, 2004; Christen et al., 2011; Claus et al., 2011b; Goonetilleke & Yigitcanlar, 2010; Harris, 2002; Schrobback et al., 2011). Originating over 15 years ago in organizational business language as "people, planet, profit", this approach attempts to quantify measures of social, environmental, and economic values for a wetland site. Assessments of these three values are underpinned by, and are directly influenced by the biological community, its processes and health under investigation (Schrobback et al., 2011) and many scoring schemes use inventoried data to estimate the risks and different levels of threat to these values for wetlands under assessment (Claus et al., 2011b; Finlayson et al., 2005; Frankiewicz & Wainwright, 2009).

Decisions made using the triple-bottom-line approach invariably involve managers making value judgements and guesstimates as to the true ecological condition of the wetlands under study, the inherent risks or potential environmental effects of probable threats upon them, and the vulnerability of a system to withstand change (Dale et al., 2010; French & Geldermann, 2005; Gitay et al., 2011; Schrobback et al., 2011). There is a great assortment in the complexity of methods used in wetland assessments along with trade-offs made in gauging differing ecological, social and economic demands, threats and vulnerabilities (Claus et al., 2011a; DEC, 2008; DSE, 2005b;

Gitay et al., 2011; Jensen, 1997; Schrobback et al., 2011; Springate-Baginski, et al., 2009; Stevens, 2009). For instance, the hydrogeomorphic (HGM) wetland classification system uses hydrology and geomorphic features to define and describe wetland characteristics and condition (Brinson, 1993). Founded on observed relationships between hydrogeomorphic processes and floodplain functions in the well-watered regions of Northern America, HGM classifies wetlands according to their location, source of water and hydrodynamics (Franklin et al., 2009). HGM has been broadly adopted and applied but over time it has been adapted and shaped to account for effects of vegetation, soil pH and texture and how these impact wetland function (Cole, 2006; United States Department of Agriculture [U.S.D.A], 2008). Elsewhere, human activity and interactions with wetlands have been the focus of assessment efforts. In particular, the Millennium Ecosystem Assessment undertook a four-year international investigation in an attempt to quantify the world's wetlands and water assets and record changes in their condition. The assessment covered all types of wetlands described by the Ramsar Convention, and it considered multiple scales on which human influence on the chemical, biological and physical attributes of wetlands (values) and the functions and products that wetlands provide were measured. The assessment put forward a set of possible scenarios or futures for wetland ecosystems under different world orders (globalized or regional) using approaches to either reactive or proactive management practice as a framework in which to make forecasts of the effects of human decision making on future wetland services (Millennium Ecosystem Assessment, 2005).

These examples demonstrate that undertaking assessments and rankings to decide high-value wetlands is not for the faint hearted. It is an involved and complex process that should be fit for purpose. Often the process consumes a great deal of time and generates much controversy (Finlayson, 1999a; Finlayson & van der Valk 1995; Goosen et al., 2007). In fact, the degree of difficulty in making wetland assessments was explored in a workshop where three synthesized wetland cases were used as a framework for experts to discuss priorities and rules used in decision-making (Finlayson et al., 2004). In this case, as in others, it was found that the experts' wetland assessments comprised two components: evaluation and risk assessment. In the evaluation process, biophysical, socio-economic, institutional and governance criteria were used to prioritise wetlands, and that a main issue for participants was the need to create a hierarchy within these criteria to arrive at a final ranking.

Novel emerging approaches

The assessment and ranking of wetland sites across a catchment area necessarily involves the collection of large amounts of data on a variety of biological, hydrological, chemical and geological indicators from which wetland value can be ascertained. To support this process, a computer database is almost always used for data storage and ease of retrieval and querying. The computer has the potential to be used for so much more. Twenty-five years ago, Noble discussed the likely positive impacts upon vegetation science and ecology through the application of mathematical, statistical and computing algorithms (Noble, 1987). When databases are coupled with other modelling software to rank various alternate scenarios, such systems are known as “decision support systems” (Environmental Modelling and Software, 2007; Goosen et al., 2007; McIntosh et al., 2007; Mowrer, 2000). A well-known, Australian example for use in planning reserve systems is Marxan (formally known as Spexan), which was developed by Ball and Possingham (Marxan, 2005) and uses simulated annealing (Kirkpatrick et al., 1983) for its search strategy. Marxan suggests multiple alternate reserve design solutions which meet user-defined biodiversity targets at a minimum cost. In its setup stage, the software relies, amongst other things, upon appropriate planning units being chosen, reserve costs and boundary arrangements being specified and conservation targets being detailed. Marxan has been used by the Great Barrier Reef Marine Planning to assist in determining rezoning plans (Ball et al., 2009) and by others (Klien et al., 2009) to develop an Australia-wide conservation prioritization at subcatchment level that cost effectively meets specific wilderness quality and biodiversity representation targets.

Before using any decision support system, it is necessary to understand and account for the real-world system being modelled (Environmental Modelling and Software, 2007; Goosen et al., 2007). However wetland assessment, like many real-world problems, is described as a “data is rich and knowledge is poor” situation (Last & Kandel, 1999; Pedrycz, 1998) the difficulty is the identification of suitable input variables and an understanding of their interactions under various conditions (Goosen et al., 2007; Spencer et al., 1998). In such circumstances, the use of data-mining techniques holds promise, particularly where access to raw inventory data can be gained and the outcome of wetland assessments is already known, as in the WGCMA case study.

2.5 Aims of this project

Priorities for protection and restoration of wetlands should be based upon the assessment of those wetlands deemed to have the highest value and/or be in the best condition with respect to ecological, economic and social values (DSE, 2012; West Gippsland Catchment Management Authority [WGCMA], 2007). Wetland management decisions need to consider a broad range of factors in assessing the character of a wetland and its value, along with the risks/threats likely to impact upon the services that the wetland provides (Breckenridge et al., 1995; Lui et al., 2006; Ticehurst et al., 2007). As elucidated earlier, undertaking wetland assessment is a complex and difficult procedure; it is expensive, labour intensive and time consuming and it needs to be tailored to its local context. Wetland assessment is frustrated by the concerns of various wetland definitions (Section 2.2.1 and Section 2.2.2), the use of differing classification schemes involved (Section 2.2.3), the transient nature of wetlands (Section 2.4), and difficulties in deciding condition of wetlands under investigation (Section 2.3 and Section 2.4).

There are two major issues identified in the literature concerning Australian wetland assessments to identify high-value wetlands. First, there is a dearth of reliable information on the status and condition of much of Australia’s wetlands despite large investments in State data collections (Australia-wide report: Finlayson, 2000; New South Wales: Claus et al., 2011a & 2011b; Northern Territory: Duguid et al., 2005; South Australia: Stevens, 2009; Victoria: Victorian Catchment Management Council, 2007; and, Western Australia: DEC, 2008) and second, historical wetland assessments had been determined not objectively, but rather through reference to anecdotal knowledge of local conditions (Centre for Environmental Management, 2005). Recently, a group of prominent environmentalists (Morton et al., 2009) has identified one of the important “big ecological questions inhibiting effective environmental management in Australia" as "How can datasets be rigorously gathered, analysed and reported to establish environmental trend, critical thresholds, and feedbacks to management?" This thesis examines the practice of wetland assessment and investigates the contribution, and potencies, of component biological, chemical, hydrological and physical data inputs, individually and collectively, to the identification of high social, economic and environmental value wetlands as an important feedback mechanism to management in undertaking wetland assessments. The identification of minimal set of useful indicators, whose values are meaningful for the evaluation process and are easily assessed in the field, together with the quantification of any relationships amongst them, will be useful for monitoring activities and future inventory and wetland assessment cycles.

As pointed out earlier, there is a great assortment in the complexity of methods used to evaluate, score and rank wetlands, and that the classification schema also impacts high-value rankings (Fitzsimons & Robertson, 2003; Robertson & Fitzsimons, 2004). This thesis then investigates how the two wetland classification schemes used in Victoria, EVCs and the Corrick and Norman scheme, influence high-value outcomes. To do this, it was necessary to find a Victorian case study of wetland fulfilling several requirements. Firstly, the assessment process needs to have used both schemes; secondly, access to all inventoried data needs to be gained; and thirdly, final site assessment values need to be known.

An investigation of a best practice case study undertaken in Victoria's West Gippsland region during 2006 met these requirements handsomely as: a large dataset was collected that encompasses several biological, hydrological, chemical and physical site features; the details of the assessment process have been well documented, and the assessment attempts to measure site condition and take account of threats to condition; both classification schemes were used to describe individual wetland sites, and the dataset holds several instances of each wetland type; and, individual site assessments have been established for over 160 wetlands of over 1 hectare size, and there are separate economic, social and environmental values recorded for each site.

This thesis applies predictive data-mining techniques to the West Gippsland case study data. Predictive data-mining techniques marry specific input factors, and their data values, to different wetland assessment values, thereby illuminating the relationship between collected raw data values and their degree of influence on high-value wetland assessments. However as Guisan and Thuiller (2005) point out, it is the choice of the "right" data-mining technique for a given context that is of most importance. In wetland evaluation, where a mixture of quantitative and qualitative data is used, the usual statistical approaches based on analyses of variance and normally distributed data are not considered appropriate (Hruby, 1999). In this research, traditional univariate statistics are used to describe the data, and a more advanced, data-mining approach using multivariate analyses is used to find patterns (correlations, trends and clusters) within the data that highlight relationships between input variables and, in particular, help identify those relationships predicating high-value wetlands. These results indicate a minimal set of predictors from the input data for collection in the field.

In addition, this thesis investigates and identifies opportunities where efficiencies can be made in wetland classification and evaluations. The use of artificial neural networks (ANNs) is investigated as a promising data-mining strategy since they can be trained to mimic human decision-making processes and, as a black-box tool, they rely only on input and output data and not on being told of the connecting processes. ANNs are often chosen as "the weapon of choice" for handling complex ecological and biological data problems (Brosse et al., 2001; Noble & Tribou, 2007; Recknagel et al., 2006; Shanmuganathan et al., 2006; Whigham et al., 2006). They are known to cope well where other statistical approaches, such as multiple regression, fail due to non-linear relationships between variables, the presence of unusual but ecologically relevant outliers, and other problems with handling uncertainty (Brosse et al., 2001; Findlay & Zheng, 1999; Olden et al., 2006).

The steps in this investigation were to:

a. Undertake a detailed examination of a case study of a best-practice wetland assessment to document the mechanisms of data collection and the decision-making processes involved;

b. Analyse the case study's input dataset using univariate and multivariate statistical analyses to identify the most important input variables that predicate high-value wetland assessments;

c. Compare outcomes of the statistical analyses with those noted during the original case study and report any disparities;

d. Examine the effects of the two wetland classification schemes, EVCs and Corrick and Norman, in predicting high-value assessments;

e. Use a neural network approach to "data mine" biological, hydrological and physical features in the case study inventory that infer high-value assessments;

f. Assess the abilities of neural networks to automate the processing of input data and predict wetland assessments;

g. Through the statistical and neural networks analyses, pinpoint the most important factors, or collections of factors, that can be used as a minimal set for inventory collection and for monitoring purposes;

h. Evaluate the effectiveness of statistical analyses and the neural network approaches for use in wetland assessments;

i. Describe the lessons learnt from these analyses that can be applied to wetland assessments;

j. Formulate recommendations for future West Gippsland wetland assessments and monitoring efforts; and,

k. Explore the applicability of the novel approaches, multivariate statistical analyses and neural networks, to wetland assessments elsewhere.

The next chapter details the 2006 wetlands assessment undertaken by the West Gippsland Catchment Management Authority (WGCMA) in Victoria. The large inventory data collection used in the WGCMA wetlands assessment process forms the basis of this research, with analyses being done on contributing values of various hydrologic, biological, chemical and physical factors found in the dataset, and for comparisons to be made to the economic, social, and environmental value assessment outcomes for the 163 sites surveyed.

Corner Inlet, Victoria.
Image courtesy of Michelle Dickson, WGCMA

Chapter 3

Background to the WGCMA case study

To better understand how assessments of wetland value are made, it is necessary to explore the case study used in this research by surveying its input data collection, unravelling its evaluation process and noting its outcomes. The case study is based on the wetlands assessments undertaken by the West Gippsland Catchment Management Authority (WGCMA) in 2006 where the outcomes were evaluations and rankings of wetland sites for economic, social and environmental values.

This chapter locates the wetland evaluation exercise within its geographical and political contexts. It enumerates the features of the WGCMA wetland evaluation exercise that make it suitable for study before describing the steps taken to identify high social, economic and environmental value wetlands. A summary of the wetlands assessment outcomes is given, for they will used in comparison against the results of statistical and data-mining approaches of subsequent chapters. Finally, the case study evaluation is reviewed to identify the benefits and problems of traditional wetland assessments, which have lead to this research.

3.1 West Gippsland and its wetlands

The West Gippsland Catchment Management Authority (WGCMA) is one of 10 Catchment Management Authorities (CMAs) established by the Victorian government in 1994 to oversee the sustainable development of the State's water catchments. The geographic areas managed by the various CMAs are shown in Figure 3.1. The West Gippsland CMA, shaded yellow on the Victorian map in Figure 3.1, manages the Thomson, Latrobe and South Gippsland river basins, which comprise seven major catchments and 34 subcatchments, totalling 17,685 km^2 in area (Figure 3.2).

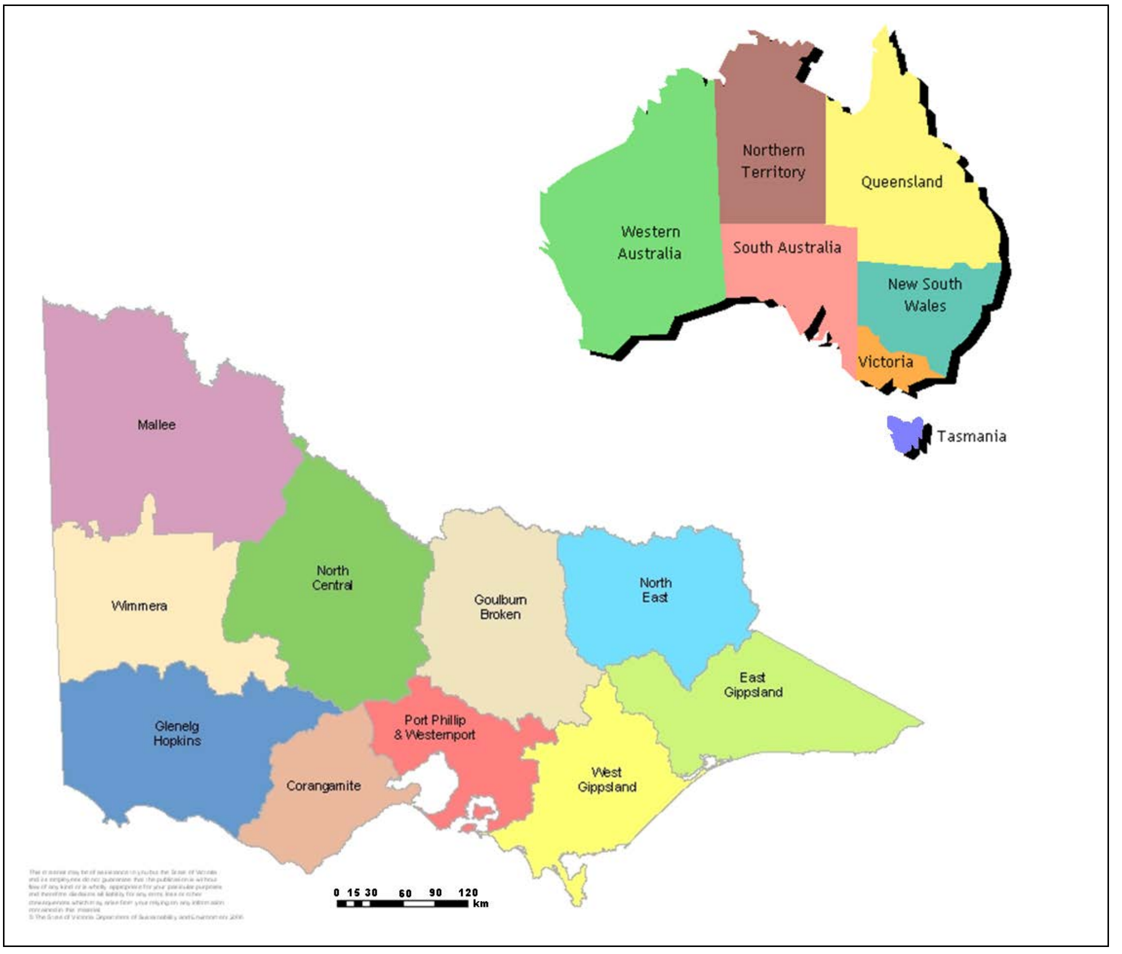


Figure 3.1: Map of Australia and map of Victoria showing the jurisdiction of each of Victoria's Catchment Management Authorities. Original maps sourced from http://wwp.greenwichmeantime.com/ website and the Victorian Department of Sustainability and Environment website http://www.dse.vic.gov.au/land-management/catchments/catchment-management-authorities

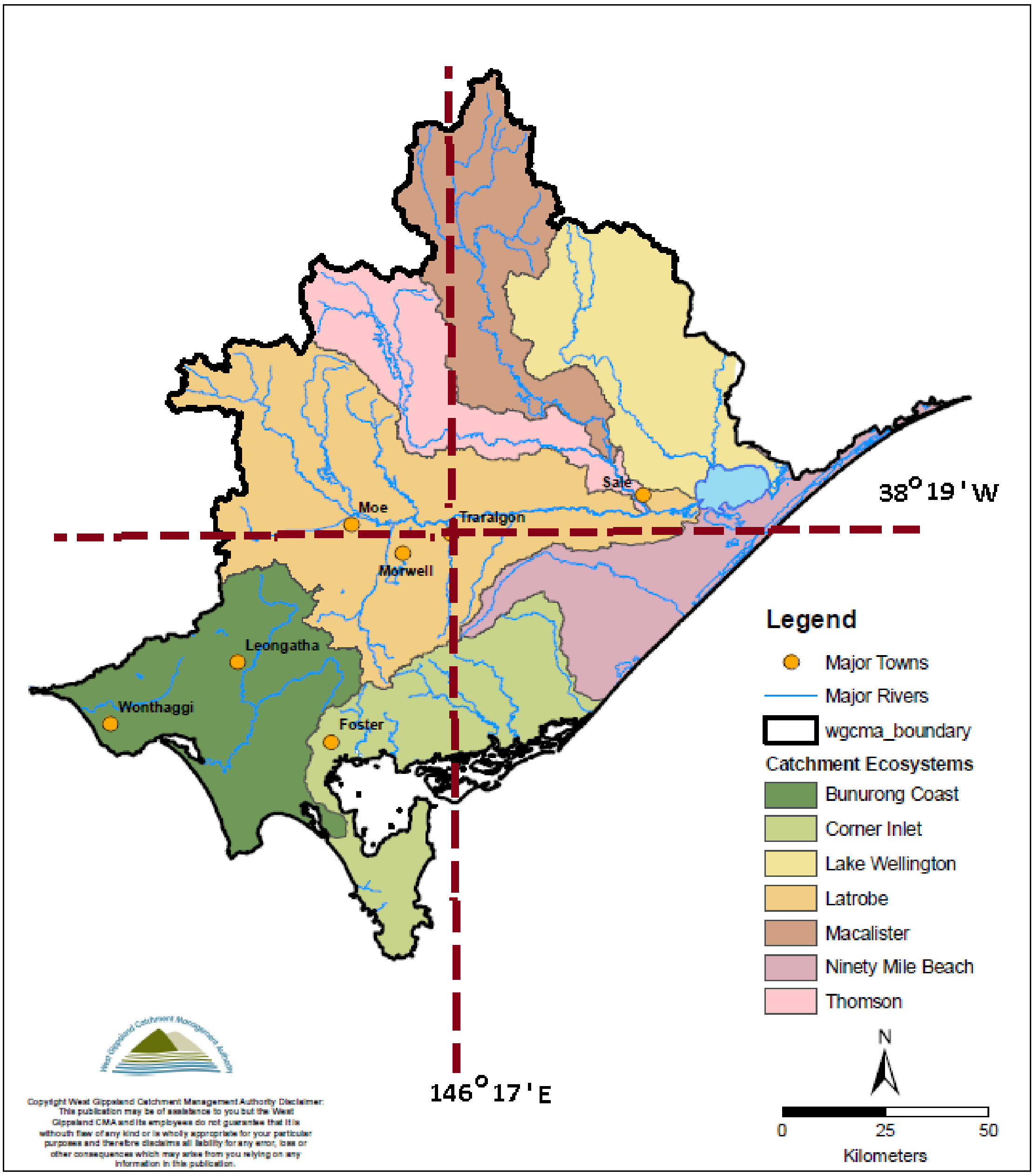


Figure 3.2: Map of West Gippsland, Victoria showing the catchment region overseen by West Gippsland Catchment Management Authority and the boundaries of its seven major catchments. Original map from http://www.wgcma.vic.gov.au.

Six of Victoria's 22 terrestrial bioregions are found within the West Gippsland region: the Alps bioregion; Highlands Southern Fall bioregion; Strzelecki Ranges bioregion; Wilsons Promontory bioregion; East Gippsland Lowland bioregion; and, Gippsland Plains bioregion. Each bioregion is characterized by a set of climate and soils characteristics which are responsible for shaping the associated collection of native floristic communities and representative ecosystems.

Historically much of the West Gippsland region has been heavily modified by agriculture, industry and urban settlement. The region provides much of the State's electricity from brown coal-fired power stations and considerable water storage capacity for the State capital of Melbourne (Fisher, 2006). The area contains several regional centres, substantial farming tracts and large protected areas, such as National Parks. Land use is strongly influenced by tenure, private or public, with the two main commercial activities of the region being grazing (for beef and dairy) and conservation (WGCMA, 2006b).

Within its catchment, the Authority is responsible for a suite of over 1500 wetland sites (greater than 1 ha in size), including several wetlands of international and national importance, which are listed on the Ramsar Convention and identified in the Directory of Important Wetlands Australia, respectively. Note a listing of these significant wetlands has been given in Appendix C. Collectively, the region's wetlands represent a rich diversity of types, from alpine bogs, floodplain billabongs and morasses, to coastal lagoons and estuaries. Wetlands occur on both public (e.g. Crown land) and private lands (e.g. on private owned farms) (WGCMA, 2006b & 2006c). The distribution of wetlands greater than 1 ha in the WGCMA is shown in Figure 3.3.

As outlined in the previous chapter, there is a need to establish reliable information on the status and condition of much of Victoria's wetlands (Centre for Environmental Management, 2005; Victorian Catchment Management Council, 2007). To redress this situation, several Catchment Management Authorities including the Corangamite and West Gippsland, commenced systematic stocktaking of their wetland resources in the mid 2000s (Centre for Environmental Management, 2005; WGCMA, 2007). In 2005, the WGCMA embarked upon the preparation of a comprehensive and overarching regional Wetlands Plan "to help ensure that future investment in significant wetlands is targeted towards the highest priority activities and wetland assets over the next five years" (WGCMA, 2006c, p.6).

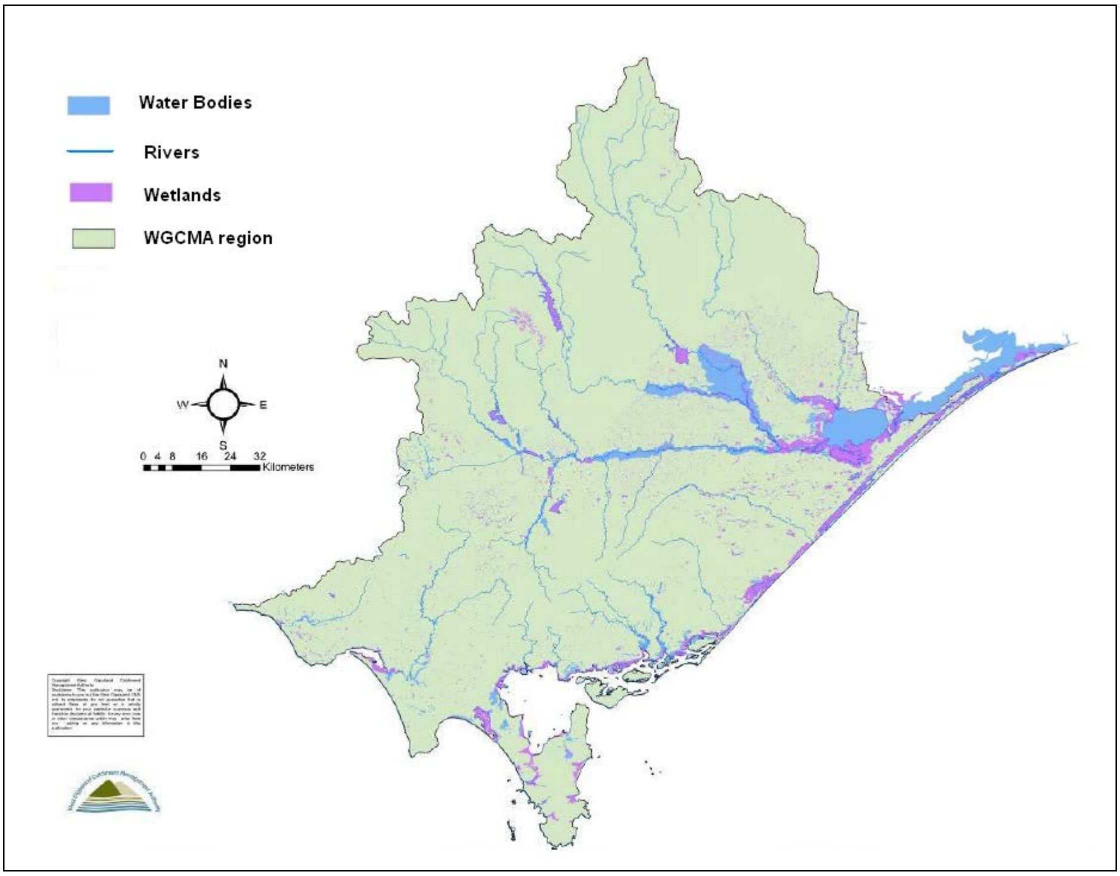


Figure 3.3: Map of wetlands greater than 1 ha in the West Gippsland Catchment Management Authority region. The original image is found as Figure 4 on pg 19 WGCMA Wetlands Plan Part A-Background and Method (2007). The copyright belongs to the WGCMA.

3.1.1 The WGCMA Wetlands Plan

Early in the development of the Wetlands Plan, the need to fill gaps in knowledge of the region's wetlands extent and condition was identified (WGCMA, 2007). As part of Stage 1 of the Plan, wetland mapping and wetland inventory projects were organised to help establish the baseline condition of individual significant and non-significant wetlands. An assets-based assessment approach was devised to quantify the wetland services or functions at each site; the approach was applied to evaluate and classify non-significant wetlands during Stage 2 of the Plan.

The WGCMA wetland inventory was undertaken by collecting baseline data for a representative sample of 163 wetlands, 7% of the 1,500 (>1 ha) naturally occurring wetlands in its region. The sampling regime was devised by Greening Australia Victoria to ensure that the proportions and distributions of the major types of wetlands present in the study region were mirrored in the sample set, both at catchment and at sub-catchment levels, and across private (56%) and public land tenures (46%). Within a given sub-catchment, individual wetlands were then randomly selected from a candidate pool using an arithmetic sequence applied to an assigned, yet arbitrary, wetland number to ensure representative sampling of different wetland types (Greening Australia, 2006). Constructed wetlands, such as dams and impoundments, were not included. Existing wetland records were validated and supplemented by onsite visits by a small team of trained assessors from Greening Australia, Victoria Incorporated, during May 2006 (WGCMA, 2006c). All data were collated and desk-checked before being used in the assessment process to identify wetlands of high environmental, social or economic value within the sample. In the process, the data was used in the estimation of the type, and magnitude, of likely threats to each sampled site and a risk assessment was made as to the likelihood and consequence of potential threats on each of the values being estimated (WGCMA, 2005).

The remainder of this chapter describes various aspects of the WGCMA wetlands assessment process. First, important features of 2006 wetlands assessment, which make it suitable for examination in this thesis, are explained. Following is a detailed description of wetland evaluation processes including its inventory collection, data collation and outcomes. Finally, a discussion of the benefits and difficulties of traditional wetland assessments is undertaken, which points to the research method taken.

3.2 The WGCMA 2006 wetland assessment

There are several features of the wetland assessment exercise undertaken by the WGCMA in 2006 that make it well suited for use as the case study for this thesis. These features of the assessment relate to:

- **Ramsar Convention guidelines**: The wetlands assessment undertaken by Greening Australia for the WGCMA incorporated each of the five tasks of rapid assessment listed in Resolution IX.1 Annex E (Ramsar, 2005) and mentioned in Section 2.4.2. As well, the best-practice framework for wetland assessments described in the Annex was followed in the approach used by the WGCMA to conduct their assessments (WGCMA, 2006b & 2006c);

- **Physical scope**: The assessment covered the subcatchments of the Lower Macalister, Lower Thomson, Lower Avon and Lower Latrobe rivers. The size of the incorporated region (over 17,000 km^2) ensured that contrasting wetland types across private and public land tenures were represented within the analysis;

- **Diversity of wetland types**: Using the descriptions of the Corrick and Norman scheme (1980), the assessment covered six of the seven wetland types recognized in the State of Victoria (Greening Australia, 2006). All six types have suffered significant losses due to European settlement, most significant being 77% loss of Freshwater Meadows and 39% of Deep Freshwater Marshes having been recorded (WGCMA, 2007). To capture this diversity, the inventory exercise collected much information across a variety of indicators to assess economic, social and environmental values of wetlands and to quantify threat impacts for wetlands;

- **Type of assessment**: The assessment process was involved, and it required considerable time, resources and effort to implement. Commencing with the decision to take an assets-based approach recognizing the importance of economic, social and environmental values of each wetland, it attempted to quantify each value through a measure of their component factors. This step included wetland classification using the EVCs and Corrick and Norman (1980) schemes, as well as the application of known heuristics, consensus amongst wetland experts, and verification with historical records. Next in consultation with stakeholders, a scoring system was devised for each wetland value, economic, social and environmental, and applied to the inventory data. This was followed by desk checking and proofing through site checks and interviews with land managers of the sampled wetlands. Finally, using the computed value scores, the wetland sites were ranked so that high and very high economic, social and environmental value sites were identified and analyzed at a subcatchment scale to assist in the determination of future conservation investments (Greening Australia, 2006; WGCMA, 2006b);

- **Timing**: The rapid assessment occurred at a time when much international discussion of the practice was being made. The Ramsar Convention, for example, was publishing its Resolution IX.1 Annex E (Ramsar, 2005) detailing the process. Additionally, there were several differing approaches regarding choice of indicators for assessment reported in the literature, principally being the Hydrogeomorphic (HGM) and Index of Biological Integrity (IBI) methods (Brinson, 1993; United States Environment Protection Agency [U.S. EPA], 2003);

- **Currency**: The base-line inventory, upon which the wetland assessment evaluation rests, is one of the most recent collections of wetland site data available for study. It is also one of the largest and comprehensive datasets of its kind, occupying 7.61 Megabytes and comprising over 42 major tables and 37 minor lookup tables, for which there are over 200 standard queries saved. Throughout this thesis, the dataset will be known as the West Gippsland Catchment Management Authority (WGCMA) Wetland Inventory Database;

- **Political and local contexts**: The wetland evaluation has become the cornerstone upon which the WGCMA Wetlands Plan has been built (WGCMA, 2007). The Plan is a major contribution to a comprehensive regional plan and it continues to guide management activities and investments for wetlands in the region during the following five years after its release. As illustrated in Figure 3.4, the Plan is one component of a larger legislative and policy framework and it was influenced by the need to comply with international agreements, such as the Ramsar Convention, JAMBA and CAMBA, various National and State policy and Acts, along with other regional management plans (WGCMA, 2007); and,

- **Collaborative links and generosity of spirit**: The author wishes to acknowledge the willingness with which staff of the Authority, principally Ms. Michelle Dickson, who provided access to the inventory data files and for her time taken over several occasions in detailed explanation of how the assessment and evaluation process was undertaken.

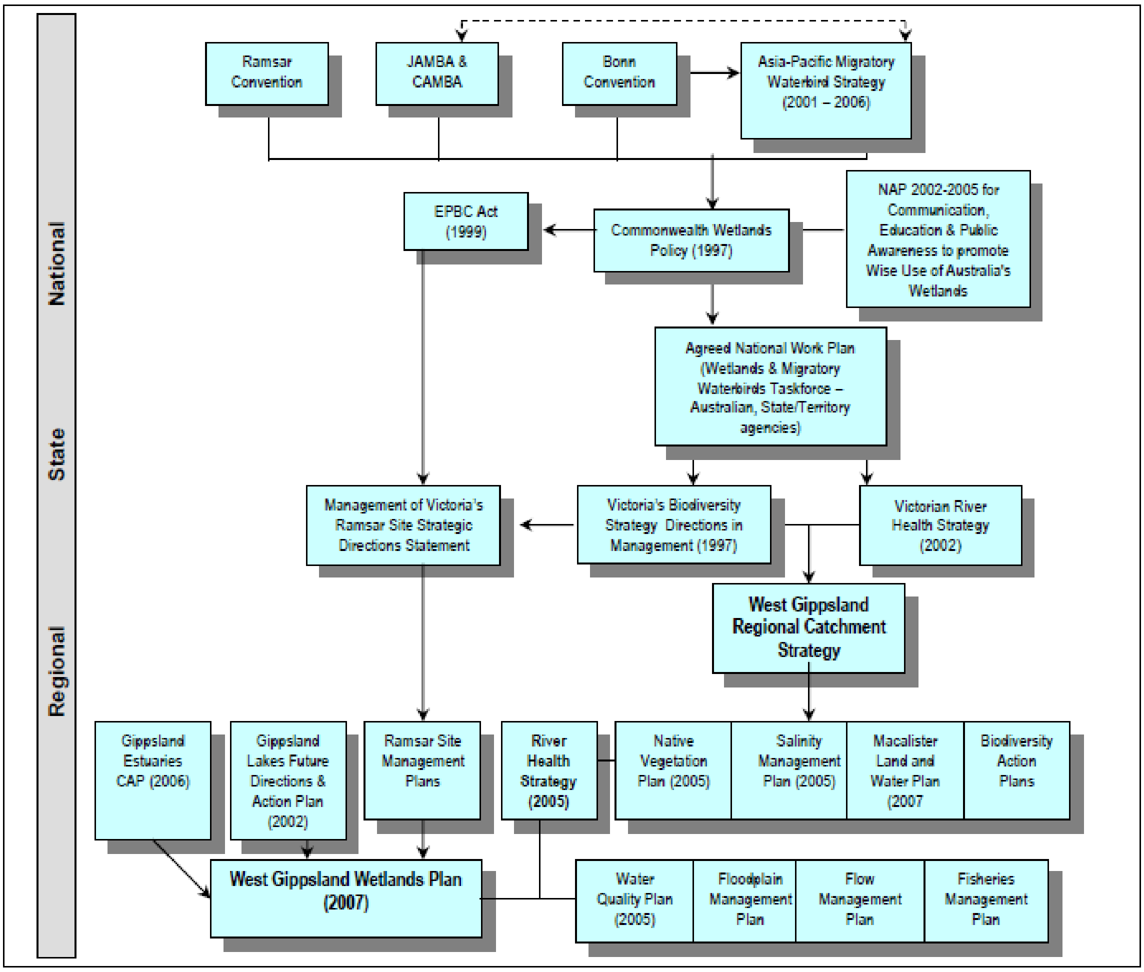


Figure 3.4: The main legislation and policy relationships for the management of wetlands under the West Gippsland Catchment Management Authority jurisdiction. The original version of this figure can be found as Figure 2 in the West Gippsland Catchment Management Authority Wetlands Plan: Part A-Background and Method (2007).

3.3 WGCMA wetland assessment process

3.3.1 Assets-based management approach for wetland evaluation

Prior to 2004, the West Gippsland Catchment Management held several workshops amongst stakeholders and technical experts to gain a consensus view on the most important assets in the region. Amongst nine major assets identified, four biophysical assets were recognizable, Land, Water, Biodiversity, and Atmosphere and Climate. Wetlands were seen to be an important component of the Water asset class.

To identify and prioritize wetlands within the catchment according to the value of the wetland's services it provides, a Wetlands Plan Steering Committee was set up. Their work helped decide the significant wetland values to be measured and used in the WCGMA wetland assessment process (WGCMA, 2006b). The lists of economic, social and environmental values categories decided upon are given in Table 3.1 with the five economic values: commercial fishing; tourism; production value; drainage disposal; and water supply. The Table includes nine social values: recreational fishing; swimming; camping; hunting; boating; passive recreation; bird watching; education; and park value; and seven environmental values given as: wetland rarity; significant flora; significant fauna; habitat value; hydrology; vegetation intactness–critical lifeforms; and vegetation intactness–width of vegetation fringe. More information regarding these values, including their descriptions and how they were assessed is given in the upcoming Section 3.3.3: Data collection protocols.

Further the Committee identified a set of threats, shown given in Table 3.1. Threats were defined as actions or processes that could have negative consequences for wetland assets within the catchment, and they are seen to come from many quarters. Specifically, threats may derive from a range of uses of an asset, from within or outside of the region, and may occur in the present, past or future. It was noted that the use of an asset for one purpose might, in itself, be a threat to the value of an asset. For example, a wetland drained and used in industrial development may have an increased economic value, which in turn would lower its environmental value. The fourteen identified threats for the 2006 assessment were loss of wetland connectivity; stock access; pest plants; pest animals; urban development; native vegetation decline; land use; physical alteration; erosion; fire regime; recreation; water source; and, salinity. Thus, the identification of specific economic, social and environmental values and possible threats categories augured the most appropriate indicators to be collected during the field inventory.

Table 3.1: Significant wetland values and threat categories used in the West Gippsland Catchment Management Authority wetland assessment process (WGCMA, 2006b).

Economic values	**Social values**	**Environmental values**	**Threats**
Commercial fishing	Recreational fishing	Wetland rarity	Loss of wetland connectivity
Tourism	Swimming	Significant flora	Stock access
Production value	Camping	Significant fauna	Pest plants
Drainage disposal	Hunting	Habitat value	Pest animals
Water supply	Boating	Hydrology	Urban development
	Passive recreation	Vegetation intactness–critical lifeforms	Altered hydrology
	Bird watching	Vegetation intactness–width of vegetation fringe	Native vegetation decline
	Education		Land use
	Park value		Physical alteration
			Erosion
			Fire regime
			Recreation
			Water source
			Salinity

3.3.2 WGCMA process for evaluating wetlands

The WGCMA wetland evaluation process was conducted on a per site basis for 163 wetlands surveyed during the inventory exercise. The process involved four major steps which are shown in Figure 3.5 and described following.

1. Data collection and validation
2. Score calculations
3. Risk assessments
4. Wetlands rankings and identifications

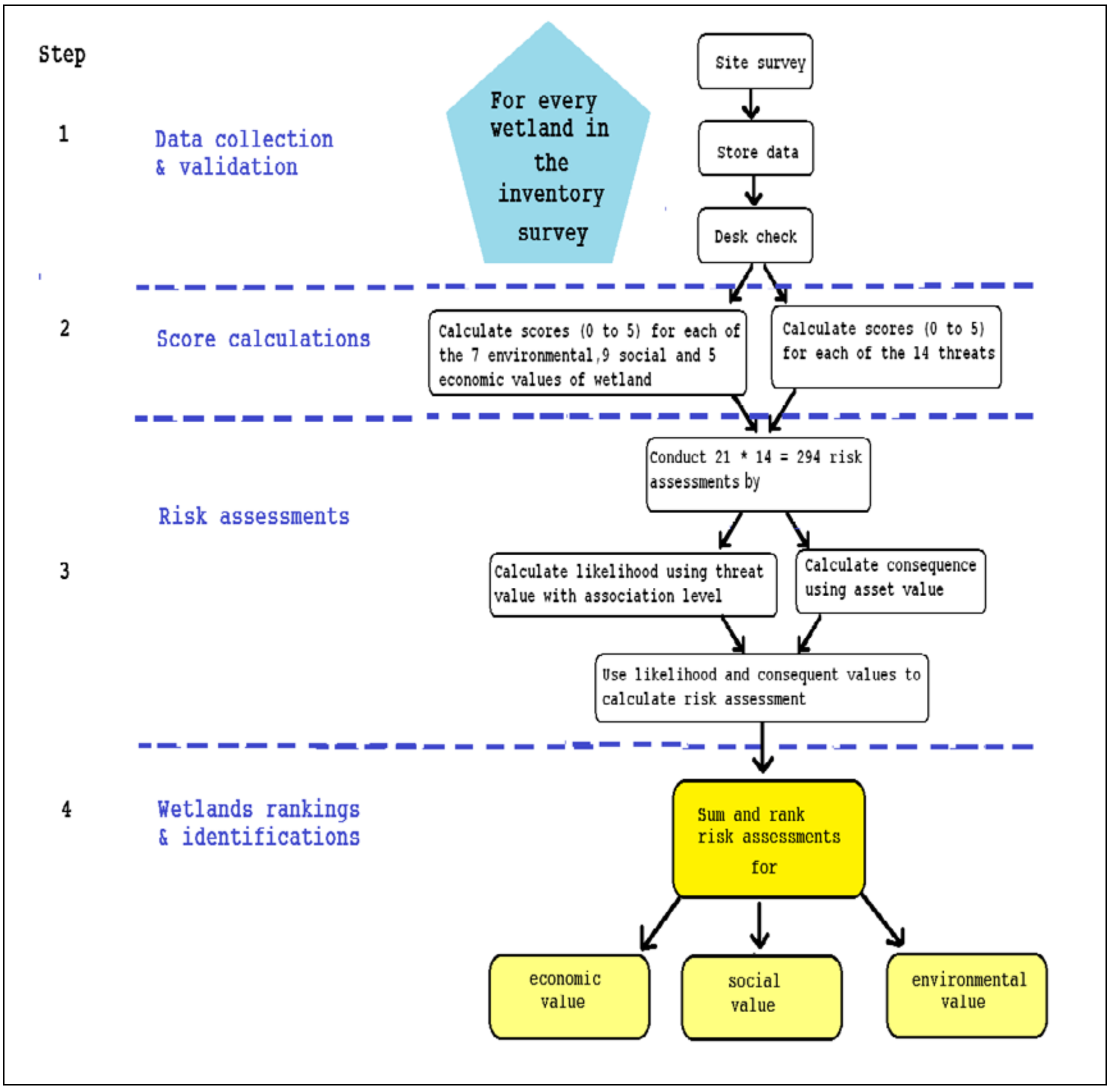


Figure 3.5: The steps taken to compute a rapid assessment of each inventoried wetland of the West Gippsland region. The figure is a collation and summary of information supplied by WGCMA Wetlands Officer, Ms. Michelle Dickson (personal communications) and various documents (WGCMA 2006b, 2006c & 2007).

1. Data collection and validation: The economic, social and environmental values and threat categories listed in Table 3.1 were used by the Steering Committee to formulate a set of wetland attributes, for which data could be collected during the site visits, and then used in assessment of these values. Their decisions regarding the appropriateness of one attribute over another were influenced by consideration of data availability, consistency with the Draft Policy Framework for Wetlands in Victoria (DSE, 2003) and the Index of Wetland Condition specification (DSE, 2005b), and relevance to the region (WGCMA, 2006b). Details of the data collection protocols for these attributes are given in the next subsection.

Site visits were undertaken by Greening Australia staff in May 2006, who completed extensive field surveys and, where possible, undertook interviews with the respective land managers. This work was followed up by data entry and desk checking for data validity of field-collected attribute measurements against other data sources including: Ramsar information sheets; the Directory of Important Wetlands, Australia; Parks Victoria management plans; Department of Sustainability and Environment spatial datasets; Victorian Heritage Register; and, Department of Sustainability and Environment Gippsland Lakes Index of Wetland Condition data (WGCMA, 2006b).

Upon completion of the field surveys, the WGCMA entered data into Microsoft Access 2000® format database known as the "Wetland Inventory Database." The recorded measurements comprising 7.61 megabytes of data served as the primary repository for information required during the wetland assessment process. Additional existing information was found through literature review and desk checking and expert and local knowledge was gained through workshops and interviews. As in other similar collaborative exercises (Costa, Farinha, Hecker & Vives, 1996), these meetings helped promote networking opportunities amongst staff and contacts as well as highlight regional wetland conservation issues.

For all statistical and data-mining analyses of this research, I directly accessed the WGCMA Wetland Inventory Database for individual wetland's records of the biological, chemical, hydrological and physical attributes in order to find the most important attributes and features of wetlands that predict high economic, social and environmental values, without needing to repeat steps 2, 3 and 4 outlined next. Additionally, I examined the Database records to see the effect of wetland classification schemes on wetland assessments.

2. <u>Score calculations:</u> After data collection, validation and storage, the next step undertaken by the WGCMA was the assessment of condition and threats for each sampled wetland site. Condition assessment involved deciding a score for each of the Table 3.1 listed economic, social and environmental values, which resulted in 21 separate scores, each rated on a scale of 0 to 5. As well, threat assessment for each of the 14 threat categories used a scoring system on a 0 to 5 scale. Full detail

of the scoring system is given in Appendix D. As an illustration, for the environmental value of Significant flora, the scoring was 0 if no data was available, 1 if no threatened species were listed, 2 for a Victorian conservation status value listed as 'poorly known', 3 for a Victorian conservation status value listed as 'rare', 4 for a Victorian conservation status value listed as 'vulnerable', and 5 for any category listing under the national Environmental Protection and Biodiversity Conservation Act, or a Victorian conservation status value listed as 'presumed extinct, or endangered', or listed as 'threatened in Vic' Flora and Fauna Guarantee Act. To help decide these scores, data was queried from the West Gippsland Catchment Management Authority Wetland Inventory Database. The resultant scores were checked with relevant experts and land managers, before their use in the risk assessment computation as detailed following (WGCMA, 2006c).

3. <u>Risk assessments:</u> After the collection of each of the 21 values (5 economic + 9 social + 7 environmental) and 14 threat scores for each wetland in the survey, WGCMA staff calculated 294 (21*14) individual risk assessments representing all interactions between the possible threats present and the wetland's economic, social and environmental values. It is the overall magnitude of these 294 assessments that decided the ranking of individual wetlands under assessment within the catchment.

   The process of calculating a risk assessment for a particular wetland value/threat pairing was determined by the WGCMA as the likelihoods that a threat may impact on a particular economic, social or environmental value, and if the threat occurred, the consequence of that impact on the value. This was done through the use of three scoring matrices, whose design was informed by local knowledge, review of wetland management literature, the professional judgement of WGCMA officers and in consultation with scientists and land managers (WGCMA, 2006b). The scoring matrices were the likelihood matrix, the consequence matrix and the risk level matrix, as shown in Figure 3.6. The likelihood matrix was used first to tie varying threat levels to their associated impact levels on any wetland value, through a graded scoring system. The level of association was based on professional judgement and the literature searches before validation through consultation. The level of association was used to compute the likelihood (the relationship of the level of association to varying threat levels) as seen in the values of the likelihood matrix. Next, the consequence matrix was used to measure the impact of a particular threat upon an asset's value rankings. Note that the higher the wetland value, the higher the consequence, since it is a one-to-one scoring relationship. Finally, when the results of the lookups from the likelihood and the consequence matrices had been done to ascertain their respective values, the risk level matrix was used to calculate whether the combined effects of likelihood and consequence were very high, high, moderate or low risk values. These different value levels were associated a number, derived from the sum of consequence and likelihood values resulting in a grading from 2 to 10 in the matrix, as shown in Figure 3.6.

4. <u>Wetlands rankings and identifications</u>**:** All risk values were totalled for each wetland. The sums were used to rank wetlands and decide which sites were of very high and high economic, social and environmental values within the catchment. These rankings were then used to initiate management discussions and planning for prioritizing and targeting wetland investment in the West Gippsland region (WGCMA, 2006c).

Throughout the remainder of this thesis, I will use capital letters to distinguish the outcomes of the WGCMA wetland assessment rankings for economic value as Economic value. On the occasions where I use lowercase for economic value, I am referring to the broader meaning of this term and not its specific WGCMA assessment ranking. Likewise when specifically referring to the WGCMA assessments of social value and environmental value, I use the capitalized Social value and Environmental value respectively.

Likelihood matrix		Threat Level				
		1	2	3	4	5
Association Level	HIGH	1	2	3	4	5
	MODERATE	1	1	1	2	3
	LOW	1	1	1	1	1

Consequence matrix	Asset Value Ranking				
	1	2	3	4	5
Consequence	1	2	3	4	5

Risk level matrix		Consequence				
		1	2	3	4	5
Likelihood	5	MODERATE 6	HIGH 7	VERY HIGH 8	VERY HIGH 9	VERY HIGH 10
	4	MODERATE 5	MODERATE 6	HIGH 7	VERY HIGH 8	VERY HIGH 9
	3	LOW 4	MODERATE 5	MODERATE 6	HIGH 7	VERY HIGH 8
	2	LOW 3	LOW 4	MODERATE 5	MODERATE 6	HIGH 7
	1	LOW 2	LOW 3	LOW 4	MODERATE 5	MODERATE 6

Figure 3.6: The Likelihood, Consequence and Risk level matrices used in the rapid assessment of individual wetlands of the West Gippsland region. Original sources of the matrices are Tables 11, 12 and 13 of the West Gippsland Catchment Management Authority (2006c).

3.3.3 Data collection protocols

At each site visit, Greening Australia assessors completed extensive field surveys and, where possible, undertook interviews with the respective land managers. Some of the information recorded included:

- Identification details of the wetland, size, geographic location, photographic record, date of assessment, name of assessor;
- Land tenure details, including current land and wetland usage, owners' plans for the wetland;
- Physical features of the wetland, incorporating wetland category type, substrate, inundation status;

- Vegetation status, including types of vegetation present, EVC classification, width of vegetation fringe, presence and types of weeds;
- Fauna diversity and types;
- Habitat types and their nature;
- Water quality, including pH and turbidity;
- Hydrology, including recording of modification activities;
- Recreational activities and commercial uses of the wetland site;
- Evidence for threats, including exotic flora and introduced fauna, loss of native vegetation, eutrophication, erosion, drainage activities and physical alterations; and,
- Survey of land managers' views on wetlands, their management practices and their understanding of the functions of wetlands and services they provide. A copy of the infield survey, notes for completion of the survey and interview form for recording results are supplied in Appendices E and F.

The analyses undertaken in my research rely on the field-collected attribute values used to measure each of the wetland values and threat categories. Therefore more information of each of the major categories in the inventory collection, and salient details follow. A more detailed and thorough description of the wetland inventory process, its limitations and difficulties in data assemblage is given in the West Gippsland Wetland Inventory Report, July 2006 by Greening Australia Victoria Inc. (Greening Australia, 2006).

Wetland type

As mentioned in Chapter 2, Section 2.2.3, the most widespread wetland classification scheme in use in Victoria at a regional scale is that of Corrick and Norman (1980) and Corrick (1981). Based on discrete characteristics of depth, period of inundation and vegetation subcategories, this scheme was used in deciding the sampling regime to ensure that there would be adequate representation of each wetland type. Table 3.2 lists the number of wetlands of each wetland category in the West Gippsland region as identified in State-wide mapping, together with the numbers of wetlands surveyed in the inventory sample. A check of the representations of each wetland category is somewhat skewed since over 40% of wetlands needed reclassification after infield assessments. This high proportion of wetland reclassification accounts for the two wetlands, one listed as unclassified and the other as flooded river flat, that do not have a record within the region listing but were included in the inventory based upon their infield identifications (Greening Australia, 2006).

Table 3.2: Wetlands in the West Gippsland region and the number of wetlands of each type included in the inventory exercise. Original table source is Greening Australia (2006, Table 4.1, p.27). Note the * denotes exclusion of Ramsar listed wetlands, as by definition these wetlands are already identified as being of high value and thus, they do not need inclusion in the inventory and rapid assessment exercise.

Wetland Category	No. of wetlands in region*	Area of wetlands in region* (ha)	Number in wetland inventory sample	Area of wetlands in sample (ha)
Unclassified wetland	0	–	1	0.9
Flooded river flat	0	–	1	1.7
Freshwater meadow	219	1171.1	31	168.8
Shallow freshwater marsh	579	5172.5	71	687.1
Deep freshwater marsh	444	3473.1	27	196.0
Permanent open freshwater wetlands	304	981.7	15	28.0
Semipermanent saline wetlands	88	2316.5	16	688.1
Permanent saline wetlands	10	559.6	3	22.9
Totals	1,644	13,675	164	1,793

Flora, fauna and habitat of wetlands

In Victoria, there are 20 broad groupings and 34 sub-grouping of Ecological Vegetation Class (EVC) used to classify native vegetation, including wetland vegetation (DSE, 2013a). Background details of the scheme are found in Chapter 2, Section 2.2.3. For the WGCMA inventory, a check was made to identify the existence of one or more wetland and terrestrial EVCs present at each location. Benchmark comparisons were made against EVC descriptions, which list minimum species diversity needed for a specific EVC qualification. Additionally, for the dominant EVC present, further infield assessments were made regarding the quality or condition of the main EVC entailing an estimate of the predominant species, or group of species, and their health. Within each EVC for a particular location, the failure to meet the relevant benchmark of minimum species diversity and cover levels for each lifeform provided evidence of wetland modification. In particular, the presence of potentially invasive indigenous species, such as River Red Gum, Tangled Lignum etc., indicated that the wetland site had undergone hydrological or hydrogeological changes. A further indication of threat or site disturbance was made by the identification of the extent of invasion by introduced plant species, i.e. weeds. For more details, the site inventory instrument is found in Appendix E.

Habitat value was assessed by noting the presence, or absence, of permanent deep water pools, shallow to medium water levels, exposed substrate, submerged or free-floating vegetation, emergent vegetation, logs and rocks, tree and shrub coverage, islands, and shoreline profiles. Further indicators recorded at each site were the measure of width of vegetation fringe or wetland buffer present and the recording of faunal evidence (burrows, tracks, bird or frog calls) of natives and invasive species at the site.

Wetland hydrology

Two steps were undertaken by the WGCMA to capture hydrological data. The first involved an onsite assessment of evidence for the presence and impact of any hydrologic modifications that appeared to be different from natural water flows. The presence of water storages and water extraction, or changes to the inflow or outflows including blockages, were looked for and recorded by Greening Australia staff. If these activities were seen, then each modification was individually assessed as to its impact on the wetland under study. The second step was formal discussion with, and the survey responses, of the current land manager. Often during interview, managers would be able to relate several historical changes or events that had impacted upon their sites, thereby substantiating the field observations.

Importantly, if discerned at a site, the extent and impact of hydrological change could be used as an indication of wetland services under threat, particularly as more than half of the wetlands surveyed had a redirection of the natural flow (Greening Australia, 2006, p.29). The type of modification and the degree of threat varied across the assessments and wetland classification types, with freshwater meadows being most severely affected. For a detailed analysis per wetland type, see the West Gippsland Wetland Inventory July 2006 report (Greening Australia, 2006, p.30-32).

Water quality

Water quality was indicated by onsite measurements of three values: pH, electrical conductivity and turbidity. Attempts were made to record these variables for the source water (runoff, groundwater, flooding) of a particular wetland. However, the efforts were in part frustrated by the autumnal timing of the assessment, which was undertaken after a number of consecutive dry seasons. Note that nitrogen and phosphorus levels were not measured.

Heritage values

An initial assessment of the heritage value was done during the site appraisal of each wetland, looking for cultural evidence of indigenous and/or post-European settlement occupation. Subsequently, the infield assessments were followed up through consultations with indigenous cultural heritage officers and local history experts.

Threats assessment

Evidence for the existence of, and extent of threats that affect wetland services is often seen during assessment of the hydrology or the vegetation, fauna and habitat at a location. Some of the considerations the inventory exercise checked to find evidence for were loss of wetland connectivity; inappropriate grazing practices; lack of reservation; exotic flora; introduced fauna; decline in condition of native riparian vegetation; loss of area since European settlement and physical alteration; surrounding land-use practices; inappropriate recreation activities urban development; altered hydrology and drainage into wetland; other than natural fire regime; salinity; and, erosion (Appendix D).

Land manager interviews

For each site visit undertaken during the inventory phase, a commitment was made to conduct an approximate 30 minute interview with the incumbent land manager. Sometimes realizing this commitment was impossible; it was difficult to identify who held exact tenure or some land managers were unwilling or unable to supply the quantitative data being requested (Greening Australia, 2006, p.23). Interviews with land managers were used to collect raw data on various social and economic attributes of their wetland, which was later validated through workshops and consultations with community stakeholders. A copy of the interview questions is given in Appendix F.

There were a number of wetlands zoned within a heavily modified and intensively farmed area, known as the Macalister Irrigation District (MID) and shaded brown in Figure 3.2. Land managers in this district were asked to complete the original questionnaire and an additional 21 questions relating to their management practices. Of interest, were their stocking practices and reasons for these, their control or otherwise of native and introduced vegetation, weeds and feral animals, and their fire prevention efforts. Additionally, these land managers were more intensively surveyed as to their beliefs about, and feelings toward the wetland services that their wetland provided using a series of statements, which were scored using a Likert-type scale. Details of this additional survey are found in Appendix F.

Collectively the returns from the land managers provided a wealth of information for the WGCMA, least of which was an understanding of how each land manager's attitude towards their wetland and the services they provided. For instance, when nominating the one feature that the land manager liked most about their respective wetland, some private land managers, although not the majority, nominated production based values over conservation based values; this was not the case for public land managers. Through analysis of these responses, it seems that there "is a significant group of private land holders who would be open to practical solutions to their production based issues that will also deliver a positive contribution to wetland preservation and protection" (Greening Australia, 2006, p.41). The WGCMA hopes to more accurately target its marketing approaches, which espouse the virtues of wetland conservation values to this group of private land managers. Recent efforts have been made to identify more specifically the views held by this group (Wise, 2010).

3.4 Findings of the WGCMA wetland assessment

The WCGMA wetland evaluation and ranking process resulted in the identification of high scoring wetlands for economic, social and environmental values, as well as the identification of wetlands most at risk of degradation (Greening Australia, 2006; WGCMA, 2007). As a consequence of these identifications, the WGCMA set about establishing and costing a Strategic Management Action Plan, which incorporated a set of Individual Wetland Management Action Plans for the identified high scoring sites (WGCMA, 2006b). The collective goals of these Plans were the protection and enhancement of the ecological character of high-value wetlands; the maintenance and improvements to wetland condition; the maintenance of social and economic values of wetlands; and, the promotion of community involvement in wetland management (WGCMA, 2007). The details of the resulting Plans are not the concern of this thesis. Of primary interest and importance for this research are the patterns observed by the WGCMA amongst the input data, and where noted and reported, the contributing attributes that were aligned to high and low value assessments in 2006. These attributes are listed so that they can be used as baselines for the comparisons made in the following chapters.

The inventory data was interrogated by Greening Australia (2006) as part of their inventory work. The data was examined at a regional, subcatchment and individual wetland scales, and mostly for indicators of economic and social values. Although very detailed, the analysis reported only the frequency of attributes collected in the field; it was not the remit of Greening Australia to undertake the scoring and evaluation of wetland sites, nor to sample wetlands of international or national significance. As described in Section 3.3.2: WGCMA process for evaluating wetlands, the WGCMA collated and validated inventory data, undertook score calculations and risk assessments to rank the inventoried subcatchment wetlands.

The character and values of all wetlands, including significant and subcatchments wetlands, is described in the WGCMA report for the Wetlands Plan (WGCMA 2007), which repeats the inventory frequencies supplied by Greening Australia and it adds descriptions of economic, social and environmental values of the identified significant wetlands. The WGCMA report suggests, although details are not specifically given, that the scoring system was also applied to significant wetlands since rankings results appear for these wetlands in each of the wetland values and in counts of high risks. A broad-brush description of economic, social and environmental attribute frequencies and the most important threats across all wetlands in the region follows. Included are any reported associations between input data and high values noticed.

Economic value

Inventoried subcatchment wetlands: It was reported that 70% of these wetlands had some commercial value, with almost half supporting grazing by beef cattle. Tourism was recorded at 29% of sites, mostly publicly owned, and dairying and forestry accounted for the remainder of recorded economic values.

Nationally and internationally significant wetlands: Tourism was the most significant economic attribute recorded at seven wetland sites. Three sites had commercial fishing operations, including one of the seven sites displaying tourism. There was some production values for the adjoining lands to significant wetlands, and a small number of wetlands were used for water disposal drainage and for water supply.

High scoring wetlands: High scores for commercial fishing, production and tourism decided the highest economic value wetland sites, and low value sites scored poorly on all of these aspects. The wetlands of highest economic value in order were Corner Inlet, Anderson Inlet and Lake Wellington, all of which are wetland sites of international and/or national significance (Appendix C). For comparison, the highest scores for other than significant wetlands were found in № 18 Lower Tarra, №.4 Lower Macalister, № 7 Lower Avon and № 9 Lower Thomson subcatchments, where the highest summative scores indicated wetlands of moderate economic value. Scores for significant wetlands and catchment wetlands are displayed together in Figure 3.7, where the vertical axis shows the range of scores from low (5) to very high (18) (WGCMA, 2007). Examination of this Figure shows that collectively significant wetlands tend to have higher economic values than wetlands within subcatchments, and evidenced by most of their mapped rankings being found to the left of the centre in the graph.

Social value

Inventoried subcatchment wetlands: The majority of wetlands, 78%, showed some recreational value, with the most reported activity being bird watching at 65% of sites. Passive recreation was recorded for 50% of sites, followed closely by hunting at 47%. Educational activities were recorded for 38% sites and motorbikes and four-wheel drive activity at 21%.

Nationally and internationally significant wetlands: Perhaps surprisingly, hunting was reported in nine significant wetlands, more so than bird watching in at least seven sites, and fishing, boating and swimming at four significant wetlands. Importantly, over half of the wetlands have sites registered for indigenous cultural significance and 40% of all sites were valued for their visual amenity.

High scoring wetlands: For social value, the highest value sites were those exhibiting indigenous and European cultural values together with high visual amenity. The wetlands deemed lower in social value did exhibit some of these features, but not in combination. As seen in Figure 3.8, wetlands of international or/and national significance have very high social value scores of above 40. The highest scoring sites were Shallow Inlet, Corner Inlet, Dowd Morass and Lake Tarli Karng, whereas the highest subcatchment social value score was 36 for № 28. Waratah Bay. The pattern observed in Figure 3.7, where most significant and important wetlands are found to the left of centre due to their higher scores, is repeated for Figure 3.8. Note the scoring systems for economic, social and environmental wetland values were different due to the number of contributing attributes used in the assessment; therefore the vertical axes of Figures 3.7, 3.8 and 3.9 are of different ranges, but it is the ranking between sites that is of importance, so each vertical axis has been scaled into very low, low, moderate, high and very high graduations where appropriate.

Environmental value

Inventoried subcatchment wetlands: Details of separate environmental value frequencies were not specifically given in either report. Rather, the number of threatened and endangered species across the study area was given together with a description of the threats present at various sites. For fauna, 84 species were listed as threatened and five species as endangered under the Environment Protection and Biodiversity Conservation Act [EPBC] (EPBC Act, 1999): Baw Baw Frog; Southern Brown Bandicoot; Orange-bellied Parrot; Swift Parrot; and, the State's faunal emblem Leadbeaters Possum. For flora, 131 species were threatened and five endangered under the EPBC Act, and four species were listed under the Flora and Fauna Guarantee [FFG] Act 1988, Victoria (FFG Act,1988). A detailed description of the impact of hydrological change was given for each Corrick and Norman (1980) wetland type and it was noted that Permanent Open Freshwater is the most at risk due to a range of threats, but details were not given.

Nationally and internationally significant wetlands: As expected, these sites provided habitat for threatened flora and fauna, and in particular water birds and migratory waders. Half of these wetlands had at least one threatened flora species and 86% had at least one threatened fauna species, and only three wetlands had none. Further, 23% of wetlands were identified as a vulnerable type in Victoria, including amongst many others, Bald Hills Wetlands, Caledonia Fen, Sale Common, and Dowd Morass.

High scoring wetlands: Wetlands ranked as the highest in environmental value scored well for vegetation intactness, habitat value and wetland significance whilst wetlands assessed as low in value scored poorly for significant flora, habitat value and wetland rarity and in some cases hydrology (WGCMA, 2007). The vertical axis of Figure 3.9 shows the range of scores assigned to each category of environmental value, that is, highest value wetlands scored between 21 and 28 in the evaluation process. These included those of national and/or international significance, being Victoria Lagoon, Dowd Morass and Sale Common and those in subcatchments № 22. Nine Mile Creek, № 1. Upper Macalister, № 26. Wilsons Promontory and № 28. Waratah Bay. Examination of Figure 3.9 shows that wetlands already identified as significant tend to be amongst the majority of higher value wetlands, although the pattern is not as strong as in Figures 3.7 and 3.8.

Threats

The assets-based management approach was concerned with threat identification and the likelihood of threat impact on a wetland. Counts were made of the total number of very high and high risks for each individual significant and subcatchment wetlands to inform prioritisation efforts for the Catchment Authority and planning for the Management Action Plans. It is important to note that the risk assessment calculations for significant wetlands (Ramsar and Directory of Important Wetlands listed) were conducted on a different set of risk categories to those listed in Table 3.1; urban development was not used, but assessments of additional risks of eutrophication, resource utilization, sedimentation, change in size and lack of reservation were included in summing the totals of high and very high risks for these sites. This change in the details of the risk assessments for significant wetlands are found buried in Appendix 4 of the West Gippsland Wetlands Plan: Part A Report (2007) and are not mentioned in its main text. The different assessment regimes mean that comparisons of risks should be made only within wetlands of significance group and within subcatchment wetlands group, and not between.

Inventoried subcatchment wetlands: The Permanent Open Freshwater wetlands recorded the greatest number of threats (Greening Australia, 2006), however, it was noted that regardless of a wetlands type, the two major threats were changes to hydrology seen in 74% of the sample, where there were changes to inflow (44%) or changes to the timing of the inflow (30%); and, grazing (40%) which was linked with declines in native vegetation, loss of reservation and associated with an influx of exotic flora. Additionally, the loss of wetland connectivity was observed at 32% of surveyed sites. Importantly, 46% of wetlands are held publicly, and it was seen collectively that wetlands under public management were in generally much better condition than those privately owned; 80% of Victoria's wetlands are in private hands (Greening Australia, 2006).

Nationally and internationally significant wetlands: The WGCMA report (WGCMA, 2007) does not specifically list the threats to these wetlands, although as mentioned above, an assessment of threats was undertaken.

High scoring wetlands: Wetlands of significance showing the greatest 'very high' risk scores are Corner Inlet and Dowd Morass, as shown in Figure 3.10. The largest 'very high' risk scores are for subcatchments № 18. Lower Tarra, № 12. Moe River and № 35. Upper Powlett as seen in Figure 3.11.

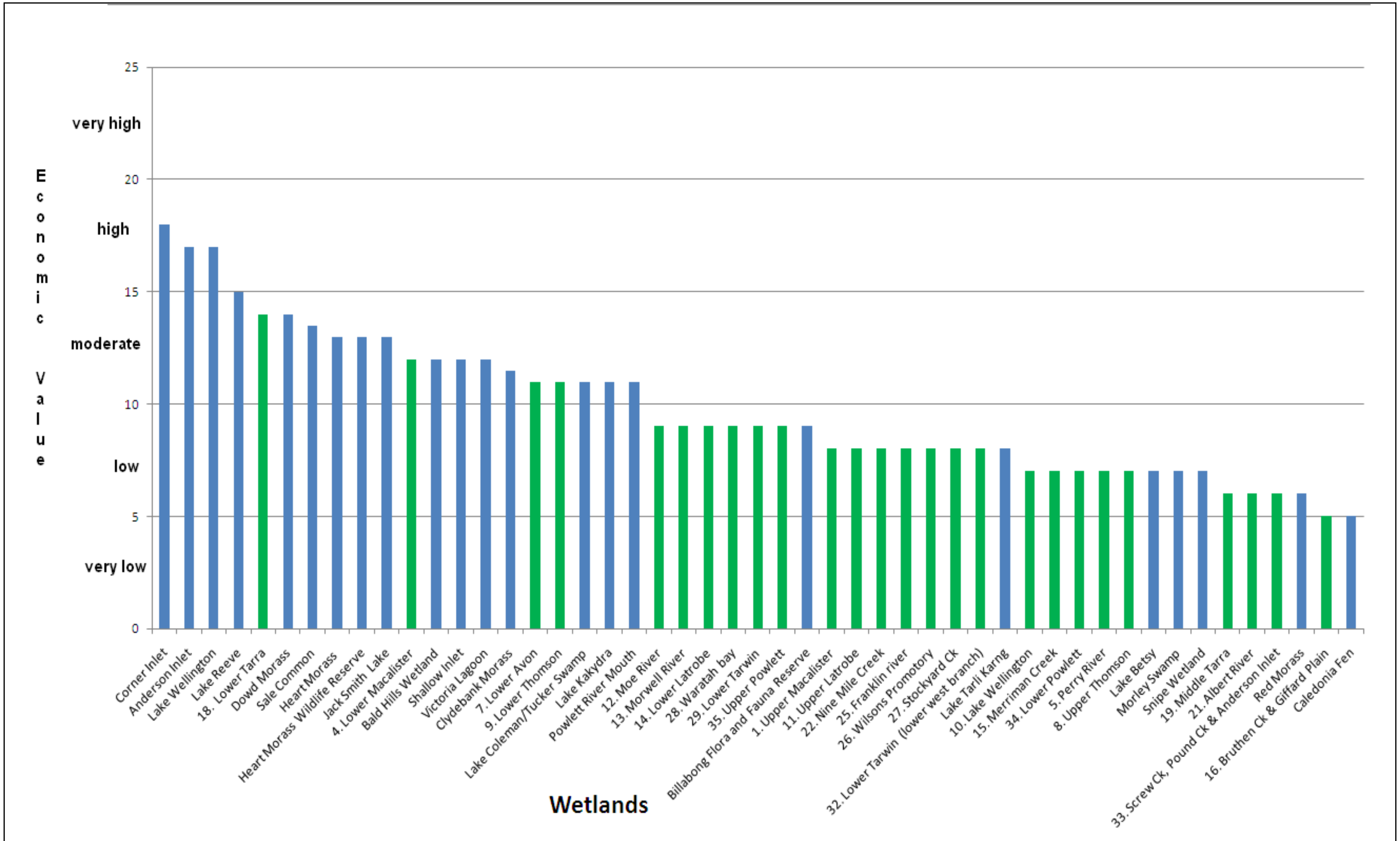


Figure 3.7: Overall Economic values assessed for identified significant wetlands and the subcatchments of the West Gippsland Catchment Management Authority region. Significant wetlands are shaded blue and subcatchments are shaded green and numbered. Data for this figure has been derived from Figures 9 and 12 of the WGCMA: Wetlands Plan Part A- Background and Method, 2007 on pages 26 and 28.

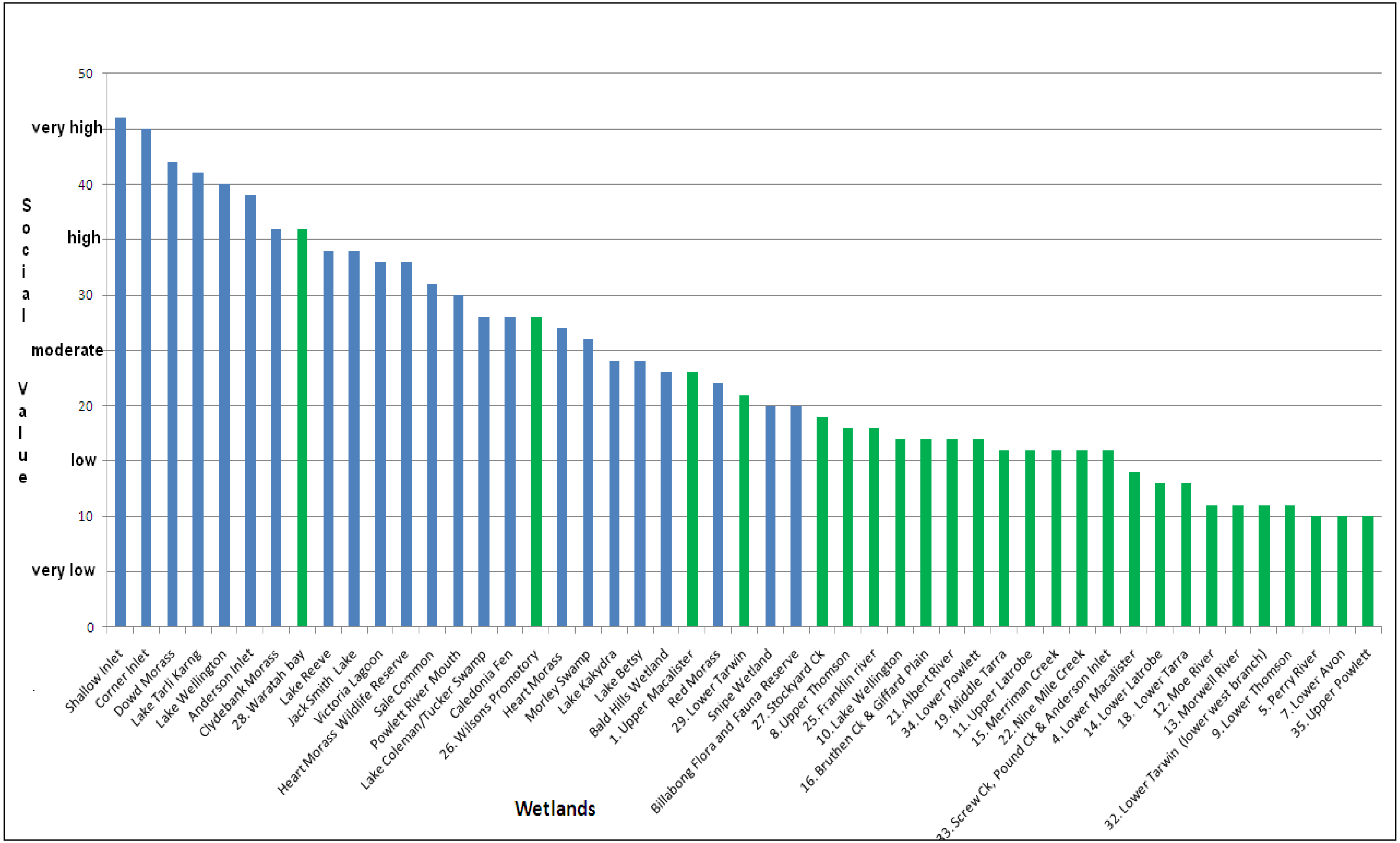


Figure 3.8: Overall Social values assessed for identified significant wetlands and the subcatchments of the West Gippsland Catchment Management Authority region. Significant wetlands are shaded blue and subcatchments are shaded green and numbered. Data for this figure has been derived from Figures 8 and 11 of the WGCMA: Wetlands Plan Part A- Background and Method, 2007on pages 26 and 28.

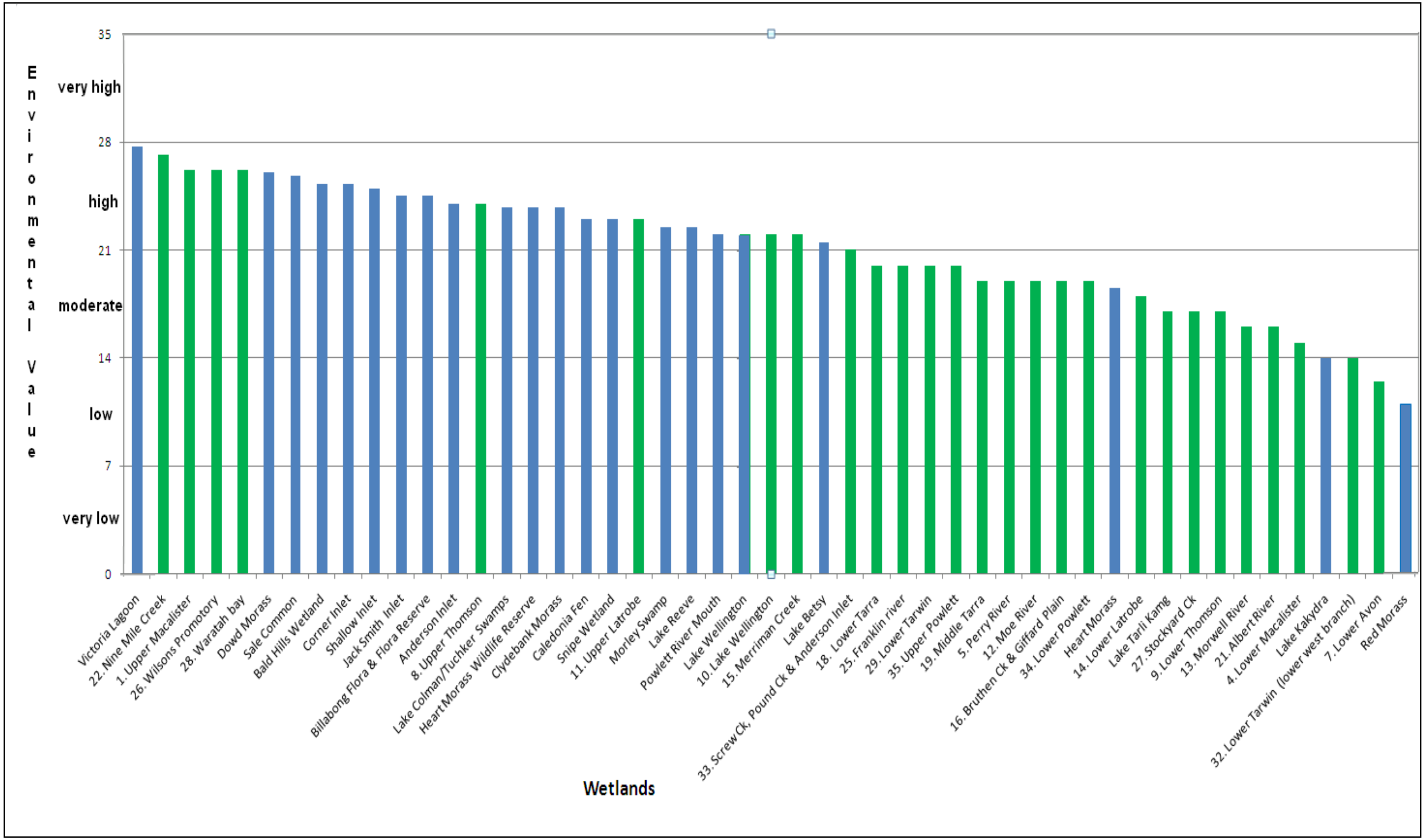


Figure 3.9: Overall Environmental values assessed for identified significant wetlands and the subcatchments of the West Gippsland Catchment Management Authority region. Significant wetlands are shaded blue and subcatchments are shaded green and numbered. Data for this figure has been derived from Figures 7 and 10 of the WGCMA: Wetlands Plan Part A- Background and Method, 2007 on pages 25 and 27.

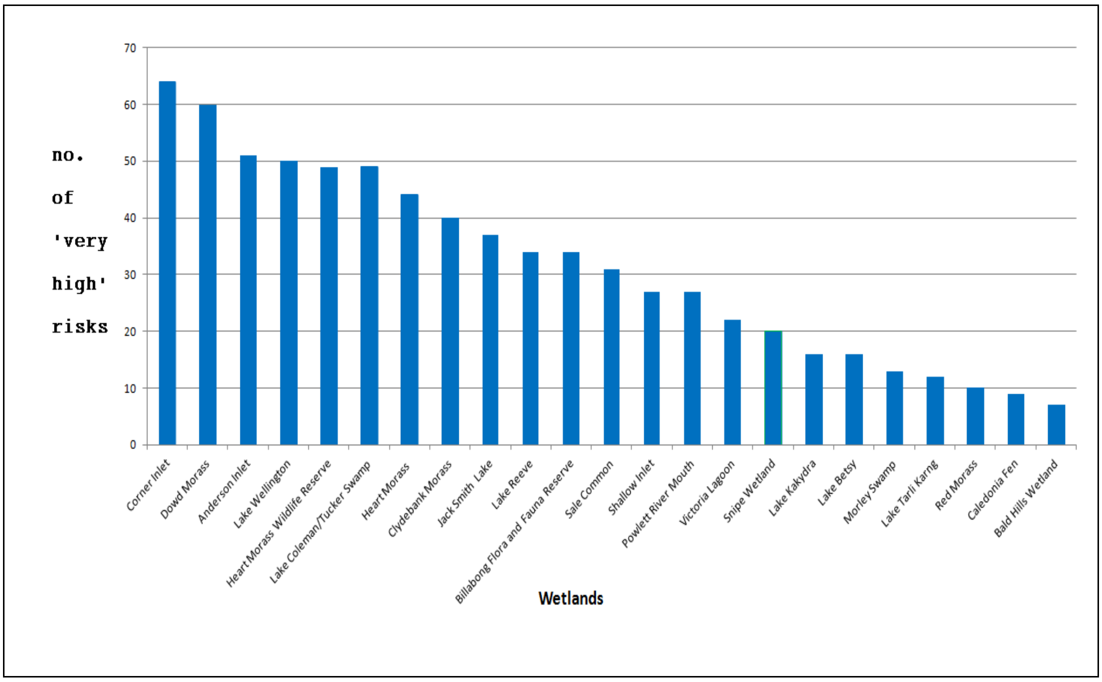


Figure 3.10: The number of 'very high' risk scores assessed for identified significant wetlands of the West Gippsland Catchment Management Authority region. Data for this figure has been derived from Figure 15 of the WGCMA: Wetlands Plan Part A- Background and Method, 2007 on page 31.

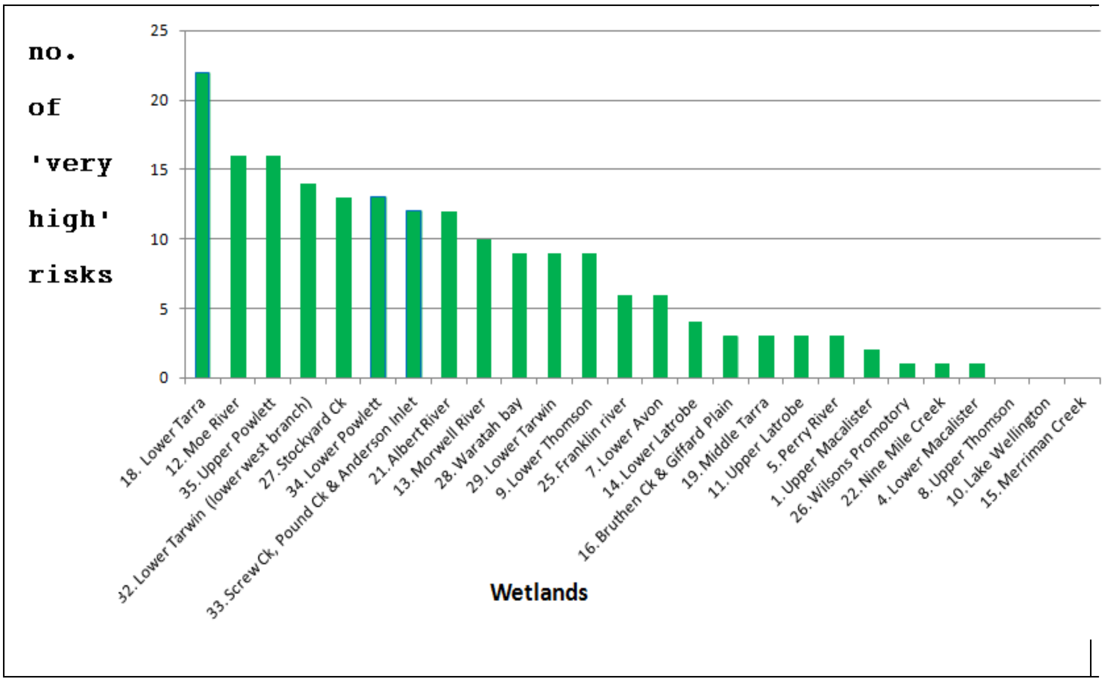


Figure 3.11: The number of 'very high' risk scores assessed for subcatchment wetlands of the West Gippsland Catchment Management Authority region. Data for this figure has been derived from Figure 13 of the WGCMA: Wetlands Plan Part A- Background and Method, 2007 on page 30.

3.5 Critique of the WGCMA assessment process

Primarily, the goal of the WGCMA assessment process was the identification of the most valuable wetlands in the region, so that strategic site-specific Individual Wetland Management Action Plans could be formulated to target future effort towards the protection and preservation of higher valued wetlands and enhancements of their condition (WGCMA, 2006b). More broadly, the assessment is an example of multi-criteria decision analysis (MCDA). MCDA has been used extensively in natural resource management decision-making worldwide (Bryan et al., 2010; Diaz-Balterio & Romero, 2008; Regan et al., 2007; Steele et al., 2009). In their review of MCDA methods, Mendoza and Martins (2006, p.1) cite the work of Belton and Stewart (2002) in listing the important properties of the MCDA approach that are useful for natural resource management as: "(1) it seeks to take explicit account of multiple, conflicting criteria, (2) it helps to structure the management problem, (3) it provides a model that can serve as a focus for discussion, and (4) it offers a process that leads to rational, justifiable, and explainable decisions." These features of the MCDA help resource managers to keep the process transparent, open to scrutiny and accountable to stakeholders and interested parties (Brouwer et al., 2003). By adopting MCDA for wetland assessment, the WGCMA was able to: focus the efforts of community stakeholders and technical experts; formulate a scoring methodology to assess wetlands that incorporated 21 economic, social and environmental values (measured using different scales) and 14 threat categories (listed in Table 3.1); rank a representative 163 wetland sites in the West Gippsland region; and, progressively report upon the process (WGCMA, 2006b, 2006c and 2007).

Specifically, the WGCMA wetland value assessments can be classified as an instance of value-measurement model (Belton & Stewart, 2002) since individual wetland assessments were made through a numerical scoring system. As previously detailed in Section 3.3.2, every economic, social and environmental value was scored using inventory data and predetermined scales, and followed by risk assessment calculations, using likelihood, consequence and risk level matrices. Totals of risk relationships were made to compute economic, social and environmental values for every wetland site surveyed (WGCMA, 2006b). Final identification of wetlands with high or very high evaluations for social or economic or environmental values involved synthesis of the risk analysis with local knowledge, database interrogation, literature reviews and workshop discussions.

One advantage of using a value-measurement model is that it allows comparative measures of wetland services and their degrees of risk to be measured across a broad diversity of wetland types under various condition states. However, as evidenced by the different ranges of scales in Figure 3.7, Figure 3.9 and Figure 3.10, the use of scoring systems results in an assessment that is somewhat arbitrary; the scales themselves have no direct meaning, and comparisons of wetlands can only be made within Figures, that is, only where the same assessment metric has been used. Steele et al. (2007) comment on the problem of scaling when using MCDA for environmental decision-making. They illustrated that it is possible to change final rankings of options by recalibrating scoring scales and weights of computation matrices. Steele et al. (2007) stress that practitioners need to be aware of this difficulty and to avoid calibration-generated problems by ensuring that the scaling within computation matrices are graded to reflect, as near as practicable, the relative importance of the criteria being calibrated. The difficulty of the WGCMA wetland assessment is that the process was based on the scoring of categories (Appendix D) and in this semi-quantitative method, the scoring of separate categories did not indicate any sense of magnitude, but it imply ordering. For example, for the environmental value of Significant flora the scoring system, a 4 assigned for any Victorian conservation status value as ‘vulnerable’ is not twice as good as a grading of 2 where a Victorian conservation status value has been assigned as ‘poorly known’.

The value-measurement model and the scoring mechanism used by the WGCMA, is in of itself, an arbitrary mechanism. In reality, its incorporation of various economic, social and environmental values and threat categories (listed in Table 3.1) was an attempt to describe and quantify the complexity of wetland function and condition. In deciding the value-measurement model, the Wetlands Plan Steering Committee was cognizant of local contexts and conditions, Victorian government policy on wetlands and components the Index of Wetland Condition. Pragmatic decisions were made as what would be the best attributes to collect data on, the autumnal timing of the onsite assessments, and the spatial scales used for measurement. Both qualitative descriptors and quantitative values in calculating ecosystem/wetland values were used as a mechanism to help cover the level of uncertainty in understanding of how these complex systems are structured (Christensen et al., 1996; Turner et al., 2003). The use of categorical data to describe wetlands has important implications for the statistical analyses undertaken in this research. Employing categories for many wetland attribute values restricts the number of suitable approaches that can be applied to the dataset, and the inferences that can be made thereafter. This impact and the resulting available options are detailed in Chapter 5.

Another aspect of the value assessment undertaken by the WGCMA is its use of a risk assessment matrix to help map probabilities or likelihoods of threats against their possible impacts or consequences. The practice of using a risk matrix to help prioritize and inform management decisions is extremely widespread, and it is not confined to natural resource management decisions (Regan et al., 2007; Steele et al., 2007). Risk matrices are often recommended in national and international standards for guiding management decisions and resource allocations and their use can be found in applications as diverse as terrorism risk analysis, highway construction projects and climate change risk assessments (Cox, 2008).

Finally, it is important to note that the benefits and transparency of WGCMA wetland value assessment came at considerable cost; it was time consuming, labour intensive and expensive. To help ensure consistency of the infield data collection, visits were conducted by as few as three Greening Australia staff, and it is assumed that any inter-user variability was noted and accounted for during the extensive desk-checking exercises by WGCMA staff. Overall, the assessment involved establishing stakeholder workshops, engaging community viewpoints, garnering of technical expert advice, deciding scoring and ranking schemes, commissioning and paying for site visits, collecting and entering of field and historic data, validating and desk checking of data entries, calculating hundreds of risk assessments per wetland site, collation of every sites' risk assessments, ranking of all sites for economic, social and environmental values, and further desk checking and validation of values and rankings through stakeholder consultation. A limitation of the reports on the assessment outcomes is an absence of the conceptual models underpinning the task and a deeper discussion of how the complexity and interconnectedness of West

Gippsland wetlands was accounted for (Greening Australia, 2006; WGCMA, 2006b and 2006c).

In this case study, it can be seen that individual wetland evaluations are the result of a synthesis of a broad range of indicators, including chemical, hydrological and biological factors and the wealth of social information from landholders collected during the inventory exercise and stored in the WGCMA Wetland Inventory Database. This thesis hypothesizes that, through interrogation of the Database using statistical and data-mining methods, it is possible to ascertain the overall social, economic and environmental value assessment for each wetland site using far fewer inputs. Building upon the frequency statistics and the associations between various site characteristics and high-value assessments noted by Greening Australia (2006), in this research, I will first apply cross-tabulation analysis and Pearson's rho correlation, to better pinpoint input features with strong links to high-value assessments. Then, using more extensive and sophisticated techniques, multivariate statistical analyses and neural networks, my research will data mine the Database depository searching for input features with high predictive potency for classifying high-value wetlands. Further, these data-mining methods will provide a set of methods and models that will perform wetland assessments using these salient inputs.

The discovery of these input features and their pertinent associations would describe a minimal dataset of variables for ascertaining wetland assessments and rankings in West Gippsland, and thereby reducing overall time and labour costs in data collection and assessment processing. Particularly, reductions in effort and expenditure would come about as it will no longer be necessary to perform three of the four steps described in Section 3.3.2: WGCMA process for evaluating wetlands, being step 2. score calculations, step 3. risk assessments, and, step 4. wetland rankings, to perform wetland assessments. The identification of a minimal dataset of input variables necessary for wetland assessments will have ramifications for future inventory collections, wetland assessments and monitoring efforts in the region.

In the next chapter, I report upon my interrogation of the Wetland Inventory Database using univariate statistical techniques for each input value and threat category listed in Table 3.1. Frequency tables will be extracted from the Database and they compared to those reported by Greening Australia (2006). Further, cross-tabulation analyses of all attributes will be generated and searched for associations to economic, social and environmental evaluations. Multivariate statistical analyses will follow in Chapter 5 and the application of neural networks to wetland assessments will be presented in Chapter 6.

Tarra River, Victoria.
Image courtesy of Paul Boon

Chapter 4

Univariate statistical analyses

Chapter 3 described the 2006 WGCMA wetlands assessment, its input data collection and evaluation process to rank wetland sites for economic, social and environmental values. The assessment process incorporated data values for 163 inventoried wetlands which were stored in the large dataset of the Wetlands Inventory Database. The Database contained data for the many attributes used to indicate the presence and condition of various economic, environmental and social values and threat categories at each inventoried site. In my research, the Database records are analysed and searched for associations between input attributes and the classifications of high economic, social and environmental value wetlands.

This chapter details the interrogation of the Wetlands Inventory Database using univariate statistics. First, frequency statistics are generated for all attributes used in the wetland assessments to determine what information can be extracted in addition to that reported by the WGCMA and described in Chapter 3. Second, cross-tabulation analyses of input attributes are carried out to create contingency tables, which are searched for attributes that predict, to some degree, high-value wetlands. These results will be compared to observations made by the WGCMA in their report.

The univariate statistical analyses presented in this chapter provide a baseline for more complex analyses described in Chapters 5 and 6.

4.1 Introduction

Statistics are employed to describe, clarify and present data, derive information and to investigate associations amongst data that helps users make sense of the real world (Australian Bureau of Statistics, 2010). As part of their Inventory Report for the West Gippsland CMA, Greening Australia used simple descriptive methods, including frequency statistics to describe the data (Greening Australia, 2006). Attribute frequencies were collated by Greening Australia at regional, subcatchment and individual wetland levels, and these were repeated in the WGCMA Wetlands Plan document (WGCMA, 2007), together with frequencies for significant wetlands (Ramsar and Directory of Important Wetlands listed). As described in Section 3.4: Findings of the WGCMA wetland assessment, some associations between attributes and high-value wetlands were detected and these were reported in the WGCMA's Wetlands Plan document. This activity appears to have been done in passing and with little emphasis; it was not reported systematically. This is not surprising as the goal of the Wetlands Plan document was to recount the Wetlands Plan development, its background, methods of the wetland inventory and assessments, and a description of its outcomes, rather than undertake a thorough inspection of the Wetlands Inventory Database data collection for attribute values that correlate with high-value wetland assessments.

In this chapter, I commence a more detailed interrogation of the Wetlands Inventory Database records to determine whether more valuable information can be extracted than was reported by the WGCMA, and was described in Chapter 3. This chapter forms a baseline for comparison with the outcomes of the more sophisticated analyses presented in the next two chapters. There, multivariate statistical methods and neural networks are used to find patterns (correlations, trends and clusters) within the data to highlight relationships between input variables and, in particular, help identify relationships predicating high-value wetlands.

Before embarking on any statistical analysis, a crucial first step is data inspection. It is important to have a good understanding of the nature of the data and its components in order to locate problems such as inaccuracies, missing data anomalies, outliers, data constraints and scale disparities that may influence deductions made from the records (Hair et al., 2006; Tabachnick & Fidell, 2007; Tan et al., 2006). It is usual to examine the descriptive statistics of all variables as their types decide the appropriateness of any statistical analysis to be done. For the WGCMA Wetland Inventory Database analysis, it was necessary to first extract the raw data upon which wetland assessments had been made. Appendix G gives a listing of the Database records accessed with explanations on how it was done.

Considering the categorical nature of majority of the data, the most suitable univariate approaches are frequency statistics and cross-tabulation analysis. In this chapter, I collate the frequency distributions and data descriptions for the component attributes of the 21 variables (5 economic + 9 social + 7 environmental) and 14 threat variables stored in the Database (variables listed in Table 3.1).

Frequency statistics are useful as a summary stocktake of the inventoried wetlands; this is seen by their inclusion in the reports of Greening Australia (2006) and the WGCMA (2007) of the 2006 wetland assessment. Here as a checking mechanism, I recalculated the frequency statistics through sourcing the WGCMA Inventory Database for the relevant records. In accessing the Database, I noted that complete records did not exist for all 163 wetlands inventoried. Regarding Economic values, 161 wetlands had complete records for measured attributes, 160 wetlands were discovered for Social values indicators, and 163 records were entire for the suite measuring Environmental values. For threat assessments, 157 wetlands had complete threat listings.

Although frequency statistics describe the amount and values of recorded variables, they are limited by their narrow univariate focus; they fail to inform in that they do not give any insight into the predictive strength of an independent attributes in deciding high-value Economic, Social or Environmental wetland assessments. To overcome this difficulty, I undertook cross-tabulation analyses to create contingency tables for each attribute against different wetland evaluations. These tables provide some insight as to the degree that raw data predicts, or not, different wetland assessments. For each contingency table, I applied the chi-squared (χ^2) test for row and column independence to indicate the statistical significance of patterns seen within tables.

A summary of frequency statistics and contingency tables for Economic, Social and Environmental values are given in each of the next subsections. Following, threat statistics are examined in the same manner. Where relevant, the results of the univariate analysis are compared with the frequency values found by Greening Australia (2006), and patterns discovered through cross-tabulation analysis are compared to the few associations observed and mentioned in the WGCMA Wetlands Plan report. A discussion of this work ends this chapter.

4.2 Economic value of wetlands

Each inventoried wetland was assessed by the WGCMA for its Economic value. The five components used in this assessment (see Table 3.1) were:

- Commercial fishing;
- Tourism;
- Production value;
- Drainage disposal; and,
- Water supply.

In turn, these components were assessed through the collection of 12 separate attributes as summarized in Table 4.1. A more comprehensive version of this table detailing the database tables and contributing columns searched in the WGCMA Wetland Inventory Database with the assigned range of values can be found in Appendix G.

Table 4.1: Component attributes of each Economic value assessed to decide the final Economic value of each inventoried wetland. See also Table 3.1.

Economic value	Attributes
Commercial fishing	Commercial fishing
Tourism	Tourism
Production value	Food production Conservation forestry Other land usage
Drainage disposal	Drainage Disposal of water Water storage Obstruction Redirection Diverted or farm runoff
Water supply	Stock water supply

4.2.1 Economic value – frequency statistics and analyses

The WGCMA Wetland Inventory Database has complete records for 161 of the surveyed wetlands across all the attributes listed in Table 4.1. The WGCMA scoring of these attributes was done across different scales: presence or absence values were recorded in the inventory for the attributes of conservation forestry, other land usage, and diverted or farm runoff. Using the Wetlands Inventory Database records, I have calculated their frequency statistics, which are given in Table 4.2a. Tourism, food production, stock water supply and commercial fishing were recorded by the WGCMA as being absent or present, and presence was further classified as in seasonal use or as unrestricted usage; their frequency statistics are given in Table 4.2b. As seen in Table 4.1, drainage, disposal of water, water storage, obstruction, redirection attributes, and diverted or farm runoff were all used in the assessment of drainage disposal. Each of these components was recorded by WGCMA as being absent or present. Present values were further graded to be of either no impact, or moderate to low impact, or severe impact. The frequency of the number of wetlands exhibiting these impacts, or not, is given in Table 4.2c.

Table 4.2a: Summary of frequency statistics for Economic value input attributes of conservation forestry, other land usage and diverted or farm runoff in the WGCMA Wetland Inventory Database.

Economic value	Absent	Present	Total
Conservation forestry	86	75	161
Other land usage	151	10	161
Diverted or farm runoff	146	15	161

Table 4.2b: Summary of frequency statistics for Economic value input attributes tourism, food production, stock water supply and commercial fishing in the WGCMA Wetland Inventory Database.

Economic value	Absent	Present		Total
		Seasonal use	Unrestricted use	
Tourism	118	23	20	161
Food production	72	15	74	161
Stock water supply	132	14	15	161
Commercial fishing	159	2	0	161

Table 4.2c: Summary of frequency statistics for Economic value input attributes drainage, disposal of water, water storage, obstruction, redirection in the WGCMA Wetland Inventory Database.

Economic value	Absent	Present			Total
		No impact	Moderate to low impact	Severe impact	
Drainage	110	15	24	12	161
Disposal of water	135	2	15	9	161
Water storage	146	2	8	5	161
Obstruction	104	2	36	19	161
Redirection	80	0	57	24	161

My frequency statistics for contributing attributes confirm those of Greening Australia and the West Gippsland CMA reports for inventoried subcatchment wetlands. The confirmed statistics are indicated by a tick (✓), and they are:

- ✓ Tourism was evidenced at just over a quarter (27 %) of the sites (report value given as 29%); and,
- ✓ The majority of wetlands showed some production value with over half (56%) used for food production, nearly half (47%) for conservation forestry or other land usages (6%).

Additionally, I note the following were not specifically mentioned in either report:

- With the exception of redirection where half of the wetlands showed evidence, other forms of drainage disposal were not being used at the majority of wetlands;
- Few sites (18%) were being used for supplying water for stock; and,
- Only two sites showed any form of commercial fishing.

4.2.2 Economic value – cross-tabulation analyses and contingency tables

Cross-tabulation analysis was undertaken to produce contingency tables for all attributes used in the WGCMA assessment of economic value. In the interests of brevity, only a representative set of contingency tables (Tables 4.3a and 4.3b; Tables 4.4a and 4.4b; and, Tables 4.5a and 4.5 b) are displayed at the end of this section. To assist the reader, I will display tables at the end of each section in this chapter and in the next two chapters. The full set of contingency tables of remaining attributes used in Economic value assessments is provided in Appendix H.

Table 4.3a shows each of the present/absent assessed attributes of Table 4.2a: conservation forestry; other land use; and, diverted or farm runoff tabulated against their final Economic value assessments; each attribute's absence or presence statistics are displayed as columns against rows for their WGCMA assessed Economic value.

A check shows that only one wetland record (wetland № 877461) was evaluated as high for Economic value in the WGCMA Wetland Inventory Database, and Table 4.3a shows its recorded attributes as an absence of conservation forestry and other land uses, and with the presence of diverted or farm runoff.

A major difficulty in the interpretation of this contingency table (Table 4.3a), and some others that follow, is the low number of records of some cells. With only one high Economic value assessed across the subcatchments, it is not possible to observe patterns between individual attributes and high-value assessments, nor is it wise to make any generalizations on the strength of one case. In an effort to resolve this difficulty for Economic values, sums of high value and moderate value wetland counts were done, and sums of very low and low value wetlands counts were made for the attributes of Table 4.3a. This was done on the assumption that predictors for very low value and low values would be most similar and likewise, attributes that indicate high value will also be predictors for moderate (nearest to high) values. Table 4.3b shows these calculations for the diverted or farm runoff attribute.

Very low and low value wetlands tend to have an absence of diverted or farm runoff, while moderate and high-value wetlands have more diverted or farm runoff presences. To check the statistical significance of this using the chi-squared (χ^2) test for row and column independence, there is a precondition that each cell used in the calculation must have a count of at least five. In Table 4.3b, the present record of very low and low Economic values combined is less than five, and the precondition is not met. Checking the other attributes, that is conservation forestry and other land use, the precondition was not met again, so that further statistical analysis cannot be done.

Contingency tables for tourism and stock water supply, two of the four attributes whose frequency statistics are shown in Table 4.2b, are given in Table 4.4a. Relationships between attributes are hard to discern in this table, so very low counts were summed with low counts and moderate counts with high counts, as seen in Table 4.4b for the attribute of stock water supply. In this Table, all cells have a minimum count of five so the chi-squared (χ^2) test was done. The test calculates the expected frequencies for each cell if there is no relationship between that particular cell's column and row. Then, the test then checks the magnitude of sum of the squared differences against what is likely to occur given chance alone, usually at a 95% confidence interval. In the case of stock water supply, the χ^2 result is 26.5, which exceeds the critical value of 5.99. Thus the result is found to be significant at 0.05 (95% confidence) at two degrees of freedom, meaning the distribution shown in Table 4.4b is very unlikely to have come about due to chance at a 0.05 significance level.

Table 4.5a shows the cross-tabulation analysis of drainage, one of the four attributes whose frequency statistics are shown in Table 4.2c, and were measured as either absent, or present with no impact or present with moderate to low impact or present with severe in impact. A preliminary look at Table 4.5a shows likely associations between the absence of drainage and very low and low Economic values, and presence with moderate and high-value sites. To explore this further, the χ^2 value was calculated after very low and low rows were added, and moderate and high value rows summed. For drainage, the precondition for χ^2 test was met, and its value was calculated as 31.4 for 3 degrees of freedom, which exceeds the critical value is 7.815 at $p = 0.05$. Thus, the values shown in Table 4.5b are unlikely to have come about due to chance, and it is more likely that there is an association between column and row values, meaning that sites with presence records for drainage at a site are more likely to have moderate and high Economic value assessments.

By calculating all cross-tabulation statistics for all Economic value attributes and summing across rows, I found that it was only possible to compute the χ^2 statistic for the attributes stock water supply and drainage, as shown in Tables 4.4b and 4.5b. Therefore, the following correlations with wetland classifications can be made:

- Higher than expected usage of a wetland for stock water supply is associated with moderate and high Economic value wetlands; and
- Higher than expected impacts due to drainage are associated with higher Economic valued wetlands.

Neither of these attributes and their associations were reported by the WGCMA, and this result indicates that quite important associations can be extracted from their Wetlands Inventory Database by the application of quite simple (i.e. univariate) statistical procedures.

More importantly, no statistically significant associations were found for the attributes of commercial fishing, conservation forestry, disposal of water, diverted or farm runoff, food production, obstruction, other land usages, redirection, tourism, and water storage. This brings into question the WGCMA (2007) conclusion that high scores for commercial fishing, tourism and, to a lesser degree, the production value of land surrounding wetlands had an impact in deciding Economic value. Using the data recorded in the Wetlands Inventory Database, there is no evidence in the frequency and cross-tabulation analyses of these attributes of any such associations for inventoried subcatchment wetlands. It can only be assumed that this pattern was observed at the wetland sites of international and/or national significance, like Corner Inlet, Anderson Inlet and Lake Wellington, as it is not evidenced for subcatchment wetlands whose records were stored in the Inventory Database.

Table 4.3a: Contingency table for the Economic value input attributes of conservation forestry, other land use and diverted or farm runoff. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Economic values. Non-empty cells have been shaded.

Economic value		**Conservation forestry**		**Other land usage**		**Diverted or farm runoff**		**Total**
		Absent	**Present**	**Absent**	**Present**	**Absent**	**Present**	
Very low	Count	2	22	23	1	24	0	24
	%	8%	92%	96%	4%	100%	0%	
Low	Count	57	52	101	8	105	4	109
	%	52%	48%	93%	7%	96%	4%	
Moderate	Count	26	1	26	1	17	10	27
	%	96%	4%	96%	4%	63%	37%	
High	Count	1	0	1	0	0	1	1
	%	100%	0%	100%	0%	0%	100%	
Total		86	75	151	10	146	15	161
% within Economic value		53%	47%	94%	6%	91%	9%	

Table 4.3b: Contingency table for the Economic value input attribute diverted farm runoff with very low and low assessment counts added and moderate and high counts summed. The value in brackets is the computed expected frequencies for the cell if there is no association between diverted or farm runoff and the WGCMA assessment value.

Economic value	Diverted or farm runoff		Total
	Absent	Present	
Very low & low	129 (121)	4 (12)	133
Moderate & high	17 (25)	11 (3)	28
Total	146	15	161

Table 4.4a: Contingency table for the Economic value input attributes of tourism and stock water supply. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Economic values. The abbreviation Season is used for Seasonal, and Unres'd is used for unrestricted. Non-empty cells have been shaded.

Economic value		Tourism			Stock water supply			Total
		Absent	Present		Absent	Present		
			Season	Unres'd		Season	Unres'd	
Very low	Count	20	3	1	24	0	0	24
	%	83%	13%	4%	100%	0%	0%	
Low	Count	71	20	18	94	9	6	109
	%	65%	18%	17%	86%	8%	6%	
Moderate	Count	26	0	1	14	5	8	27
	%	96%	0%	17%	30%	0%	70%	
High	Count	1	0	0	0	0	1	1
	%	100%	0%	0%	0%	0%	100%	
Total		118	23	20	132	14	15	161
% within Economic value		73%	14%	13%	82%	9%	9%	

Table 4.4b: Contingency table for the Economic value input attribute stock water supply with very low and low assessment counts added and moderate and high counts summed. The abbreviation Season is used for Seasonal, and Unres'd is used for unrestricted. The value in brackets is the computed expected frequencies for the cell if there is no association between stock water supply and the WGCMA assessment value. $\chi^2_{(df=2)}$ value = 26.5 and one-tailed p-value < 0.0001 is extremely statistically significant.

Economic value	**Stock water supply**			**Total**
	Absent	**Present**		
		Season	Unres'd	
Very low & low	118 (109)	9 (12)	6 (12)	133
Moderate & high	14 (23)	5 (2)	9 (3)	28
Total	132	14	15	161

Table 4.5a: Contingency table for the Economic value input attribute of drainage. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Economic values. Non-empty cells have been shaded.

Economic value		**Drainage**				**Total**
		Absent	**Present**			
			No impact	Moderate to low impact	Severe impact	
Very low	Count	21	1	1	1	24
	%	88%	4%	4%	4%	
Low	Count	82	7	15	5	109
	%	75%	6%	14%	5%	
Moderate	Count	7	7	7	6	27
	%	26%	26%	26%	22%	
High	Count	0	0	1	0	1
	%	0%	0%	100%	0%	
Total		110	15	24	12	161
% within Economic value		68%	9%	15%	8%	

Table 4.5b: Contingency table for the Economic value input attribute of drainage with very low and low assessment counts added and moderate and high counts summed. The value in brackets is the computed expected frequencies for the cell if there is no association between drainage and the WGCMA value. $\chi^2_{(df=3)}$ value = 31.4 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Economic value	Drainage				Total
	Absent	Present			
		No impact	Moderate to low impact	Severe impact	
Very low & low	103 (91)	8 (12)	16 (20)	6 (10)	133
Moderate & high	7 (19)	7 (3)	8 (4)	6 (2)	28
Total	110	15	24	12	161

4.3 Social value of wetlands

Final Social values for wetlands were computed using nine component Social values:

- Recreational fishing;
- Swimming;
- Camping;
- Hunting;
- Boating;
- Passive recreation;
- Bird watching;
- Education; and,
- Park value.

These were quantified using 12 attributes as summarized in Table 4.6. Appendix G includes a more detailed version of this information with the ranges for values and a listing of database tables and attributes used by the WGCMA.

Table 4.6: Component attributes of each Social value assessed to decide the final Social value of each inventoried wetland. See also Table 3.1.

Social value	Attributes
Recreational fishing	Recreational fishing
Swimming	Swimming
Camping	Camping
Hunting	Hunting
Boating	Boating Water skiing
Passive recreation	Passive recreation Motorized four-wheel drive vehicles
Bird watching	Bird watching
Education	Education Research
Park value	Park value

4.3.1 Social value – frequency statistics and analyses

The WGCMA Wetland Inventory Database holds 160 complete records for the 12 attributes needed to assess Social values for inventoried sites. The scorings for all values, except park value, were scaled as no use, occasional use, seasonal use, and frequent use. The frequency statistics of these are given in Table 4.7a. Park value was quantified using the GIS crown land tenure layer and then assigned a value of 0 to 5 accordingly using:

- 0 represented no data available;
- 1 represented wetlands not located in a park or reserved crown land;
- 2 represented wetlands located in a State forest or other reserved crown land;
- 3 was used for wetlands located in nature conservation reserves or which had historic and cultural features documented;
- 4 represented wetlands located in Regional or State Parks, Coastal or a Marine and Coastal Park; and,

- 5 represented wetlands located in National Parks, Reference area or Wilderness area, Marine National Park or Marine Sanctuary or Marine Park. The frequency statistics for park value using this scale are given in Table 4.7b.

Making some allowances for small differences, my frequency statistics for Social value contributing attributes (Tables 4.7a and 4.7b) confirm those previously reported by Greening Australia (2006) and the WGCMA (2007) for inventoried subcatchment wetlands. The confirmed statistics are indicated by a tick (✓), and they are:

- ✓ The majority of sites showed some recreational value;
- ✓ Bird watching was the most recorded social activity seen at nearly 60% of sites (WGCMA reported 65% of sites);
- ✓ Passive recreation was recorded at nearly 45% of all sites, and 42% of those sites were used on a frequent basis (WGCMA reported at least 50% of sites);
- ✓ Some form of hunting occurred at over 54% of sites (WCGMA value was 47%);
- ✓ Education occurred at nearly 35% of sites, with half the sites recording occasional use (WGCMA report gave 38%); and,
- ✓ Motor bikes and four-wheel drive activities occurred at 20% of inventoried sites.

Further summarising the frequency statistics displayed in Table 4.7a and Table 4.7b, I note in addition to what was reported by Greening Australia and the WGCMA, that:

- Recreational fishing occurred at only 30% of inventoried sites, and it was mostly occasional in nature;
- Swimming was recorded at fewer than 10% of all surveyed sites, and most usage was occasional or seasonal;
- Camping occurred at just over 15% of sites, where it was only occasional or seasonal in nature;
- Boating was recorded at over 22% of sites;

- Only two (1.2%) sites were used for water skiing, one occasionally and one frequently;
- Likewise, research was recorded at only two sites of 160, but not regularly; and
- Nearly 60% of wetlands in the inventory were not located in a protected area or on any reserved crown land, thereby they were most likely to be privately owned.

Table 4.7a: Summary of frequency statistics for all Social value input variables, except park value, in the WGCMA Wetland Inventory Database.

Social value	Attribute	Usage				Total
		None	Occasional	Season	Frequent	
Recreational fishing	Recreational fishing	112	35	2	11	160
Swimming	Swimming	145	7	7	1	160
Camping	Camping	134	19	7	0	160
Hunting	Hunting	73	44	41	2	160
Boating	Boating	124	15	18	3	160
	Water skiing	158	1	0	1	160
Passive recreation	Passive recreation	89	24	17	30	160
	Motorized four-wheel	128	21	4	7	160
Bird watching	Bird watching	65	53	16	26	160
Education	Education	105	28	16	11	160
	Research	158	0	0	2	160

Table 4.7b: Frequency statistics for Social value input variable Park value as supplied from GIS crown land tenure layer in the Social input data file.

Social value	0	1	2	3	4	5	Total
Park value	10	95	17	9	12	17	160

4.3.2 Social value – cross-tabulation analyses and contingency tables

As was done for Economic value in the previous section, cross-tabulation analyses were done for all attributes used in Social value assessments. A representative set of the contingency tables are given here and the full set are provided in Appendix I. Within the dataset, there were four wetlands whose final Social value was not assigned within the Inventory Database, even though all attributes had been recorded for them; the contingency tables display the assessments for these wetlands in a row labelled unknown.

Broadly speaking, the contingency tables of the attributes share common patterns in regard to where high-value wetlands are found. In the cases of boating, camping, education, hunting, recreational fishing, research, and swimming, wetlands assessed as high Social value are equally spread across columns of no value, occasional use, seasonal use and frequent use. The hunting attribute illustrates this with its contingency table shown as Table 4.8a. The attributes of bird watching and passive recreation have all high-value wetlands associated with frequent use; it is important to note in both cases, there are also wetlands of moderate or low value which had frequent use as well. In illustration, Table 4.9 shows the contingency table for bird watching. For the Social values of motorized four-wheel drive use and water skiing (shown in Table 4.10), the observed pattern is high-value wetlands did not record a value for either of these activities.

The low number of high Social value wetlands, five out of 160, frustrated the use of the chi-squared (χ^2) test for row and column independence from being conducted for most attributes. To assist in meeting the necessary precondition for the test (at least a count of five in each table cell), I grouped very low and low values together, and I added moderate and high values, as I had done previously for Economic values. It was also necessary to combine data across columns; occasional, seasonal and frequent use into one category titled present, for use with absent counts in calculation of the χ^2 test. The resulting amalgamation for hunting is shown in Table 4.8b with the expected frequencies for each cell shown in brackets if there were no relationship between that particular cell's column and row. In this instance, the χ^2 was calculated as 2.1 with 1 degree of freedom. This returned a result that was not significant at 0.05. In other words, the actual distribution of values seen for hunting is not significantly different to that may be found due to chance.

Likewise the rows and columns of each contingency table for all remaining attributes listed in Table 4.7a were done. For water skiing, shown as Table 4.10, and bird watching and research attributes, the precondition for the χ^2 test was not met. For hunting, the observed values recorded were not significantly different to those that may occur due to chance. However, the χ^2 test values of all remaining attributes (recreation fishing, swimming, camping, boating, passive recreation, motorized four-wheel drive, and education) were different to those expected due to chance at a 95% confidence interval. The following results are given in order of strength of the association as indicated by the χ^2 value shown in brackets, are:

- Sites used for passive recreation were strongly associated with moderate and high Social values assessments, in that, twice as many sites were recorded for than would be expected due to chance ($\chi^2 = 50.86$);
- Double the expected proportion of sites with moderate and high Social values assessments showed usage of recreational fishing, and low and very low sites characteristically did not have fishing ($\chi^2 = 45.12$);
- A third of sites were used for education, and amongst these twice the expected proportion were moderate and high Social value assessed wetlands ($\chi^2 = 34.31$);
- Although only 17% of sites were used for camping, proportionally double the expected number of moderate and high-value sites had camping use ($\chi^2 = 12.65$);

- Swimming was only seen at 10% sites, but there were double the expected number of moderate and high-value sites were used for swimming ($\chi^2 = 11.71$);
- Higher than expected proportion of wetlands were associated with boating ($\chi^2 = 11.71$); and,
- Motorized four-wheel drive use is slightly higher than expected for moderate and high wetlands ($\chi^2 = 4.41$).

Finally the cross-tabulation statistics were done for park value and these are displayed in Table 4.11a. Note that there were 10 wetlands recorded where no data was available for its park value (column 0) and there were 95 wetlands in non-protected locations (column 1). Table 4.11b shows the addition of rows for very low and low Social value wetlands and the summing of moderate and high Social value wetlands against their park value. The figures in brackets give the expected value if there is row and column independence and the χ^2 calculation is 68.1 for 1 degree of freedom. This exceeds the critical lookup value of 3.84 for a value of $p < 0.05$ indicating there is likely a strong relationship between park value and a wetland's Social classification. It seems that moderate and high Social value wetlands are more likely to be protected, and proportionally very low and low value wetlands are more likely to be unprotected sites.

None of the above associations were reported by the WGCMA (2007); they made no mention of the strong associations of high-value wetlands with park value, passive recreation, recreational fishing, education, camping, swimming, boating or motorized four-wheel drive usage. Rather, the WGCMA reported that the high-value sites were those exhibiting indigenous and European cultural values together with high visual amenity. Visual amenity was used as one attribute to assess significant wetlands (WGCMA, 2006b), but for subcatchment wetlands it seems that visual amenity or *beauty is in the eye of the beholder* since there are no records, tables or attributes for visual amenity, or similar, in the Wetlands Inventory Database. My electronic search of all tables in the Database for words (or their parts) *indigenous* and *European* failed to find a mention, not even in any of the recorded comments within the tables. The

WGCMA report states that only 5.6% of the sample was known to have documented historical or cultural features, presumably the indigenous and European cultural values mentioned. Searching for these amongst the 12 attributes used to calculate Social value (Table 4.6), there is no attribute that assesses these cultural values unless they were assessed under the passive recreation attribute.

Table 4.8a: Contingency table for the Social value input attribute of hunting. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells, other than for unknown, have been shaded.

Social value		Hunting				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	0	1	3	0	4
	%	0%	25%	75%	0%	
Very low	Count	36	1	0	0	37
	%	97%	3%	0%	0%	
Low	Count	20	33	20	1	74
	%	27%	45%	27%	1%	
Moderate	Count	15	8	16	1	40
	%	38%	20%	40%	2%	
High	Count	2	1	2	0	5
	%	40%	20%	40%	0%	
Total		73	44	41	2	160
% within Social value		46%	27%	26%	1%	

Table 4.8b: Contingency table for the Social value input attribute hunting with very low and low assessment counts added and moderate and high counts summed. All columns denoting any hunting activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between hunting and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 2.065 and one-tailed p-value = 0.0753, which is not statistically significant.

Social value	Hunting		Total
	Absent	Present	
Very low & low	56 (52)	55 (155)	111
Moderate & high	17 (21)	28 (24)	45
Total	73	83	156

Table 4.9: Contingency table for the Social value input attribute of bird watching. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells, other than for unknown, have been shaded.

Social value		Bird watching				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	2	0	0	2	4
	%	50%	0%	0%	50%	
Very low	Count	34	2	0	1	37
	%	92%	5%	0%	3%	
Low	Count	28	38	5	3	74
	%	38%	51%	7%	4%	
Moderate	Count	1	13	11	15	40
	%	2%	33%	27%	38%	
High	Count	0	0	0	5	5
	%	0%	0%	0%	100%	
Total		65	53	16	26	160
% within Social value		41%	33%	10%	16%	

Table 4.10: Contingency table for the Social value input attribute of water skiing. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells, other than for unknown, have been shaded.

Social value		**Water skiing**				**Total**
		Absent	**Present**			
			Occasional	Seasonal	Frequent	
Unknown	Count	4	0	0	0	4
	%	100%	0%	0%	0%	
Very low	Count	35	1	0	1	37
	%	92%	4%	0%	4%	
Low	Count	74	0	0	0	74
	%	100%	0%	0%	0%	
Moderate	Count	40	0	0	0	40
	%	100%	0%	0%	0%	
High	Count	5	0	0	0	5
	%	100%	0%	0%	0%	
Total		158	1	0	1	160
% within Social value		99%	0.5%	0%	0.5%	

Table 4.11a: Contingency table for the Social value input attribute of park value. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells, other than for unknown, and column 0 (no data available for park value) have been shaded.

Social value		Park value 0	1	2	3	4	5	Total
Unknown	Count	3	0	1	0	0	0	4
	%	75%	0%	25%	0%	0%	0%	
Very low	Count	1	33	3	0	0	0	37
	%	3%	89%	8%	0%	0%	0%	
Low	Count	3	57	8	2	1	3	74
	%	4%	77%	11%	3%	1%	4%	
Moderate	Count	3	5	5	7	8	12	40
	%	8%	13%	13%	17%	19%	30%	
High	Count	0	0	0	0	3	2	5
	%	0%	0%	0%	0%	60%	40%	
Total		10	95	17	9	12	17	160
% within Social value		6%	60%	10%	6%	8%	10%	

Table 4.11b: Contingency table for the Social value input attribute park value with very low and low assessment counts added and moderate and high counts summed. All columns denoting any protected area have been summed. Values in brackets are the expected frequencies for each cell if there is no association between protected areas and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 68.056 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Social value	Park value: Not protected	Park value: Protected	Total
Very low & low	90 (68)	17 (39)	107
Moderate & high	5 (27)	37 (15)	45
Total	95	54	149

4.4 Environmental value of wetlands

Environmental wetland values were computed using seven component Environmental values:

- Wetland rarity;
- Significant flora;
- Significant fauna;
- Habitat value;
- Hydrology;
- Vegetation intactness– critical lifeforms; and,
- Vegetation intactness– width of the vegetation fringe.

Assessment of these values was done through the collection of 16 separate attributes, as summarized in Table 4.12. Appendix G includes a more comprehensive version of this table detailing the 16 attributes, and their subattributes, with a listing of the database tables and contributing columns which were searched to find values for individual wetlands in the WGCMA Wetland Inventory Database.

4.4.1 Environmental value – frequency statistics and analyses

The WGCMA Wetland Inventory Database holds complete records for 163 inventoried sites where all seven Environmental values were assessed. Greening Australia (2006) reported frequency statistics on at a catchment level, however the WGCMA (2007) did not report frequency statistics for any Environmental value attributes. Therefore, I have computed frequency tables for wetlands across the region by sourcing the WGCMA Wetlands Inventory Database. Since these statistics are not obtainable elsewhere, I provide frequency tables for each of the seven Environmental values at the end of this subsection.

Table 4.12: Component attributes of each Environmental value assessed to decide the final Environmental value of each inventoried wetland. See also Table 3.1.

Environmental value	Attributes
Wetland rarity	Wetland rarity
Significant flora	Significant flora
Significant fauna	Significant fauna listed in Victorian Rare or Threatened Species (VROT) register Significant fauna listed in Flora and Fauna Guarantee (FFG) Act
Habitat value	Wetland rarity Terrestrial zone habitat type Shoreline profile
Hydrology	Drainage Disposal of water Water storage Obstruction Redirection
Vegetation intactness– critical lifeforms	Floral types of the most dominant wetland EVC Number of floral species present Substantial modifications
Vegetation intactness– width of vegetation fringe	Width of vegetation fringe

Wetland rarity was indicated in the Database by each site's wetland classification under the Corrick and Norman (1980) scheme. The frequency statistics for wetland types in the region and within the inventory sample are given in Table 3.2. As a result of infield assessments 40% of wetlands were reclassified accounting for the two unexpected records in the database: one unclassified; and, one flooded river flat, where previously it was thought none existed (Greening Australia, 2006). Inventory Database recorded frequencies are shown in Table 4.13, and figures in brackets show pre-inventory counts of Table 3.2. Shallow freshwater marshes are the most represented in the West Gippsland region and flooded river flats and permanent saline wetlands are the least common.

The WGCMA ascertained the value of significant flora through species listings for rare, vulnerable or endangered in the Flora Information System (1994). The overall site value was obtained by summing the individual recorded species values for Victorian Rare or Threatened (VROT) (DSE, 2005a) species using a scale of:

- 1 for poorly known;
- 2 for rare species;
- 3 for vulnerable species; and,
- 4 for endangered species.

Table 4.14 shows that the majority of sites did not record any VROT species. For significant flora, the WGCMA originally planned to include a measure based on additional species appearing as listed in either the Flora and Fauna Guarantee (FFG) Act 1988 or under the Australian government Environment Protection and Biodiversity Conservation (EPBC) Act 1999. As no site in the inventory database had recorded species under either Acts, it was not necessary to include it in the assessment.

The WGCMA used two attribute values in the WGCMA wetland inventory database to assess significant fauna. Like significant flora and using the same scale, the presence of VROT species values was checked at each site. The second attribute checked for those species not listed in the VROT list but protected under the Flora and Fauna Guarantee Act (FFG Act, 1988). A value of 1 was given to each of these species and a total calculated per site. Like significant flora, there were no additional species or ecological communities listed under the Environment Protection and Biodiversity Conservation Act (EPBC Act, 1999). Table 4.15 shows the frequency distributions of the number of VROT and FFG records where the majority of sites did not have fauna in either lists.

Habitat value was assessed by the WGCMA using wetland rarity, terrestrial zone habitat type and the shoreline profile. Wetland rarity has already been mentioned above and frequency statistics are given in Table 3.2 and Table 4.13. Terrestrial zone habitat type was described noting the abundance, or otherwise, of nine different site features: rocks; logs; emergent vegetation; exposed substrate; submerged or free-floating vegetation; shallow to medium depth water; permanent deep pools; water edge; and, a category labelled other. The frequency statistics for terrestrial zone habitat are seen in Table 4.16a, where the frequency of each site feature is given. Shoreline profile, an attribute of habitat value, was described by two subattributes: the type of large vegetation present: shrubs; alive and dead trees; and, a description of the shoreline profile. The frequencies of vegetation types are given in Table 4.16b whilst the frequency table for differing shoreline descriptions, described as regular or irregular with islands present or not, is given in Table 4.16c.

The hydrology attribute was assessed using drainage, disposal of water, water storage, obstruction, redirection as inputs. These inputs have already been described and used in the assessment of Economic value, and their frequency statistics are found in Table 4.2c.

Three attributes were used by the WGCMA in the assessment of vegetation intactness– critical lifeforms: the floral types of the most dominant wetland EVC present; the number of floral species present; and whether or not substantial modifications had been made at the site. At each site, the EVC present with the greatest percentage cover was designated the dominant EVC and then the percentage sum of coverage of various floral types present: graminiods; shrubs; herbs; sedges (including rushes and reeds); ferns (including bryophytes); and, grasses was assessed at the site. Table 4.17a shows the frequency statistics for the number of wetlands with differing percentage covers of each floral type. Table 4.17b shows the frequency statistics of the number of floral species present, the second subattribute of vegetation intactness– critical lifeforms.

When checking how many wetlands had been substantially modified, it can be seen in Table 4.18 that 101 sites (62%) had native flora substantially modified. Finally, frequency statistics for the Environmental value vegetation intactness– width of vegetation fringe statistics are shown in Table 4.19.

As mentioned earlier, frequency statistics were not reported for Environmental values over the region by WGCMA or Greening Australia, however their reports mention the following two points, which my frequency statistics are able to confirm:

- ✓ The rarest wetland types in the region are flooded river flats and permanent saline wetlands. In fact, the inventory exercise found one flooded river flat, where previously it was not thought to exist; and,
- ✓ Freshwater marshes are the most common wetland type observed in the region.

Further examination of my frequency tables shows that:

- Most sites (88%) did not record any VROT species when assessed for significant flora and only 2% sites showed very high VROT species scores for flora;
- Most sites were devoid of significant fauna; only 14% had any registered fauna in VROT species listing and the majority of these sites had three or fewer species. In addition, only 10% of sites had fauna protected under the Flora and Fauna Guarantee (FFG) Act and the majority of these had only one listed species present;
- Site features were used in part to assess habitat value and the most common site features seen were emergent vegetation and water’s edge, followed by exposed substrate and logs. Shoreline vegetation was also used for habitat value assessment and shrubs and alive trees were most often seen at sites, and at a twice the frequency of observed dead trees. Finally for habitat value assessment, the most common shoreline profile seen was an irregular profile; shorelines with islands were only seen in 10 of the 163 sample;
- As previously stated in Section 4.2.1 Economic value for hydrology, most wetlands were not being used for other forms of drainage disposal with the exception of water redirection;
- In the assessment of vegetation intactness– critical lifeforms, the most common floral type by percentage coverage observed in the dominant wetland EVC present at each site, was herbs and the least abundant were ferns. The

majority of sites were seen to have between six to 10 different floral species present, however almost two-thirds of sites had their native flora substantially modified; and,

- The width of vegetation fringe varied significantly across sites, between values of 0 to over 1000 metres recorded at two sites. The width was used to assess vegetation intactness– width of vegetation fringe and a quarter of the sites (27%) showed no fringe vegetation width.

Table 4.13: Frequency table of wetland type classified according to the Corrick and Norman (1980) scheme and used to assess the Environmental value wetland rarity. Figures in brackets show pre-inventory counts of Table 3.2.

Environmental value	**Wetland rarity**	
	Frequency	**Percentage**
Unclassified	1	< 1
Permanent saline wetland	3	2
Semipermanent wetland	16	10
Shallow freshwater marsh	70 (71)	43
Freshwater meadow	31	19
Deep freshwater marsh	25 (27)	15
Permanent open water	16 (15)	10
Flooded river flat	1	< 1
Total	163	100

Table 4.14: Frequency and percentage distributions of total scorings of Victorian Rare or Threatened (VROT) species under the FFG Act used to evaluate significant flora Environmental value.

<table>
<tr><th rowspan="3">Environmental value</th><th colspan="2">Significant flora</th></tr>
<tr><th colspan="2">Sum of VROT species scores</th></tr>
<tr><th>Frequency</th><th>Percentage</th></tr>
<tr><td>0</td><td>143</td><td>88</td></tr>
<tr><td>2 to 6</td><td>12</td><td>7</td></tr>
<tr><td>10 to 16</td><td>5</td><td>3</td></tr>
<tr><td>5</td><td>1</td><td rowspan="3">2</td></tr>
<tr><td>53</td><td>1</td></tr>
<tr><td>63</td><td>1</td></tr>
<tr><td>Total</td><td>163</td><td>100</td></tr>
</table>

Table 4.15: Frequency and percentage distributions of the two site attributes, Fauna Victorian Rare or Threatened (VROTs) sum and fauna protected under the Flora and Fauna Guarantee (FFG) Act used to evaluate significant fauna Environmental value.

<table>
<tr><th rowspan="3">Environmental value</th><th colspan="4">Significant fauna</th></tr>
<tr><th colspan="2">Sum of fauna VROT scores</th><th colspan="2">Sum of fauna FFG scores</th></tr>
<tr><th>Frequency</th><th>Percentage</th><th>Frequency</th><th>Percentage</th></tr>
<tr><td>0</td><td>140</td><td>86</td><td>146</td><td>90</td></tr>
<tr><td>1</td><td>3</td><td>2</td><td>13</td><td>8</td></tr>
<tr><td>2</td><td>4</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>3</td><td>8</td><td>5</td><td>1</td><td rowspan="2">1</td></tr>
<tr><td>4</td><td>2</td><td>1</td><td>1</td></tr>
<tr><td>6</td><td>2</td><td>1</td><td rowspan="4"></td><td rowspan="4"></td></tr>
<tr><td>7</td><td>2</td><td>1</td></tr>
<tr><td>8</td><td>1</td><td rowspan="2">1</td></tr>
<tr><td>12</td><td>1</td></tr>
<tr><td>Total</td><td>163</td><td>100</td><td>163</td><td>100</td></tr>
</table>

Table 4.16a: Frequency values for the site features used to assess terrestrial zone habitat type, one of the subattributes of the Environmental value of habitat value.

Environmental value	Habitat value			
	Terrestrial zone habitat type			
	Site features			
	Absent	Present		Total
		Usually	Abundant	
	Frequency	Frequency	Frequency	
Rocks	144	18	1	163
Logs	62	80	21	163
Emergent vegetation	12	58	93	163
Exposed substrate	49	80	34	163
Submerged or free-floating vegetation	83	37	43	163
Shallow to medium depth water	87	63	13	163
Permanent deep pools	126	12	25	163
Water edge	20	60	83	163
Other	154	4	5	163

Table 4.16b: Frequency values for shoreline vegetation types used to assess shoreline profile, one of the subattributes of the Environmental value habitat value.

Environmental value	Habitat value			
	Shoreline profile			
	Shoreline vegetation			
	Absent	Present		Total
		Usually	Abundant	
	Frequency	Frequency	Frequency	
Shoreline shrubs	33	38	92	163
Alive trees	33	56	74	163
Dead trees	65	84	14	163

Table 4.16c: Frequency values for shoreline description used to assess shoreline profile, a subattribute of the Environmental value of habitat value.

Environmental value	Habitat value					
	Shoreline profile					
	Shoreline description					
	Unknown	**Regular**		**Irregular**		**Total**
		No island	With island	No island	With island	
	6	56	1	91	9	163

Table 4.17a: Frequency values for Floral types of dominant wetland EVC using the sum of % cover for each type of vegetation to assess the Environmental values of vegetation intactness– critical lifeforms. The abbreviation gram'ds is used for graminoids.

Environmental value	Vegetation intactness– critical lifeforms					
	Floral types of dominant wetland EVC: sum of % cover					
	gram'ds	**shrubs**	**herbs**	**sedges**	**ferns**	**grasses**
0	100	110	31	103	143	121
1 to 19%	43	23	98	35	15	32
20 to 39%	10	17	20	13	4	6
40 to 59%	5	8	7	8	1	4
60 to 79%	4	4	4	4	0	0
≥80%	1	1	3	0	0	0
Total	163	163	163	163	163	163

Table 4.17b: Frequency values for the number of wetlands sites which had varying counts of floral species recorded used to assess the Environmental value of vegetation intactness– critical lifeforms.

Environmental value	Vegetation intactness– critical lifeforms						Total
	Number of floral species at each site						
	0	**1 to 5**	**6 to 10**	**11 to 15**	**16 to 20**	**> 20**	
	20	31	75	25	10	2	163

Table 4.18: Frequency statistics for wetlands with, and without substantial modifications, a subattribute of the Environmental value of vegetation intactness–critical lifeforms.

Environmental value	Substantial modifications	
	Frequency	**Percent**
No modification	101	62
With modification	62	38
Total	163	100

Table 4.19: Frequency statistics for the width of vegetation fringe at each site used in part to decide the Environmental value assessment of vegetation intactness recognizing critical lifeform groups.

	Vegetation intactness– width of vegetation fringe	
	Width of vegetation fringe	
	Width	**Frequency**
Environmental value	**0**	44
	1	6
	2	14
	3 to 5	10
	6 to 10	15
	11 to 20	18
	21 to 30	2
	31 to 40	3
	41 to 59	33
	> **60**	18
	Total	163

4.4.2 Environmental value – cross-tabulation analyses and contingency tables

The WGCMA (2007) concluded that high-value wetlands, including those designated significant wetlands, scored well for vegetation intactness, habitat value and wetland significance. This conclusion can be checked by conducting cross-tabulation analyses and searching the resulting contingency tables for associations between contributing attributes and Environmental values. An illustrative sample of contingency tables is given at the end of this section; the remainder are found in Appendix J.

As with my prior reassessments of data used to rank Economic and Social values, Environmental value assessments include grades of very low, low value, moderate value and high value. However unlike Economic and Social value assessments, some wetlands were designated as very high Environmental value. Of the 163 wetlands eight were assessed as very high, 49 were high, 77 were moderate, 27 were low and one was classified as very low in Environmental value while one wetland's assessment was scored as unknown.

A first step in investigating the impact of the two wetland classification schemes: Corrick and Norman (1980) and EVCs on the evaluation and ranking of wetland sites was made by looking at Environmental values of Table 3.1 and Table 4.12 to see where the two schemes were used to assess Environmental value of wetlands. Wetland rarity classifies and ranks wetlands based on the Corrick and Norman scheme, and vegetation intactness– critical lifeforms uses the percentage coverage of the most common floral type of the dominant EVC at a site. In addition, wetland rarity was used as an input to the Environmental value habitat value.

The cross-tabulation statistics for wetland rarity are shown in the contingency table, Table 4.20a. Ignoring the three permanent saline wetlands, the one flooded river flat and the one shallow water marsh assessed as very low Environment value (small sample size), a number of associations can be made by comparing the percentages of wetland types surveyed and their corresponding percentage representation in various Environmental value assessments. For instance, it appears that freshwater meadows are more represented in lower-valued assessments than suggested by their proportion in the inventoried pool of wetlands. To see if this association was statistically significant, I sectioned the data so that a chi-squared (χ^2) test for independence, or otherwise, between the variables could be undertaken. In this instance, I reorganized the data of Table 4.20a into a 2 * 2 grid displaying counts of the number of wetlands that were one of (1) freshwater meadows with low value assessments; (2) freshwater meadows with other than low value assessments; (3) not freshwater meadow wetlands with low value assessments; and (4) not freshwater meadow wetlands with other than low assessments, and then did a χ^2 test. Repeating this process for all wetland types versus different value assessments, my χ^2 analyses showed that:

- There are statistically significant more than expected numbers of permanent open water wetlands assessments found to be moderate than what would be expected due to chance; and,
- There are statistically significant more than expected numbers of freshwater meadows were assessed as low Environmental value than would otherwise be expected.

The frequency values of the floral types of the dominant wetland EVC were given in Table 4.17a, with the sum of the percentage cover at a site of graminiods, shrubs, herbs, sedges, ferns and grasses. Herbs were the most often recorded vegetation site and the contingency table of cross-tabulation statistics for the sum of percentage herb coverage at sites is Table 4.21a.

Cross-tabulation analyses suggest a number of associations between various Environmental value assessments and the numbers of sites with different sums of percentages for herb coverage of the dominant wetland EVC. Ignoring unknown records and the very low Environment value (small sample size), I again partitioned the data into a 2 * 2 grids of counts of the number of wetlands with and without the characteristics being tested for independence, as was previously done for wetland rarity. In this instance, the percentage presence of herbs, or not, was compared to their numbers in very low and low wetland assessments against moderate, high and very high Environmental value assessments (Table 4.21b). The only statistically significant association found for herb coverage was between very low and low Environmental assessments and zero percentage total herb coverage.

The contingency table of the numbers of significant flora at wetland sites and their Environmental value assessment is Table 4.22. Low cell counts preclude the use of the χ^2 test. A visual inspection of the Table's shading shows a trend between higher numbers of floral VROT species numbers at a site and a shift towards high and very high-value assessments, although there are two sites of very high Environmental value where no significant flora were recorded. Likewise for the attributes used in assessing significant fauna, the contingency tables of the sum of fauna VROT species and sum of fauna FFG values against Environmental value assessments have small cell counts in most cells and similar shading patterns to those shown in Table 4.22 for significant flora. Both contingency tables can be found in Appendix J.

As stated earlier, habitat value was assessed using wetland rarity, terrestrial zone habitat type and shoreline profile, and shoreline profile was assessed using the type of large vegetation present: shrubs; alive and dead trees; and, a description of the shoreline profile. As an instance of a contingency table for habitat value, Table 4.23a shows the absence or presence of shrubs against Environmental value assessments. Higher counts for abundant shrubs are seen in high and very high-valued sites, and this was found to be statistically significant when tested (Table 4.23b).

Hydrology frequency tables were not repeated for Environmental value as they were given for Economic value (Table 4.2c). However their attributes of drainage, disposal of water, water storage, obstruction and redirection were checked against their Environmental value assessments for possible associations. The contingency table for drainage, absent or present at a site, is shown here for illustration as Table 4.24a. Shading for the table suggests, and the χ^2 test results show a significant association of very high and high Environmental value assessments with drainage being absent at a site (Table 4.24b and Table 4.24c).

Cross tabulation statistics for the vegetation intactness– width of vegetation fringe are shown in the contingency table, Table 4.25a. The shading indicates a trend to moderate, high and very high Environmental values for site with wider vegetation fringes, which when tested is highly statistically significant (Table 4.25b).

For the seven Environmental values of Table 4.12, 16 attributes were measured in their assessments. Several of the sixteen attributes were measured using subattributes, like terrestrial zone habitat type noted the presence or absence of nine different site features. For clarity and to assist the reader, only a representative set of Environmental value contingency tables have been given in this chapter with the remainder to be found in Appendix J.

A summary of all statistically significant associations between all Environmental values and their attributes detected in my analyses follows:

Wetland rarity

- Permanent open water assessments are proportionally more likely to be found amongst the moderate value wetlands; and,
- Proportionally more freshwater meadows were assessed as low Environmental value.

Significant flora

- Low individual cell counts precluded the use of the χ^2 test, so statistically significant associations cannot be made between Environmental value and significant flora using VROT species counts.

Significant fauna

- Statistically significant associations between Environmental value and significant fauna using VROT species count cannot be made due to low cell counts precluding the use of the χ^2 test; and,

- Likewise for the sum of fauna FFG, low cell counts prevented the use of the χ^2 test.

Habitat value

- The first attribute, wetland rarity, is described above;
- Terrestrial zone habitat type was assessed using presence or absence of: rocks; logs; emergent vegetation; exposed substrate; submerged of free-floating vegetation; shallow to medium depth water; permanent deep pools; water edge; and, other. The statistically significant associations of these were:
    - Proportionally as a group, low and very low Environmental value sites generally have a higher than expected number of sites where there is an absence of logs;
    - An absence of emergent vegetation is associated more often with low and very low Environmental value sites; and
    - Low and very low Environmental value sites as a group have an absence of water edge.
- Shoreline profile was assessed using the type of large vegetation present and a description of the shoreline profile. The statistically significant associations amongst these and their subattributes are:
    - An absence of shrubs is associated more often with low and very low Environmental value sites;
    - Low and very low Environmental value sites are more likely to have an absence of alive trees in the wetlands;
    - Proportionally as a group, low and very low Environmental value sites tended not to have dead trees present; whereas,
    - High and very high Environmental value sites had generally greater numbers of dead trees present.

Hydrology

Hydrology was assessed using the attributes of drainage, disposal of water, water storage, obstruction and redirection. All attributes were tested for associations with their Environmental value assessments, and the statistically significant ones were:

- Larger than expected numbers of high and very high Environmental value wetlands do not have drainage at their sites;
- Low and very low Environmental value sites are more often used for water storage than other sites;
- Obstruction has an impact in more low and very low Environmental value sites than would be expected due to chance;
- More high and very high Environmental value sites have a significantly greater absence of obstruction than other sites; and,
- An absence of redirection is seen at a proportionally greater number of high value and very high Environmental value sites than would be expected.

Vegetation intactness – critical lifeforms

As previously mentioned, vegetation intactness– critical lifeforms was assessed using three attributes: the floral types of the most dominant wetland EVC present by checking the percentage sum of the dominant EVC at each site; the number of floral species present; and, whether a site had been substantially modified or not. The statistically significant associations found in the cross-tabulation analyses for these attributes and their component subattributes are:

- Proportionally more high and very high-value wetlands have shrubs;
- More often than other sites, low and very low Environmental value sites do not have herbs present;
- More high and very high Environmental value sites have a significantly greater presence of sedges, including rushes and reeds;
- Ferns and bryophytes are more likely to be seen at sites of high and very high Environmental value sites;
- Low and very low Environmental value sites have very low species totals;

- Very high and high Environmental value sites are usually unmodified; and,
- There is a strong association between site modifications and very low and low assessed sites.

Vegetation intactness – width of vegetation fringe

- Low and very low Environmental value sites have very small vegetation widths onsite.

It is possible to confirm the WGCMA (2007) assertions that high Economic value wetlands score well for vegetation intactness, habitat value and wetland significance through the collation of the statistically significant patterns above. This analysis showed that higher-valued sites typically will not be a freshwater meadow (wetland type) and the wetland will have presence values vegetation intactness attributes: shrubs; sedges; ferns; and, bryophytes and dead trees (a measure of habitat value) will be present. It can be added that higher-value sites are usually unmodified and they have an absence of drainage, redirection and obstruction (hydrology attributes) in the wetland. Whilst, lower-valued sites are more strongly associated with absences of: logs; emergent vegetation; water's edge; shrubs; herbs; alive trees; and, dead trees (habitat value attributes). These sites typically have low species totals, small vegetation widths and site modifications (vegetation intactness measures) and often they are used for water storages and will have obstructions.

Table 4.20a: Contingency table for wetland rarity against overall WGCMA Environmental value assessment. Excluding cells for unknown Environmental value and unknown Norman and Corrick classification, non-empty cells are shaded.

Environmental value		Wetland rarity								Total
		Unknown	Permanent saline wetland	Semi-permanent saline	Shallow freshwater marsh	Freshwater meadow	Deep freshwater marsh	Permanent open water wetlands	Flooded river flat	
Unknown	Count	1	0	0	0	0	0	0	1	1
	%	0%	0%	0%	0%	0%	0%	0%	100%	
Very low	Count	0	0	0	1	0	0	0	0	1
	%	0%	0%	0%	100%	0%	0%	0%	0%	
Low	Count	1	0	2	11	9	1	3	0	27
	%	4%	0%	7%	41%	33%	4%	11%	0%	
Moderate	Count	0	2	8	28	16	11	12	0	77
	%	0%	3 %	10%	36%	21%	14%	16%	0%	
High	Count	0	1	5	24	6	12	1	0	49
	%	0%	2%	10%	49%	12%	25%	2%	0%	
Very high	Count	0	0	1	6	0	1	0	0	8
	%	0%	0%	13%	74%	0%	13%	0%	0%	
Total		1	3	16	70	31	25	16	1	163
% within Environmental value		< 1%	2%	10%	43%	19%	15%	10%	< 1%	

Table 4.20b: Contingency table for the attribute wetland rarity freshwater meadows for low and not low Environmental value counts. Values in brackets are the expected frequencies for each cell if there is no association between freshwater meadows and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 4.221 and one-tailed p-value = 0.02, which is statistically significant.

Environmental value	**Wetland rarity**		**Total**
	Freshwater meadows	**Not freshwater meadows**	
Low	9 (5)	18 (22)	27
Not low	22 (26)	113 (109)	135
Total	31	131	162

Table 4.21a: Contingency table for the percentage total herbs coverage at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Vegetation intactness– critical lifeforms						Total
		Floral types of most dominant wetland EVC						
		Sum of % herbs coverage per site						
		0%	1 to 19%	20 to 39%	40 to 59%	60 to 79%	≥80%	
Unknown	Count	0	1	0	0	0	0	1
	%	0%	100%	0%	0%	0%	0%	
Very low	Count	0	0	1	0	0	0	1
	%	0%	0%	100%	0%	0%	0%	
Low	Count	16	9	1	1	0	0	27
	%	59%	33%	4%	4%	0%	0%	
Moderate	Count	11	48	9	4	3	2	77
	%	14%	62%	12%	5%	4%	3%	
High	Count	1	37	8	1	1	1	49
	%	2%	76%	16%	2%	2%	2%	
Very high	Count	3	3	1	1	0	0	8
	%	38%	38%	13%	13%	0%	0%	
Total		31	98	20	7	4	3	163
% within Environmental value		19%	60%	12%	4%	3%	2%	

Table 4.21b: Contingency table for the attribute herbs in dominant EVC with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any herb presence in dominant EVC have been summed. Values in brackets are the expected frequencies for each cell if there is no association between herbs in the dominant EVC and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 31.6 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	Herbs		Total
	0	> 0	
Very low & low	16 (5)	12 (23)	28
Moderate, high & very high	15 (26)	119 (108)	134
Total	31	131	162

Table 4.22: Contingency table for the Environmental value significant flora which is indicated by sum at each site of all floral Victorian Rare or Threatened (VROTs) species values. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Significant flora: Sum of VROT species scores						Total
		0	2 to 6	10 to 16	25	53	63	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Low	Count	27	0	0	0	0	0	27
	%	100%	0%	0%	0%	0%	0%	
Moderate	Count	74	3	0	0	0	0	77
	%	96%	4%	0%	0%	0%	0%	
High	Count	38	8	2	1	0	0	49
	%	78%	16%	4%	2%	0%	0%	
Very high	Count	2	1	3	0	1	1	8
	%	25%	13%	37%	0%	13%	13%	
Total		143	12	5	1	1	1	163
% within Environmental value		88%	7%	3%	2%			

Table 4.23a: Contingency table for the shoreline vegetation subattribute of shrubs against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Habitat value – Shoreline profile – Shoreline vegetation – Shrubs**			
		Absent	**Present**		**Total**
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	0	0	1	1
	%	0%	0%	100%	
Low	Count	18	3	6	27
	%	67%	11%	22%	
Moderate	Count	12	27	38	77
	%	16%	35%	49%	
High	Count	2	8	39	49
	%	4%	16%	80%	
Very high	Count	0	0	8	8
	%	0%	0%	100%	
Total		33	38	92	163
% within Environmental value		20%	23%	57%	

Table 4.23b: Contingency table for the attribute shoreline vegetation shrubs with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any shoreline vegetation shrubs have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shoreline vegetation shrubs and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 42.351 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Shrubs**		**Total**
	Absent	**Present**	
Very low & low	18 (6)	10 (22)	28
Moderate, high & very high	14 (26)	120 (108)	134
Total	32	130	162

Table 4.24a: Contingency table for the attribute drainage against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Hydrology**				
		Drainage				
		Absent	**Present**			**Total**
			No impact	Low to moderate impact	Severe impact	
Unknown	Count	0	1	0	0	1
	%	0%	100%	0%	0%	
Very low	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Low	Count	17	0	5	5	27
	%	62%	0%	19%	19%	
Moderate	Count	42	9	17	9	77
	%	54%	12%	22%	12%	
High	Count	42	4	3	0	49
	%	86%	8%	6%	0%	
Very high	Count	8	0	0	0	8
	%	100%	0%	0%	0%	
Total		110	14	25	14	163
% within Environmental value		68%	9%	15%	9%	

Table 4.24b: Contingency table for the attribute drainage with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any drainage activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between drainage and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.203 and one-tailed p-value = 0.3261, which is not statistically significant.

Environmental value	**Drainage**		**Total**
	Absent	**Present**	
Very low & low	18 (19)	10 (9)	28
Moderate, high & very high	92 (91)	42 (43)	134
Total	110	52	162

Table 4.24c: Contingency table for the attribute drainage with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any drainage activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between drainage and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 15.847 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Drainage**		**Total**
	Absent	**Present**	
Very low, low & moderate	60 (71)	45 (34)	105
High & very high	50 (39)	7 (18)	57
Total	110	52	162

Table 4.25a: Contingency table for the Environmental vegetation intactness– width of vegetation fringe against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Vegetation intactness– width of vegetation fringe						Total
		0	1 to 5	6 to 10	11 to 15	16 to 20	>20	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	0	0	0	0	0	1	1
	%	0%	0%	0%	0%	0%	100%	
Low	Count	22	3	1	1	0	0	27
	%	81%	11%	4%	4%	0%	0%	
Moderate	Count	19	24	12	3	8	11	77
	%	25%	31%	16%	4%	10%	14%	
High	Count	1	3	2	0	5	38	49
	%	2%	6%	4%	0%	10%	77%	
Very high	Count	1	0	0	0	1	6	8
	%	13%	0%	0%	0%	13%	74%	
Total		44	30	15	4	14	56	163
% within Environmental value		27%	18%	10%	2%	9%	34%	

Table 4.25b: Contingency table for the attribute vegetation intactness– width of vegetation fringe at a site with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any vegetation widths have been summed. Values in brackets are the expected frequencies for each cell if there is no association between width of vegetation fringe and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 46.996 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Width of vegetation fringe**		**Total**
	0	**> 0**	
Very low & low	22 (7)	6 (21)	28
Moderate, high & very high	21 (36)	113 (98)	134
Total	43	119	162

4.5 Threat results analyses

The WGCMA's assets-based management approach also involved an assessment of the threats likely to downgrade high economic, social and environmental wetland values. Threat values were used to compute risk assessments through the use of Likelihood, Consequence and Risk level matrices, as described in Section 3.3.2 WGCMA process for evaluating wetlands.

Table 3.1 lists 14 threat categories used in risk assessments for inventoried wetlands as: loss of wetland connectivity; stock access; pest plants; pest animals; urban development; altered hydrology; native vegetation decline; land use; physical alteration; erosion; fire regime; recreation; water source; and, salinity. Brief definitions of these threat categories are given in Table 4.26a. Various documents (WGCMA, 2006a, 2006b & 2006c) provide evidence that up to seven extra threat categories were originally planned for use in risk assessments. Additional categories were: lack of reservation; sedimentation; change in size since European settlement; eutrophication, drainage; resource utilisation, other than grazing; and, other. Reported in the next two chapters, my investigations revealed that several of these additional threat categories were closely associated to high-value wetland assessments, more so than some of the 14 threat categories used in the WGCMA assessments. For this reason, I provide definitions, where known, in Table 4.26b for these additional threat categories.

An inspection of the WGCMA Wetland Inventory Database reveals that field data was collected by Greening Australia for all threat categories (14 listed in Table 3.1 and defined in Table 4.26a, plus the additional seven defined in Table 4.26b). Prior to assessments, the WGCMA discussed the validity and usefulness of all threat categories through workshops and interviews with technical experts and stakeholders (WGCMA, 2006b) and they decided to use the 14 threats listed in Table 3.1 and Table 4.26a in their risk assessments for the inventoried subcatchment wetlands. As previously noted in Chapter 2, a different set of threats were used in the risk assessment calculations for significant wetlands (Ramsar and Directory of Important Wetlands listed). There, urban development was not included, rather changes in size since European settlement, eutrophication, lack of reservation, resource utilization, and sedimentation were used.

According to all WGCMA documentation (2006a, 2006b & 2006c) all risk assessments used threat categories scored as:

- 0 for no data available;
- 1 where no threat exists;
- 2 for low threat presence;
- 4 for medium threat presence; and,
- 5 for high threat presence.

However the actual threat values for each wetland site in the Database were recorded as either absent or present, and where present as either as a minor or a key threat. The frequency distributions of the values of threat categories stored in the Database are discussed in the next section for their relevance to subcatchment and significant wetlands.

4.5.1 Threats – frequency statistics and analyses

For the inventoried sites, the WGCMA Wetland Inventory Database holds 157 complete records for all threat categories. The frequency statistics for the 14 threat types, except water source, are given in Table 4.27a. As mentioned above and irrespective of the scoring scheme published by the WGCMA, threats were recorded as absent/present at each inventoried site, and present threats are further classified as minor or key threats.

The threat category water source, values were assigned a scale of 1 to 7:

- 1 represents wetlands filled primarily by rainfall;
- 2 represents wetlands whose major water source was groundwater;
- 3 is used for wetlands associated with natural flooding;
- 4 for wetlands filled primarily by diverted farm drainage;
- 5 represents wetlands filled primarily by irrigation runoff or urban stormwater;
- 6 is used where the water source is unknown; and,
- 7 for the value other water sources not already included.

The frequency statistics for threat category water source using this scale are given in Table 4.27b.

Greening Australia (2006) reported the major threats for inventoried wetlands in the region as changes to hydrology and grazing, which is linked to declines in native vegetation, loss of reservation and an influx of exotic flora. Their observations relate to only seven of the 14 threat categories, and they are verified through examination of Tables 4.27a and 4.27b, being:

- ✓ Loss of wetland connectivity occurs at 60% of inventoried sites, where it is a key concern at more than half of these;
- ✓ Over half of the wetlands are subject to stock access, where inappropriate grazing is most often recorded as a major threat;

- ✓ Pest plants were seen at nearly three quarters of all sites (73%), and at half of these it is recorded as a major threat;
- ✓ Likewise, pest animals are prolific, being found at two thirds of sites (67%);
- ✓ Urban development is a minor threat affecting only 21 sites;
- ✓ Altered hydrology, seen in 74% of the sample, is one of the most significant threats; and,
- ✓ Two thirds of wetlands evidence noticeable native vegetation decline;

Not reported was the significant impact at the majority of sites of incompatible surrounding land use. Additionally, my analyses of the threat categories frequency statistics show that:

- Surrounding land use impacts almost 70% of inventoried sites, where it is recorded as a significant threat;
- Half of the inventoried sites show physical alterations;
- Erosion occurs at just over 30% of sites, and it is key threat at 10% of all wetlands;
- An inappropriate fire regime was recorded at just over a quarter of sites, where it is usually a minor threat;
- Evidence of inappropriate recreation activities was seen at 21 sites;
- 80% of sites are not threatened by salinity, but at nine sites where it is recorded it is of great concern; and,
- Nearly 60% of wetlands have rainfall as their water source and manmade sources of diverted farm drainage and irrigation runoff affect only seven of the 160 sites.

Because of their prevalence amongst sampled wetlands, incompatible surrounding land use should be targeted in management plans together with the threats noted by Greening Australia (2006) as the loss of wetland connectivity, the amount of stock access and altered hydrology.

For completeness, Table 4.28 provides the frequency statistics for the additional seven threat categories not used in the final risk assessments for subcatchment wetlands. These statistics indicate that a lack of reservation is a significant threat affecting almost half of all surveyed sites. Sedimentation and resource utilization impact relatively few sites, analyses later in this research reveal these threats and a lack of reservation to be influential predictors for assessments for Environmental value; all should definitely be targeted in management plans.

Threat assessment was undertaken as an input for risk assessment calculations. However, final risk assessments data on a per-site basis have not been supplied by the WGCMA to this study and given that risk assessments were not known, it was not possible to undertake cross-tabulations analyses for threat categories.

Table 4.26a: Threat category definitions for threats used in risk assessments of subcatchment wetlands as supplied by the WGCMA (2006a, 2006b & 2006c).

Threat category	WGCMA definition
Loss of wetland connectivity	The loss of connection between wetlands and between wetland and waterway so that it is no longer connected under any flow conditions or degradation of native flora connecting two wetlands.
Stock access	Stock access and/or grazing practices that causes damage to a wetland.
Pest plants	Flora that is not native to the area that has potential to become invasive and displace endemic flora. May result from planting of inappropriate species, introduction of diseases, spread of invasive species, translocation of live aquatic organisms.
Pest animals	Fauna not native to the area that has potential to become invasive or displace endemic fauna.
Urban development	Definition not supplied in WGCMA documents.
Altered hydrology	Alteration of a wetlands' water regime such that it receives less or more water and/or water at different times to its undisturbed condition (including impacts of irrigation).
Native vegetation decline	Degradation of aquatic and terrestrial indigenous wetland vegetation.
Land use	Impacts associated with incompatible surrounding land use and/or poor land-use practices in area surrounding wetland.
Physical alteration	Large scale movement of soil (excavation or infilling or land-forming) within a wetland that changes its shape and possibly the flow of water.
Erosion	The dislodgement of soil particles, their removal and eventual deposition away from the original position.
Fire regime	A fire regime that differs from the undisturbed condition.
Recreation	Impacts associated with inappropriate recreational use of a wetland, i.e. trampling, soil compaction, litter.
Water source	Definition not supplied in WGCMA documents.
Salinity	The concentration of salt in the soil and/or water. Disposal of irrigation tailwater, rise of groundwater OR a change in the salt content of a wetland from the natural or desired state.

Table 4.26b: Additional threat category definitions for threats used in risk assessments of subcatchment wetlands as supplied by the WGCMA (2006a, 2006b & 2006c). Field-recorded values for each of these categories can be found in the WGCMA Wetland Inventory Database.

Threat category	WGCMA definition
Lack of reservation	Lack of formal protection for wetland as can be achieved through a reserve and/or covenant.
Sedimentation	The deposit of soil particles
Change in size since European settlement	Loss of wetland area since European settlement.
Eutrophication	The nutrient enrichment of a water body, usually leading to growth and proliferation of large masses of plant material (phytoplankton, macrophytes or both).
Drainage into wetland	Disposal of irrigation drainage, groundwater disposal or forms of agricultural, industrial or urban runoff.
Resource utilisation, other than grazing	Unsustainable resource utilisation other than grazing.
Other	Definition not supplied in WGCMA document. Comments recorded with this data included the presence of wind farms in the wetland vicinity.

Table 4.27a: Frequency statistics for 14 threat category data used for risk assessments of inventoried subcatchment wetlands.

Threat	Absent	Present		Total
		Minor	Key	
Loss of wetland connectivity	63	42	55	160
Stock access	77	19	64	160
Pest plant	43	51	66	160
Pest animal	53	71	36	160
Urban development	136	12	9	157
Altered hydrology	58	51	51	160
Native vegetation decline	56	42	62	160
Land use	50	39	71	160
Physical alteration	82	43	35	160
Erosion	116	27	17	160
Fire regime	117	38	5	160
Recreation	139	18	3	160
Salinity	128	22	9	159

Table 4.27b: Frequency statistics for threat category water source.

Threat	1	2	3	4	5	6	7	Total
Water source value	94	9	34	3	4	12	4	160

Table 4.28: Frequency statistics for additional threat category data in the WGCMA Wetland Inventory Database that were not directly used for risk assessments.

Threat	Absent	Present		Total
		Minor	Key	
Lack of reservation	56	29	74	159
Sedimentation	104	46	10	160
Change in size since European settlement	88	34	38	160
Eutrophication	116	33	11	160
Drainage	124	28	8	160
Resource utilisation, other than grazing	150	8	2	160
Other	159	1	0	160

4.6 Synthesis and discussion

The WGCMA wetland assessment relied on the data collected by Greening Australia and stored in the Wetlands Inventory Database. As mentioned earlier, neither the WGCMA nor Greening Australia undertook a systematic analysis of the amassed data collection stored in the Database. In their reports of the 2006 wetlands assessment (Greening Australia, 2006; WGCMA, 2007), very few associations between input values of attributes with high-value assessments were noticed by either organisation. The reporting of any observed associations was, at best, piecemeal, and, at worst, not supported by the data.

For Economic value assessments, the WGCMA (2007) reported that commercial fishing, tourism and, to a lesser extent, the production of the surrounding land were important attributes for deciding value. My frequency and cross-tabulation analyses found no statistically significant associations for any of these attributes with moderate and high-value assessments. However, there were two statistically significant relationships not mentioned by WGCMA (2007) and Greening Australia (2006), being the association of stock water supply with moderate and high Economic value wetlands, and the presence of drainage at sites with higher valued wetlands.

For Social value assessments, my analyses showed that park value, passive recreation, recreational fishing, education, camping, swimming, boating or motorized four-wheel drive usage were strongly associated with higher-valued wetland sites and with each other, as seen in the correlation statistics reported in the next chapter. None of these statistically significant associations were reported by the WGCMA. Instead they stated that indigenous and European cultural values together with high visual amenity were most important in deciding Social value (WGCMA, 2007). There are no records of any data relating to visual amenity stored in the Wetlands Inventory Database.

For Environmental value assessments, the only published statistics were frequency statistics done at catchment and subcatchment levels (Greening Australia, 2006); there were no reports of collated statistics for the West Gippsland region. In this chapter, I have provided the frequency statistics for the seven major environmental values used in the assessment process. For these values and their component attributes and subattributes, my cross-tabulation analyses discovered over twenty statistically significant associations with high-value and very high-value wetland assessments, none of which were reported by Greening Australia or the WGCMA. Several of these associations related to wetland type, an input to wetland rarity and habitat value used in the scoring of Environmental value. The efficacy of including wetland type in Environmental value assessment is doubtful since field visits revealed that 40% of inventoried wetlands were found to be misclassified for type under the Corrick and Norman (1980) scheme, which is based on characteristics of depth, period of inundation and vegetation types. Rather, as supported by the statistically significant associations within the data, it is better to score each site for the presences of vegetation types, such as sedges, ferns and bryophytes, shrubs, and dead trees, which are linked to higher Environmental value scores, and the absences of logs, emergent vegetation, shrubs, herbs, dead and alive trees, that are more strongly correlated with lower Environmental scores. This is argued particularly in the case of freshwater meadows type, where proportionally more than expected inventoried wetlands were assessed as low Environmental value. This wetland type has vegetation sub-categories including herb-dominated and sedge-dominated classes, and when there are absences of these vegetation types, it is likely that the classification of freshwater meadows wetland is acting in surrogacy. On these grounds it is better to measure the vegetation absence/presence values more directly and avoid problems when wetlands need to be reclassified under the Corrick and Norman (1980) scheme.

Threat categories were used by the WGCMA to undertake risk assessments; data was collected for a broad range of threat categories. There were several problems in the application of threat category data during the assessment. First, different wetland types used different threat categories in their risk assessment evaluations; those for inventoried wetlands were different to significant wetlands. Second, the documentation (WGCMA, 2006a, 2006b & 2006c) does not provide definitions for all threat categories, so it is difficult to know the nature of various threats (urban development, water source and other). Thirdly, there is a disparity in the scales used to categorize all threat categories. Published scales had a range from zero to five while the data values stored in the Database were either absent, present as a minor threat or present as a key threat. It is not obvious how the two threat scales related to one another. Fourthly, individual wetland risk assessments are not known and therefore cannot be tied directly to each wetland's assessments for Economic, Social or Environmental value. This has meant that cross-tabulation analyses could not be done for any of the threat categories; and if analyses could be done, the results would provide a baseline for discussion of the findings reported in upcoming chapters, where multivariate statistical analyses and neural networks indicate strongly that some threat values, more than others, are associated with each assessment value. For Economic value, the linked threats are erosion and resource utilization, and for Social value, it is salinity. For Environmental value, it is more complicated as significant threats include those used in the WGCMA risk assessments: pest plants; altered hydrology; erosion; salinity; and, water source type, and threats not used by the WGCMA, but for which data was collected: drainage into wetland; lack of reservation; resource utilization; and, sedimentation.

The above disparities between what was reported and the actual data values stored in the Database are concerning. My analyses using frequency statistics were identical, or nearly so, to those reported by Greening Australia (2006) confirming that the dataset analysed by themselves and the WGCMA is in fact the same dataset that I have studied. There were many patterns observed within the frequency statistics that described wetlands within the region, and these were not reported by either organisation (listed in the dot-point bulleted lists in previous sections of this chapter; tick-point bulleted lists are WGCMA statistics that were confirmed). My cross-tabulation analyses suggest that the relatively few associations between various attributes and high-value wetlands reported by the WGCMA and Greening Australia were not based in fact or were the result of any statistical analysis. Much more could have been learnt about wetlands in West Gippsland region through a more thorough analysis of frequency distributions and cross-tabulation statistics, and the failure of Greening Australia and the WGCMA to do so, is truly an opportunity lost. For management, the missed association between the presences of stock water supply and drainage to higher Economic value assessments is of particular interest; it a marked contradiction to the relationship observed for higher Environmental value assessments with the absences of drainage, obstruction and redirection. The contradiction raises resource management issues. Should management plans prioritize for economic value or for environmental value? More broadly, for wetlands in the region: Are the desirable features of economic values and environmental values at odds with each other? The simple statistical analysis here suggests so.

By their univariate nature, frequency and cross-tabulation table analyses presented in this chapter are unsophisticated; they can only examine one variable at a time and they cannot point to multi-faceted relationships between variables, which are likely to be of more interest and use. In the next chapter, multivariate statistics are used to discover combinations of variables that best predict high-value wetland assessments, and the predictive power of these will be used for comparison to test the efficacy of neural networks in making wetland assessments in Chapter 6.

Corner Inlet, Victoria.
Image courtesy of Michelle Dickson, WGCMA

Chapter 5

Multivariate statistical analyses

The univariate analyses outlined in Chapter 4 revealed that a number of WGCMA conclusions about associations between particular attributes and high wetland values could not be supported from the data. The analysis also showed that a number of other important conclusions regarding data values of input variables and the assessments of high, and sometimes low, Economic, Social and Environmental values could be extracted from the Database via simple statistical methods.

This chapter explores the cumulative effects of input variables in deciding wetland assessments through the use of multivariate analyses. Statistical models are constructed and examined for their ability to describe the collective contribution of input variables to wetland assessments. The predictive powers of these models are quantified and their usefulness is discussed; the outcomes provide a comparative baseline for neural networks assessments made in Chapter 6.

5.1 Introduction

Multivariate statistics offers a set of methods designed to detect relationships between multiple variables that are correlated with one another to varying degrees (Spicer, 2005; Tabachnick & Fidell 2007). Historically, some multivariate techniques are extensions of simpler univariate statistical analyses, such as single-variable distributions and bivariate analysis, like cross-tabulation, correlation, analysis of variance, and simple regression used to analyse two variables. Other multivariate data-analysis techniques, including multiple discriminant, principal components and logistic regression analyses, have been uniquely designed to cope with multivariate issues not encountered in traditional statistical applications or to handle the different effects of variables which cannot be separated meaningfully by other, univariate, means (Hair et al., 2006; Spicer, 2005).

All multivariate statistics can be described using a single relationship for a variate value, as shown here as Formula 5.1 and supplied by Hair et al. (2006, page 5).

$$\textit{variate value} = w_1 X_1 + w_2 X_2 + w_3 X_3 + \ldots\ldots\ldots\ldots + w_n X_n$$

[Formula 5.1]

The variate is described as a linear combination of *n* variables specified for each application, with each variable being multiplied by an empirically computed weight determined by the chosen multivariate technique.

The problem to be surmounted in the first instance is the selection of the most appropriate multivariate technique from the wide range that is currently available. Many multivariate techniques are based on mathematical assumptions that place strict requirements upon the type of data that can be used. The choice of method needs to be mindful of these. Excellent help in deciding the correct multivariate technique is given in the Hair et al. (2006, Figure 1-2, pages 14 and 15) textbook by means of a flowchart reproduced here as Figure 5.1. The flowchart has been designed around the possible answers to the following three questions:

1. Can the variables be divided into independent and dependent classification based on some theory?
2. If yes, how many variables are treated as dependent in a single analysis?

3. How are the variables, both dependent and independent, measured? Are they metric, non-metric or a combination?

The nature of the variables stored in the WGCMA Inventory Database greatly constrains the navigation through the Hair et al. (2006) flowchart. Prediction is sought for one data variate which can take one of five wetland values (very high, high, moderate, low and very low). This single variate is non-metric (categorical) data, thereby limiting an appropriate choice to either multiple discriminant analysis or logistic regression analysis, and the relevant path through the flowchart (Figure 5.1) has been indicated by a dotted line (Antonogeorgos et al., 2009; Fernandes et al., 2006; Hair et al., 2006). Note: other methods, such as, non-metric multidimensional scaling (NMDS) and redundancy analysis (RDA) are not suitable to this application due to their data requirements (Kenkel et al., 2002; Palmer, 2006).

Multiple discriminant analysis offers a description of how the various wetland value groups differ in relation to selected site characteristics by forming the variate that creates scores for each observation that maximally differentiates between groups. The precondition for multiple discriminant analysis is that all the independent variables must be normally distributed, quantitative (or metric, numeric) data. This is not the case with most of the values recorded in the WGCMA database, since they often relate to either presence or absence. Logistic regression, multinomial and ordinal, is more flexible than multiple discriminant analysis in that it allows the explanatory, independent variables to be of any type, qualitative or quantitative (Sage Publishing, 2012). They predict values for binary, multinomal or ordinal dependent variables, such as wetland values through the use of probabilities and odds of belonging to very high, high, moderate, low or very low wetland value groups. Therefore, logistic regression is the most appropriate multivariate statistical technique to use in the analysis of data stored in the WGCMA Wetlands Inventory Database as it can deal with a great variety of dependent variable types to predict the variate, which is the probability of a high-value wetland assessment. The next subsection describes logistic regression analysis in more detail, and it is followed by a discussion of the considerations to be made when applying the multivariate technique to the Database.

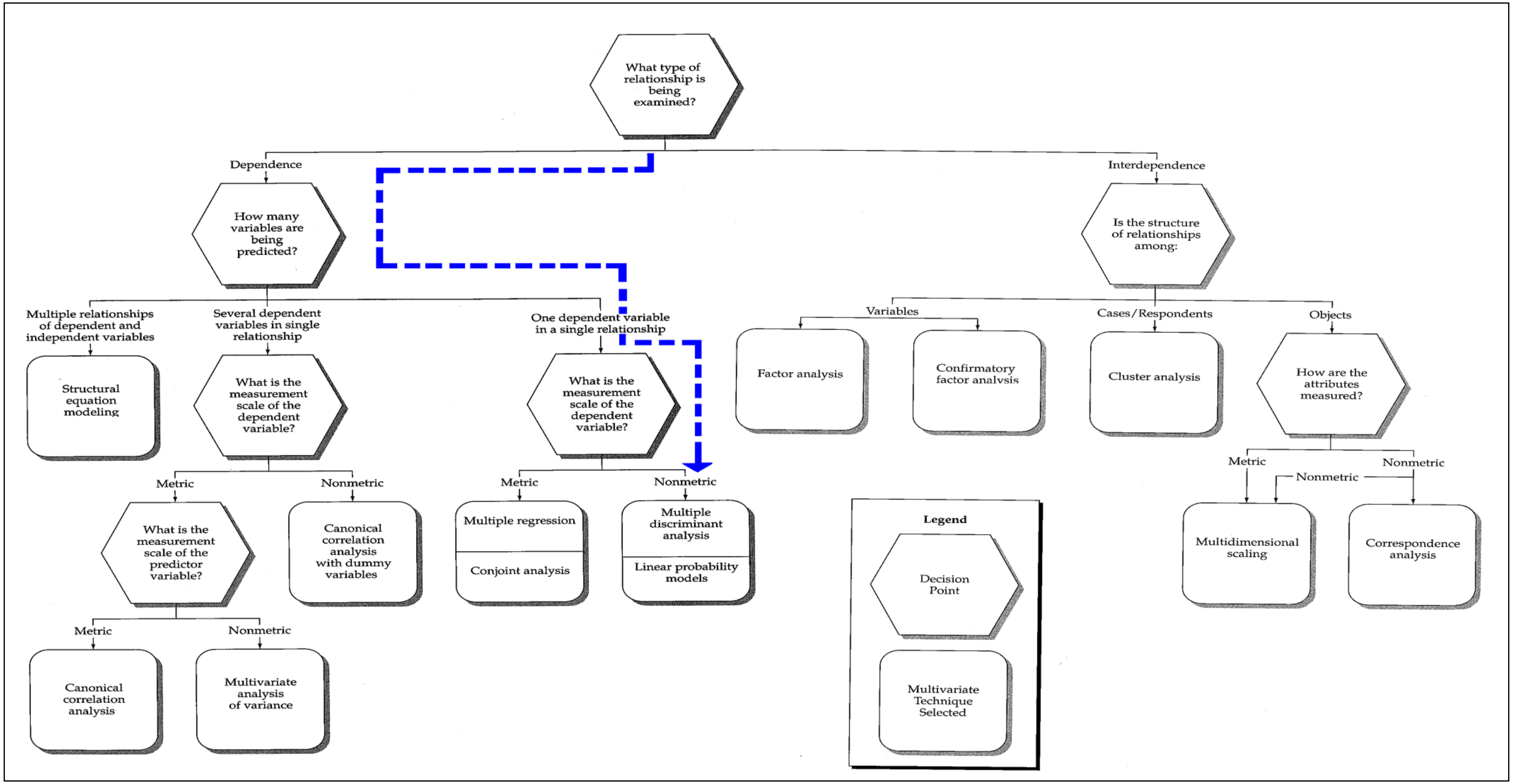


Figure 5.1: Flowchart for deciding appropriate multivariate data-analysis technique as given in Multivariate Data Analysis text by Hair et al. (2006) as Figure 1-2, pages 14 and 15. The selection of the most appropriate multivariate technique for use in analysing the WGCMA Wetlands Inventory Database is shown as a dotted line.

5.1.1 Logistic regression analysis

Logistic regression is concerned with the prediction of group membership for binary dependent variables. Multinomial and ordinal logistic regressions are extensions of this base case. As shown in Formula 5.2, logistic regression can be equated to a modified version of Formula 5.1, where natural logarithms (*ln*) have been taken of various terms. Note the natural logarithm of any number is the power to which *e* (approximately 2.718) must be raised to produce that number (Spicer, 2005).

$$ln\ (odds\ of\ (variate\ value)\ ) = ln\ (w_1)X_1 + \ ln\ (w_2)\ X_2 + \ \ldots\ ln\ (w_n)\ X_n \quad + constant$$

[Formula 5.2]

For mathematical conciseness in the calculations of logistic regression, the odds of the variate value are used to represent the likelihood of membership in the dependent variable, rather than raw probability values. Odds express the ratio of two probabilities, success versus failure as shown in Formula 5.3 where s is the probability of success.

$$odds\ of\ success = \frac{s}{1-s}$$

[Formula 5.3]

If the probability of success is 0.8, then the probability of failure is 1– 0.8 = 0.2 and the odds of success to failure would be 0.8/0.2. This ratio can be expressed as being 4/1 or odds of 4 to 1 in favour of success. It is equally legitimate to be interested in the odds of failure compared to success, being 0.2/0.8 or ¼. Here, the odds are expressed as failure occurs at one-fourth of the rate of success (Hair et al., 2006).

Important to the logistic regression technique is the reality that binary dependent variables can only have values of 0 or 1, and that any predicted probabilities of group membership must fall within the range of 0 to 1. To accommodate this, a logistic curve, as shown in Figure 5.2, is used to describe the relationship between an independent variable and the probability of event/group membership of a dependent variable. Although the process is entirely different to that used in multiple regression, the parallel is that the curve of predicted values is modified to fit actual input data (Hair et al., 2006). Figure 5.2 shows that a probability of 0.5 represents the critical value for membership; a score above 0.5 means inclusion, otherwise not. A probability of 0.5 equates to odds of 1.0, that is, the outcome is equally is as likely as not. The natural logarithm of the odds value is called the logit value and in this case *ln* (1) = 0. Thus in Formula 5.2 any calculation resulting in a value less than 0, means the odds are less than 1; likewise, any calculation resulting in a value greater than 0, means the odds are greater than 1 (Hair et al., 2006; Spicer, 2005).

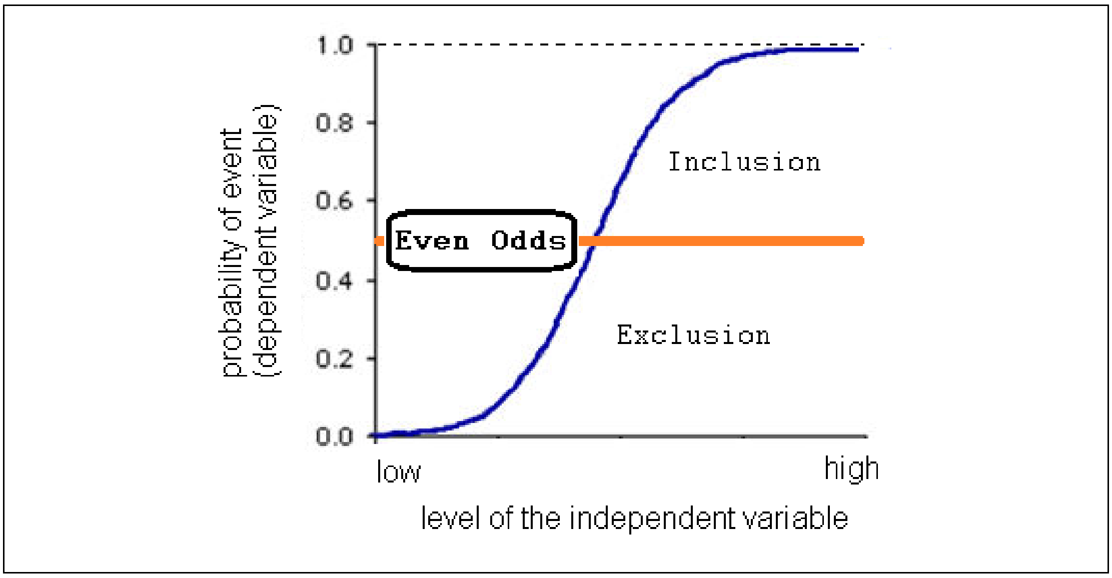


Figure 5.2: The logistic relationship between dependent and independent variables. This figure has been adapted from Figure 5-11 of Hair et al. (2006, page 356.)

In attempting to fit the empirical data of differing input values by computing the various coefficients of w_n in Formula 5.2, a suitable measure of fit is needed. The non-linear nature of logistic relationship in Figure 5.2 requires that an appropriate likelihood value be calculated. Perfect-fit models would have a likelihood of 1. However for mathematical convenience, it usual to compute the value as –2 * log (likelihood). The –2 manipulation helps turn the calculation into a very useful, distribution-free log likelihood chi-squared (χ^2) statistic with 1 degree of freedom. So in a perfect-fit model, the –2 * log (likelihood) will have a value of 0 and poorly fitting models can have values up to positive infinity. Therefore, the Wald χ^2 statistic is used to measure and decide the statistical significance of individual estimated coefficients in Formula 5.2 (Spicer, 2005). The Wald statistic, known as Z^2, is calculated using Formula 5.4, where w_n is the estimated coefficient of a variable in Formula 5.2.

$$Z^2 = \left(\frac{w_n}{Standard\ Error(\ w_n)}\right)^2$$

[Formula 5.4]

Reduced hardware costs and recent advances in computing power have allowed the development and proliferation of sophisticated 'point-and-click' statistical packages. The availability of these, with their computing intensive algorithms, has empowered users and organisations with more advanced multivariate data-analysis methods, with which to derive knowledge from datasets and inform their decision making processes (Hair et al., 2006; Spicer, 2005; Tabachnick & Fidell 2007). The analysis undertaken in this chapter has been done using the IBM® SPSS® 20 Statistics package (http://www.spss.com/).

5.1.2 Considerations in applying logistic regression to WGCMA Wetlands Inventory Database

Most statistical software packages, including SPSS, offer the convenience of selecting between binary, multinominal and ordinal forms of logistic regression. Binary logistic regression, the simplest form, has been described above, whereas multinomial and ordinal logistic regression forms are better when the outcome/dependent variable can have three or more possible types. Ordinal analysis is used for outcomes that have inherent ordering or grading, like very low, low, moderate, high and very high wetland assessments; multinomial analysis handles cases where there is no ordering. Both multinomial and ordinal logistic regressions divide the data into smaller pools, each representing an outcome type before performing a set of pair-wise binary logistic regressions for memberships in, and out of each pool. For interrogation of the WGCMA Wetlands Inventory Database, it seems that ordinal logistic regression is the best fit selection for examination of the case study data. However, the small numbers of high-value and very high-value assessments compared to other categories renders the use of ordinal logistic regression, and multinomial logistic regression impracticable. This is the same problem encountered and tackled whilst undertaking cross-tabulation analyses in Chapter 4. For the same reasons, it is practical to use binary logistic regression to decide the likelihood of membership in one group over an alternative group for:

- Economic value: Combine the records of moderate and high Economic[2] values and compare them to the records of very low and low value assessments together;
- Social value: Use the records of moderate and high Social value assessments and contrast them to the very low and low value records; and,
- Environmental value: Combine the records of high and very high Environmental value assessments and compare them against very low, low and moderate value assessments.

There is the need to understand the underlying assumptions of the binary logistic regression method, and to check for compliance with them (Sage, 2012). All assumptions are complied with, and they are:

- The dependent variable is dichotomous, that is inclusion, or exclusion, in moderate and high assessments for Economic and Social values, and inclusion or exclusion in very high and high assessments for Environment value;
- No linear relationship is assumed between independent input variables and the dependent variables;
- No assumptions need to be made about input independent variables; they do not need to be normally distributed, nor linearly related, nor of equal variance within each group;
- All categories or groupings must be mutually exclusive and exhaustive, that is for each case there can one group membership, and every case must be a member of a group; and,
- Wherever possible, a minimum of 50 cases per predictor is recommended; it will be identified whenever this is not the case.

For many of the categorical input variables, compliance with the last criterion is improved by employing the strategy used for some cross-tabulation analyses in

[2] The practice in this Chapter, and others, is to denote WGCMA wetland assessments for economic, social and environmental values with capital letters, that is, Economic, Social and Environmental. Where lowercase versions have been used, it has been done to indicate the broader meanings of these terms.

Chapter 4, the addition of columns of values for varying types of ‘present’ data. In each case, collating data into one of two types, the absence or presence of an attribute, resulted in an additional significant improvement to the binary logistic regression modelling, through the elimination of the need for dummy input variables to run the algorithm.

To illustrate this improvement, drainage, an attribute used to assess Economic value is used as an example. Drainage was described in the field and in the Inventory Database through four different categories: (1) absent; (2) present with no impact; (3) present with low to moderate impact; or, (4) present with severe impact for each site. A variable with n categories is handled by the software through the creation of n–1 dichotomous variables using a process known as dummy coding. Subsequently, each dummy variable needs to be computed into any binary logistic regression model generated, along with its own separate, and not necessarily meaningful, coefficients. The result is a more complicated version of Formula 5.2, which needs to be deciphered for its meaning. For simplicity and the ability to make comparisons to cross-tabulation analyses and contingency tables of Chapter 4, many attributes were incorporated into the modelling with dichotomous values, as either absent or present. This coding has another benefit; it allows comparisons to be made of the magnitudes of the coefficients for each independent variable where absent/present coding has been used. Normally, care needs to be exercised as the coefficients are not standardised and they are impacted when different scales are used for various input variables. For the cases of attributes values designated either absent or present, the coefficients can be directly compared for they are an indication of the relationships and strengths between contributing variables to the outcome wetland assessment.

In setting up the SPSS software to undertake binary logistic regression, it is necessary to specify which group is the baseline group against which comparisons are made. It is assumed that the derived binary logistic regression models give the probability of success over failure of predicting moderate and high values for Economic and Social values, and high and very high Environmental values. In each case, comparison will be made to a baseline scenario where all input variables have coefficients of 0 in Formula 5.2, resulting in the calculation of the *constant* value. As seen in the following sections, this step and resulting classification tables are useful in evaluating the predictive abilities of the binary logistic regression models generated.

The next three sections describe binary logistic regression analyses for Economic, Social and Environmental value, respectively. For each value, correlation statistics are presented and logistic regression models are built, followed by model evaluations. Each section concludes with an investigation of the effect of including threat categories in binary regression models for its particular value. The final section of this chapter discusses the performance of binary logistic regression models in predicting high-value wetland assessments, and the implications of these analyses.

5.2 Economic value of wetlands

5.2.1 Economic value – correlations

In Chapter 4, cross-tabulation analyses were used to search for associations between the 12 input attributes used in Economic value assessments, which were listed in Table 4.1. Spearman's rank correlation coefficient (rho ρ) was computed for all input attributes and their association with a moderate or high assessment as a first step in setting up and examining statistical models to explain moderate and high Economic value assessments. Spearman's rho is a non-parametric measure of how two variables relate to one another. It is used for ranked or ordinal data and, like Pearson's correlation coefficient employed for continuous variables, takes values between +1, for direct one-to-one correspondences, through to –1, for presence of a perfectly negative correlation where one variable increases and the other variable decreases by the same proportion. Importantly, Spearman's ρ is unaffected by log transformations, which makes it an appropriate measure of association for use in conjunction with logistic regression models (Trochim, 2006). It is important to remember that statistical correlation does not equate to causation, that is, an association between variables X and Y, does not mean X causes Y, or vice versa. Correlation is simply an indication of association by describing the behaviour of variables in comparison to one another.

Spearman's rho was calculated for all Economic value attributes, absent/present statistics against presence or absence in high or moderate Economic value assessments. In the interests of highlighting the most significant correlations, only those associations with a value greater than or equal to + 0.400 or less than or equal to –0.400 are mentioned here. In order of strength, they are:

- The presence of diverted or farm runoff is moderately correlated to a moderate or high Economic value assessment ($\rho = 0.473$);
- The presence of drainage at a site is moderately correlated to a moderate or high Economic value assessment ($\rho = 0.427$); and,
- The presence of water storage at a site is moderately correlated to a moderate or high Economic value assessment ($\rho = 0.417$).

The second and third dot correlations above agree with the associations found through the χ^2 tests in Section 4.2.2: Economic value – cross-tabulation analyses and contingency tables. The first correlation was not discovered through χ^2 testing in the previous chapter, however its presence here can, in part, be explained by correlations between diverted or farm runoff to other input attributes, discussed next.

It is possible to quantify the degree to which all input attributes are correlated to each other through the use of Spearman's ρ. The positive associations with values greater than or equal to 0.400 in order of strength are:

- The presence of water redirection and is correlated strongly to the presence of obstruction ($\rho = 0.606$), which also means that the absence of redirection is associated with an absence of obstruction;
- The presence of water storage at a site is moderately correlated to disposal of water ($\rho = 0.498$);
- The presences, along with absences, of tourism and conservation forestry are moderately correlated to each other ($\rho = 0.478$);
- The presence of diverted or farm runoff is moderately correlated to the presence of drainage ($\rho = 0.471$), as are their respective absences;

- The presence of drainage at a site is also moderately correlated to the presence of disposal of water (ρ = 0.427), water storage presence ((ρ = 0.425), and presence of obstructions (ρ = 0.417); and,
- The presence of obstruction is also positively correlated to the disposal of water at a site (ρ = 0.416).

The positive correlation of diverted or farm runoff with moderate and high Economic value assessments, can be accounted for by this attribute's correlation with drainage, whose cross-tabulation analysis and χ^2 test showed a higher than expected association with moderate and high Economic values (see Chapter 4). The above correlations show interconnected relationships between attributes used to assess the Economic value of drainage disposal and supports their inclusion in the assessment of this value.

The negative correlations between attributes with values less than or equal to –0.400 are:

- The presence of conservation forestry has a strong negative correlation to food production which means that the presence of conservation forestry is most often associated with an absence of food production, and the absence of conservation forestry at a site is most often associated with a presence of food production (ρ = –0.587); and,
- There is a moderate negative correlation between conservation forestry and stock water supply (ρ = –0.438).

These correlations suggest associations which are plausible relationships between attributes likely to be seen in the field.

5.2.2 Economic value – logistic regression models

Excluding the attribute commercial fishing (with only two records), data preparation for model building was done by partitioning the values of each input attribute into absence and presence groups. As well, wetland Economic value assessment records were partitioned into one of two groups: moderate and high-value cases or very low and low assessments. Note there are only 28 moderate and high-value records, which is less than the optimal 50 cases recommended for logistic regression which may impact the adequacy of the fitted model as evaluated by its goodness-of-fit (Sage, 2012).

SPSS software makes two steps in binary linear regression model building. The first step is the construction of the baseline model, labelled Block 0: Beginning Block. In this step, an equation based on Formula 5.2 is calculated, where the values of X, through to X_n are assigned 0 as shown in Formula 5.5. As each X_i value equates to either an absence or presence category of an attribute, this is the equivalent of not adding any of the input attributes to model, resulting in the quantification of the *constant* value. Note that although the *constant* value is the Y-intercept for the model created in the next step, there is no other simple practical interpretation of its meaning.

$$ln\ (odds\ of\ (variate\ value)\ ) = ln\ (w_1)*0 + ln\ (w_2)*0 + \dots ln\ (w_n)*0 \quad + constant$$

or

$$ln\ (odds\ of\ (variate\ value)\ ) = constant$$

[Formula 5.5]

The second step is construction of the binary logistic regression model through the inclusion of all attributes' absence and presence classes into Formula 5.2 and using the maximum likelihood function to calculate the coefficients, w_i through to w_n for all input attributes.

The binomial logistic regression model with the highest predictive power for Economic value assessments is given in Equation 5.1.

ln (odds of a moderate or high Economic value assessment) =

*ln (39.418)**diverted or farm runoff + *ln (19.075)**stock water supply +
*ln (11.386)** water storage + *ln (1.440)** tourism +
*ln (1.301)** disposal of water + *ln (1.221)** drainage +
*ln (1.018)** redirection + *ln (0.651* * obstruction +
*ln (0.152)** other land usage + *ln (0.075)** food production +
*ln (0.015)** conservation forestry + *ln (0.426)*

[Equation 5.1]

Equation 5.2 results when all natural logarithms are computed in the Equation 5.1.

ln (odds of a moderate or high Economic value assessment) =

$$3.674*\text{diverted or farm runoff} + 2.948*\text{stock water supply} + 2.432*\text{water storage} + 0.364*\text{tourism} + 0.263*\text{disposal of water} + 0.199*\text{drainage} + 0.018\ \text{redirection} + -0.430*\text{obstruction} + -1.886*\text{other land usage} + -2.590*\text{food production} + -4.205*\text{conservation forestry} + -0.854$$

[Equation 5.2]

To illustrate how Equation 5.2 can be used in Economic value assessments, two records have been taken from the WGCMA Wetland Inventory Database and analysed separately. Wetland № 877461 had presence values for food production, commercial fishing, stock water supply, drainage, disposal of water, water storage, obstruction, redirection and diverted or farm runoff. Substituting for these presence values in Equation 5.2 gives the following.

ln (odds of a moderate or high Economic value assessment) =

$$3.674 * 1 + 2.948 * 1 + 2.432 * 1 + 0.263 * 1 + 0.199 * 1 + 0.018 * 1 + -0.430 * 1 + -2.590 * 1 + -0.854$$

$$= 5.66$$

To better understand this result, the exponential of both sides of the equation is taken.

$$\textit{odds of a moderate or high Economic value assessment} = e^{5.66}$$

$$\textit{odds of a moderate or high Economic value assessment} = 287.15$$

Odds are the ratio of success compared to failure calculated using Formula 5.3 where success is a high or moderate Economic value assessment.

$$\textit{odds of a moderate or high Economic value assessment} = 287.15 = \frac{s}{1-s}$$

Transposing this equation, results in a probability value for s being found.

$$s = 0.997$$

It is not surprising that this high probability of this wetland being a moderate or high Economic value is associated with the Inventory records for the only wetland to be assessed as high Economic value.

The second record chosen to test Equation 5.2 for its suitability as a model for predicting moderate and high Economic value assessments is of a wetland that only had presence values for tourism and conservation forestry. This wetland was assessed as very low Economic value.

ln (odds of a moderate or high Economic value assessment)

$$= +0.364 * 1 + -4.205 * 1 + -0.854$$

$$= -4.695$$

Again, the exponential of both sides of the equation is taken and substituted into Formula 5.3 to result in an extremely low probability value, $s = 0.0095$, which is interpreted as it is extremely unlikely that this wetland would be assessed as a high or moderate Economic value.

5.2.3 Economic value – model evaluation

Testing the model, Equation 5.2, for its effectiveness in making Economic value assessments on a case by case basis is tedious and unnecessary. A measure of model effectiveness in classifying wetland data as belonging to moderate and high Economic values can be made by comparing two classification tables produced by the SPSS software. The first classification table, shown as Table 5.1a, was generated during the initial Block 0 calculation, and the second classification table, shown as Table 5.1b, was computed after the model was decided. Each classification table shows the proportion of cases correctly classified.

For the Block 0 calculation seen in Table 5.1a, the software goes with the highest proportion in the data and classifies all cases as very low or low assessment. This results in the correct classification of all low and very low assessments and the misclassification of the 28 wetlands of interest to this study. Table 5.1a shows it is possible to correctly guess 83% of Economic values due to the high proportion of low and very low assessments made, 133 of the total 161. After the binary logistic regression model is computed for Equation 5.2, the classification Table 5.1b shows that 91% of sites are correctly classified. Further it shows that two very low or low-value wetlands were decided to be moderate or high classifications and 12 moderate and high-value wetlands were classified as being low or very low.

Binary logistic regression models can be used to succinctly describe the impact of all contributing variables X_i (X_1 to X_n in Formula 5.2) through examination of the magnitude and signs of their corresponding w_i coefficients.

$$\ln \text{(odds of (variate value))} = \ln (w_1)X_1 + \ln (w_2) X_2 + \ldots \ln (w_n) X_n + \text{constant}$$

[Formula 5.2]

For instance in Equation 5.1, stock water supply is multiplied by *ln(19.075),* which means its w_i is *19.075*. On the assumption that all other attributes are held constant and not varied in the model, this coefficient is interpreted as one unit increment in the measurement of stock water supply will have a corresponding 19.075-fold impact on the odds of predicting a moderate or high Economic value assessment. Revisiting Equation 5.1, it is possible to see the relative effects of each attribute in computing the logarithm of the odds of moderate or high Economic values by comparing the magnitudes of each attributes w_i value. For drainage, the w_i value is *1.22;* this is near to odds of 1, so the outcome is nearly equally likely as it is not, indicating that drainage has little to no impact on the odds of predicting high or moderate Economic value assessments.

Another approach to checking the validity of the model and its appropriateness is made by looking at statistical tests of the significance of the coefficients in the model (Bewick et al., 2005). First, the overall model χ^2 statistic is 80.613 with 11 degrees of freedom, which has a significance of $p < 1.123 * 10^{-12}$; this is rounded to three decimal places and reported by the software as $p < 0.000$. This statistic is used to compare the constant-only model of Block 0 and the computed model described as Equation 5.2. It indicates that the Equation 5.2 model is significantly different from Block 0 version, in that, it contains some predictors that have a statistically significant effect on the outcome. This is supported by the –2LL value given as 68.163 computed after 8 iterations. Of more significance is the value of pseudo R^2 statistic, Nagelkerke's R^2 which can take on values between 0 and close to 1[3]. The Nagelkerke's R^2 statistic was computed as 0.653 and it is interpreted as meaning that there is a moderately strong relationship of 65% between predictors and the prediction in the model.

[3] As all observations are absence (0) or presence (1) records, the typical R^2 statistic is of no use in describing how well the new model fits the data.

To help decide if all attributes are contributing to the effect, the significance associated with the Wald statistic for each variable is examined; a significance value of $p < 0.05$ indicates that the variable may be making a significant contribution to the prediction. The variables identified in this manner were diverted runoff ($p < 0.002$), stock water supply ($p < 0.003$), water storage ($p < 0.027$), food production ($p < 0.008$) and conservation forestry ($p < 0.023$). Note the corresponding w_i values for these are *39.418*, *19.075*, *11.386*, *0.075* and *0.01*. A classification table of a model built with only these predictors is identical to the one shown in Table 5.1b and this equal performance model of fewer variables is expressed as Equation 5.3.

ln (odds of a moderate or high Economic value assessment) =

*ln (39.100)**diverted or farm runoff + *ln (18.552)**stock water supply +

*ln (12.565)**water storage + *ln (0.094)**food production +

*ln (0.026)**conservation forestry + *ln (0.306)*

[Equation 5.3]

More interesting are the w_i values for the attributes missing in Equation 5.3, being *1.440* for tourism, *1.301* for disposal of water, *1.221* for drainage, *1.018* for redirection, *0.651* for obstruction, and *0.152* for other land usage. These values indicate odds either side of 1, meaning they do not positively or negatively impact model performance. Equation 5.4 results when all natural logarithms are computed in the Equation 5.3.

ln (odds of a moderate or high Economic value assessment) =

*3.666**diverted or farm runoff + *2.921**stock water supply +

*2.531**water storage + *–2.37**food production +

*–3.646**conservation forestry + *–1.183*

[Equation 5.4]

The conclusion to be drawn from these detailed analyses is that simpler models [Equation 5.4] using absence/presence records for only five attributes (diverted or farm runoff, stock water supply, water storage, food production and conservation forestry) are equally adequate to more complex models [Equation 5.2] using the 12 attributes in predicting 91% of all Economic value assessments. The significance of this matter is discussed in the final section of this chapter in some detail where the relevance of this conclusion to WGCMA assessments is explored and the questions: How many variables are enough? and What do the model input variables tell us about wetland evaluations? are answered.

Table 5.1a: Classification table for Economic value shows the proportion of cases correctly classified prior to binary logistic regression model building for 161 wetland records.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	133	0	100
	Moderate + high	28	0	0
			Overall percentage correctly classified	83

Table 5.1b: Classification table for Economic value shows the proportion of cases correctly classified after the binary logistic regression model, Equation 5.2, has been built.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	131	2	99
	Moderate + high	12	16	57
			Overall percentage correctly classified	91

5.2.4 Economic value – logistic regression model using threats

The WGCMA assessment process, as described in Section 3.3.2, scored economic values and threats separately before combining them in the calculation of risk assessments of each contributing attribute for Economic value. To understand the contribution of threat assessments in deciding moderate and high Economic value assessments, a set of new logistic regression models were built using wetland data for all Economic value inputs combined with threat values for the 151 wetlands, where there were entire records. Trials with withholding and adding different Economic value and threat inputs, and examination of their respective Wald statistics resulted in the model presented here as Equation 5.5. The model has an improved prediction rate of 97% over the previous Economic value model described as Equation 5.4 (with 91% prediction efficacy). The classification table for this with-threatsmodel using threats and Economic value attributes is shown as Table 5.2.

ln (odds of a moderate or high Economic value assessment) =

*7.939**diverted or farm runoff + *6.874* *stock water supply +
*5.868**resource utilization + *2.615**erosion +
*2.572**sedimentation + *1.667**water source– rainfall +
*–3.498**lack of reservation + *–19.888**water source– groundwater +
*–22.684**urban development + *–6.906*

[Equation 5.5]

Equation 5.5 indicates that absence or presence values are needed for nine inputs representing eight different attributes; the absence or presence values for two different values of the water source attribute are needed. Of the eight variables, only the first two are for Economic value attributes: diverted or farm runoff and stock water supply; both are also found in the Equation 5.4 model. Of the remaining six threat attributes only three can be found listed in Table 3.1: erosion, water source, and urban development, suggesting that the remaining three threats: resource utilization, sedimentation and lack of reservation should have been used in risk assessment calculations done by the WGCMA to assess subcatchment wetlands. As mentioned in Chapter 3, risk assessment calculations for significant wetlands (Ramsar and Directory of Important Wetlands listed) included resource utilization, sedimentation, and lack of reservation. To compare the influence of input variables in Equation 5.5, it is necessary to express the coefficients in their logarithmic form as presented in Equation 5.6.

ln (odds of a moderate or high Economic value assessment) =

$$\begin{aligned} & \ln(2805.387)*\text{diverted or farm runoff} + \\ & \ln(966.808)*\text{stock water supply} + \\ & \ln(353.406)*\text{resource utilization} + \ln(13.667)*\text{erosion} + \\ & \ln(13.093)*\text{sedimentation} + \ln(5.296)*\text{water source– rainfall} + \\ & \ln(0.030)*\text{lack of reservation} + \\ & \ln(2.306 * 10^{-9})*\text{water source– groundwater} + \\ & \ln(1.407 * 10^{-10})*\text{urban development} + \ln(0.001) \end{aligned}$$

[Equation 5.6]

Equation 5.6 shows that the presence of diverted or farm runoff impacts most significantly the odds of wetland being classified as moderate or high Economic value, since when all other values are held constant in the Equation, a one unit increase from absence to presence increases the odds likelihood by a magnitude of 2804.555. The magnitude of the coefficients, w_i in $ln(w_i)$ for resource utilization and sedimentation suggests that these are suitable input variables for use in assessing subcatchment wetlands as well those of significance and national importance. The very small coefficients for water source– groundwater and urban development means that the presence of these attributes strongly reduces the odds of a wetland being classified as moderate or high Economic value, that is, the presence of either attribute for a wetland site increases the probability that the wetland will be assessed as very low or low Economic value.

Discussion of all Economic value models, with and without threat input, is presented in the concluding section of this chapter.

Table 5.2: Classification table for Economic value and threat input values showing the proportion of cases correctly classified after the binary logistic regression model, Equation 5.5, has been built for 151 wetlands. Table 5.1a shows the classification table prior to model building

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	127	2	99
	Moderate + high	3	19	86
			Overall percentage correctly classified	97

5.3 *Social value of wetlands*

5.3.1 Social value – correlations

Correlations were made of the 12 attributes used in the WGCMA evaluation of Social values, which were listed in Table 4.6. As with the Economic value analyses just described, correlations were made between the absence or presence of these attributes and the absence or presence in high or moderate Social value assessments using Spearman's rank correlation coefficient (ρ). Associations with a value greater than or equal to +0.400 or less than or equal to –0.400 are mentioned here. In order of strength, they are:

- The wetlands protected in some sort of reserve system as seen by their park values exhibit a strong association with moderate or high Social value assessments ($\rho = 0.676$);
- The presence of passive recreation at a site is strongly correlated to a moderate or high Social value assessments ($\rho = 0.573$);
- Moderate and high Social value assessments are strongly correlated with the presence of recreational fishing at a site ($\rho = 0.538$);
- The presence of bird watching at a site is moderately correlated to a moderate or high Social value assessments ($\rho = 0.495$);

- Sites used for education are moderately correlated with moderate or high Social values ($\rho = 0.469$); and,
- The presence of boating is moderately associated with moderate or high Social values ($\rho = 0.424$).

All of the above correlations were found to be significant using χ^2 tests reported in Section 4.3.2: Social value – cross-tabulation analyses and contingency tables. As mentioned there, none of these relationships were reported by the WGCMA; rather their associations for high-value sites were to relate with the characteristics of high visual amenity and indigenous and European cultural values, neither of which was found stored in the Inventory Database. Interestingly, the χ^2 tests of the previous chapter also found significant relationships with the presence of camping, swimming and motorized 4WD attributes at sites and moderate or high-value assessments, which have relatively low ρ values being 0.285, 0.272 and 0.167 respectively.

Testing for correlations between attributes using Spearman's ρ showed positive associations with values greater than or equal to 0.400 in order of strength as:

- The presence of recreational fishing is correlated strongly with the presence of boating at wetlands ($\rho = 0.692$), which also means that the absence of recreational fishing is associated with an absence of boating;
- The presence of education is correlated strongly to protected wetlands park value ($\rho = 0.651$);
- With the same ρ value (0.651), the presence of education is correlated strongly to the passive recreation and the same association exists between the absence of each attribute;
- Passive recreation at a site is strongly correlated with protected park values ($\rho = 0.624$) and it also associated with recreational fishing ($\rho = 0.568$) and more moderately associated with boating ($\rho = 0.453$);
- The presences, along with absences of swimming and boating are moderately correlated to each other ($\rho = 0.597$);

- The presence of swimming is also moderately correlated to the presence of recreational fishing ($\rho = 0.491$), as are their respective absences;
- The presence of bird watching at a site is strongly correlated with passive recreation ($\rho = 0.662$), and also moderately correlated to the presence of education ($\rho = 0.518$), recreational fishing ($\rho = 0.486$), boating ($\rho = 0.415$) and a protected park value ($\rho = 0.480$);
- The presence of camping is also positively correlated to motorized 4WD at a site ($\rho = 0.415$); and,
- Recreational fishing is moderately associated with the presence of protected park values ($\rho = 0.438$) and education ($\rho = 0.416$).

The above positive correlations, and the obvious interconnectedness among different attributes, support their use as a set of measures attempting to assess interrelated aspects of a wetland's overall Social value. There were no negative correlations between attributes with values less than or equal to –0.400, indicating that there are no instances where presence of attribute is strongly associated with the absence of another.

5.3.2 Social value – logistic regression models

In the Inventory Database there are only two records for water skiing and research attributes used in Social value assessments. Accordingly, the presence or absences of these attributes were excluded from the building of the Social value logistic regression models. For frequency and cross-tabulation analyses of Chapter 4, there were 160 records of Social value assessments including one record labelled as unknown. In preparation for logistic regression modelling, it was necessary to partition all attributes into two groups: records of wetlands where the attribute was absent and records where the attribute was present. A difficulty occurs with the attribute park value, in that there were 10 records assigned a park value of 0, equating to an unknown status for park value; for these, it is not possible to say whether the record should be included or excluded when partitioning the park value attribute into absent or present groups. Removing these records and the unknown Social value record, there were 149 Social value assessments where the absent and present values for all attributes are known. Of these, a total of 42 wetlands were assessed as moderate or high Social value wetlands, which is slightly less than the 50 cases desired for logistic regression model building.

As with Economic value logistic regression model building reported in Section 5.2.2, Block 0 is the baseline model constructed by the SPSS software which quantifies the *constant* value, as previously illustrated in Formula 5.5. Likewise, the second step of model building is the inclusion of all contributing attributes' absence and presence values into Formula 5.2 and the use of the maximum likelihood function in the calculation of all coefficients, w_i through to w_n for every input attribute. For Social value assessments, the binomial logistic regression model with the highest predictive power of 93% is given as Equation 5.7.

ln (odds of a moderate or high Social value assessment) =

*ln (2947292806)**bird watching + *ln (584.956)**park value +
*ln (6.190)**camping + *ln (2.283)**hunting +
*ln (1.979)**recreational fishing + *ln (1.820)**boating +
*ln (1.458)**passive recreation + *ln (0.219)**motorized 4WD +
*ln (0.178)**swimming + *ln (0.022)**education + *ln (0.000000000018)*

[Equation 5.7]

Equation 5.8 results when all natural logarithms are computed in the Equation 5.7.

ln (odds of a moderate or high Social value assessment) =

*21.804**bird watching + *6.372**park value +
*1.823**camping + *0.825**hunting +
*0.683**recreational fishing + *0.599**boating +
*0.377**passive recreation + *–1.518**motorized 4WD +
*–1.725**swimming + *–3.839**education + *–24.721*

[Equation 5.8]

To check the validity of Equation 5.8 in using input attributes to decide the probability of membership in moderate and high Social value assessments, records were taken from the WGCMA Wetland Inventory Database and analysed separately. In illustration, wetland № 38589090 was assessed as a high Social value with presence values for bird watching, protected park value, camping, recreational fishing, passive recreation, and education. Substituting for these presence values in Equation 5.8 gives *ln (odds of a moderate or high Social value assessment) = 2.499* and $s = 0.924$. There is a 92% chance that wetland № 3858909 would be classified as a moderate or high Social value wetland on the basis of its stored inventory record. This, and other testing, showed that the model could be reasonably be expected to correctly classify wetlands on the basis of their stored inventory data.

5.3.3 Social value – model evaluation

A measure of how well the model (Equation 5.8) classifies wetland data as belonging to moderate and high Social values was made by comparing two classification tables produced by the SPSS software. First, the Block 0 classification table is given in Table 5.3a. In this instance, the software presumes on the balance of probabilities that in 72% of cases a randomly selected wetland record would be classified as very low or low Social value. The resultant classification table for Equation 5.8 is shown as Table 5.3b where 93% of the wetlands are correctly classified. The classifications incorrectly assigned by Equation 5.8 were five very low and low-value wetlands designated by the model as high or moderate, and five moderate and high-value wetlands assigned as very low and low by the model.

Checking the validity of the model and its appropriateness through analysis of statistical tests of the significance of the coefficients, the overall χ^2 statistics for the model is 107.935 with 10 degrees of freedom with a significance of $p < 0.000$ calculated by the software which indicates that the model contains some useful and significant predictors amongst the included attributes. The –2LL value is computed to be 69.292 but this calculation stops after 20 iterations as a final solution was not found. However, the Nagelkerke's statistic shows that 74% agreement between the predictors in the model and the prediction of Social value assessment.

Examination of the w_i values of Equation 5.7, shows that bird watching and park value have very high positive values, meaning that when all other attributes are held steady small increments in either result in large changes in the odds of moderate and high Social value assessments. The attributes of passive recreation and motorized 4WD have coefficients, 1.458 and 0.219 indicating that their impact may be minimal.

When the significance associated with the Wald statistic for each attribute is examined; a significance value $p < 0.05$ indicates that the attribute does contribute significantly to the prediction. For Social value assessment, the attributes identified in this manner were education ($p < 0.04$) and park value ($p < 0.003$) and their significance is confirmed when the removal of either attribute from the model calculation reduces the overall prediction rate.

Trial and error model building and testing showed that passive recreation is the only attribute that may be removed without negatively influencing the predictive power of Equation 5.8. For instance, removing the attribute of motorized 4WD results in three extra misclassifications and a lower model overall reliability of 92%. The modified version of Equation 5.8 without input of passive recreation is given as Equation 5.9.

ln (odds of a moderate or high Social value assessment) =

*22.26**bird watching + *6.691**park value +
*1.854**camping + *0.826**hunting +
*0.714**recreational fishing + *0.576**boating +
*–1.681**motorized 4WD + *–1.681**swimming +
*–3.945**education + *–25.022*

[Equation 5.9]

As mentioned in Chapter 4, the WGCMA reports concluded that only indigenous and European cultural values were of importance in predicting high Social value; no direct associations relating to any of the attributes collected for the Social value data were mentioned in their reports. By way of contrast, the multivariate analyses undertaken in this chapter shows that the presence of bird watching and park value are strong predictors for moderate and high Social value assessments, and the attributes of boating, camping, education, hunting, motorized 4WD, recreational fishing and swimming less so. The significance of the different inputs of this model, Equation 5.9, and others, and what can be learned from them are further discussed at the end of this chapter in Section 5.5: Synthesis and discussion.

Table 5.3a: Classification table for Social value shows the proportion of cases correctly classified prior to binary logistic regression model building.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	107	0	100
	Moderate + high	42	0	0
Overall percentage correctly classified				72

Table 5.3b: Classification table for Social value shows the proportion of cases correctly classified after the binary logistic regression model, Equation 5.8 and Equation 5.9, have been built. Note: for Equation 5.9, the percentage correct is 92.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	102	5	95
	Moderate + high	5	37	88
Overall percentage correctly classified				93

5.3.4 Social value – logistic regression model using threats

To understand the contribution of threat assessments in deciding moderate and high Social value assessments, additional logistic regression models were built using wetland data for all Social value inputs combined with threat values for the 144 wetlands, where entire records existed. The highest performing model with a prediction rate of 95% is presented here as Equation 5.10. Of the 10 inputs to Equation 5.10, five are Social value attributes: bird watching; park value; camping; education; and, motorized 4WD. The remaining inputs are for threat values, of which four are listed in Table 3.1: water source; salinity; erosion; and, (inappropriate) recreation. Like the threat and Economic value logistic regression model, resource utilization appears, yet this attribute was not used by the WGCMA for subcatchment wetlands assessments.

$$\begin{aligned}
&\textit{ln (odds of a moderate or high Social value assessment)} = \\
&\quad 25.562\text{*bird watching} + 10.474\text{*park value} + \\
&\quad 10.381\text{*water source– other} + 5.08\text{*camping} + \\
&\quad 4.914\text{*resource utilization} + 2.166\text{*salinity} + \\
&\quad -2.163\text{*erosion} + -5.170\text{*education} + \\
&\quad -5.041\text{*motorized 4WD} + -5.906\text{*recreation} + \\
&\quad -28.396
\end{aligned}$$

[Equation 5.10]

To better understand the influence of resource utilization in predicting Social value, it is necessary to look at the logarithmic version of its coefficient, as given in Equation 5.11. Its coefficient indicates that a change from absence (0) to presence (1) for resource utilization has 136-fold impact on the odds of predicting a moderate or high Social value when all other inputs are held constant. Resource utilization is a relatively strong predictor for moderate and high Social value.

$$\begin{aligned}
&\textit{ln (odds of a moderate or high Social value assessment)} = \\
&\quad \ln(1.263 * 10^{11})\text{*bird watching} + \ln(35372.614)\text{*park value} + \\
&\quad \ln(32234.615)\text{*water source– other} + \ln(161.336)\text{*camping} + \\
&\quad \ln(136.157)\text{*resource utilization} + \ln(8.719)\text{*salinity} + \\
&\quad \ln(0.115)\text{*erosion} + \ln(0.006)\text{*education} + \\
&\quad \ln(0.006)\text{*motorized 4WD} + \ln(0.003)\text{*recreation} + \\
&\quad \ln(4.652 * 10^{-13})
\end{aligned}$$

[Equation 5.11]

The appearance of bird watching and park value in this model reinforce their importance in deciding Social value assessments, with or without threat values. Section 5.5 discusses this model in comparison to others.

Table 5.4: Classification table for Social value and threat input values showing the proportion of cases correctly classified after the binary logistic regression model, Equation 5.10, has been built for 144 wetlands using binary logistic regression. Table 5.3a shows the classification table prior to model building.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	100	3	97
	Moderate + high	4	37	91
Overall percentage correctly classified				95

5.4 Environmental value of wetlands

Undertaking frequency and cross-tabulation statistics for Environmental values in the previous chapter was complicated by the need to assess 16 contributing attributes, and several subattributes of seven individual Environmental values under consideration (see Table 4.12). Added to this, there was a variety of scales and ranges used across the assessment of attributes and subattributes, and few attributes could be easily assigned absence or presence status. To cope with this complexity, the approach taken here is to look initially at each Environmental value and its components and their association with overall Environmental value assessment, prior to looking at correlations between attribute values.

5.4.1 Environmental value – correlations

The Environmental value of wetland rarity is of particular interest. It is important to quantify the degree to which the classification scheme used to decide wetland rarity affects the identification of high and very high Environmental value wetlands (Frankiewicz & Wainwright, 2009; Ling & Jacobs, 2003; Stevens, 2009). Table 4.13 lists the pre-inventory and post-inventory frequencies of wetlands using the Corrick and Norman (1980) classification scheme. Correlations were made between the absence or presence of wetland types with the absence or presence in high and very high-value assessments using Spearman's rank correlation coefficient (ρ). Permanent saline wetlands, flooded river flats and unclassified categories are not included in the analysis due to their small frequencies, being 3, 1 and 1 wetlands respectively. For the remainder wetland types, there are no correlations of any magnitude. None of the positive correlations were statistically significant, being for semipermanent wetlands ($\rho = 0.014$), shallow freshwater marshes ($\rho = 0.138$) and deep freshwater marshes ($\rho = 0.150$). The two negative correlations for permanent open water ($\rho = -0.205$) and freshwater meadows ($\rho = -0.166$) are statistically significant at $p < 0.05$; these associations were also discovered in the cross-tabulation analyses and they mean that the presences of these wetland types are associated with Environmental assessments that are not high or very high value.

For significant flora, the majority of sites (88%) did not have registered Victorian rare or threatened (VROT) flora. There is a statistically significant ($p < 0.001$) correlation, with ρ value of 0.391 between the presence of VROT floral species and high and very high Environmental value assessments.

For significant fauna, the majority of sites did not have counts of VROT registered species, nor counts of species listed under the Flora and Fauna Guarantee (FFG) Act. Statistically significant positive correlations ($p < 0.01$) were found for faunal VROT species ($\rho = 0.33$) and faunal FFG species ($\rho = 0.338$) with high and very high-value assessments. Additionally, there is a very, very strong correlation ($\rho = 0.842$) between the presence of VROT faunal species and FFG registered species that is statistically significant ($p < 0.01$).

The Environmental value habitat value was assessed using wetland rarity, terrestrial zone habitat type and shoreline profile, As already mentioned wetland rarity was categorized using the Corrick & Norman (1980) scheme; most of the features used to assess the remaining two attributes were scored as either absent, usually present, or with abundant presence. For correlation analysis, all sites reporting any presence value, that is, usually present and with abundant presence, were grouped into a presence category. In the case of terrestrial zone habitat type the absence or presence of rocks, logs, emergent vegetation, exposed substrate, submerged or free-floating vegetation, shallow to medium depth water, permanent deep pools, water edge and other features were noted in the field. Correlations of these with high and very high

Environmental values for the most part are insignificant with the exception that the presence of rocks, which has a Spearman's rho value of 0.374 and is statistically significant at $p < 0.01$. It is interesting that many of the statistically significant relationships seen using cross-tabulations analyses were not noticed in the correlation analysis. Checking correlations between the various subattributes used in assessing terrestrial zone habitat type found only two positive associations where Spearman's ρ values were greater than or equal to 0.400, and these were:

- The presence of deep pools is moderately correlated with the presence of shallow to medium water depth ($\rho = 0.493$); and,
- The presence of deep pools is also correlated moderately with the presence of submerged or free-floating vegetation ($\rho = 0.404$).

Shoreline profile was assessed using the shoreline vegetation profile and shoreline description. For shoreline vegetation profile, the presence of shrubs was positively correlated with high and very high Environmental value ($\rho = 0.395$), the presence of alive trees ($\rho = 0.236$) and the presence of dead trees ($\rho = 0.331$); all of these associations were statistically significant at $p < 0.01$. For shoreline description, six records had unknown values and the attribute was assessed by looking at the shoreline shape as regular or irregular together with the presence, or otherwise, of an island. There is no correlation between the presence of islands and high or very high Environmental values, nor was there any correlation with the shoreline being regular or irregular.

Hydrology correlations were made using the wetland site absence/presence data for drainage, disposal of water, water storage, obstruction and water redirection. Except for water storage, all correlations of these subattributes with high and very high Environmental values were statistically significant at $p < 0.01$. This is in agreement with the cross-tabulation analyses in Chapter 4. The redirection attribute had a value of moderate significant correlation, albeit a negative one, with a Spearman's rho value of –0.445, that is, the absence of water redirection at a site is moderately associated with high and very high Environmental value assessments. The ρ values of correlations between hydrology subattributes show the interconnectedness of these subattributes.

The statistically significant correlations greater than or equal to 0.400 were:

- A strong correlation exists between obstruction at a site and redirection ($\rho = 0.582$);
- The presence of water storage is correlated moderately with the presence of water disposal at wetlands ($\rho = 0.441$);
- Obstruction is moderately correlated with disposal of water ($\rho = 0.418$);
- The presence of water disposal is also correlated with drainage ($\rho = 0.413$);
- Similarly and with the same ρ value (0.413), the presence of drainage correlates with water storage; and,
- Redirection and drainage have a correlation of 0.411.

The floral type by percentage of total cover of the dominant wetland EVC type was one of three subattributes used to assess vegetation intactness– critical lifeforms; the other two subattributes measured were the number of floral species present and whether or not substantial modifications had taken place at a site. The percentage sum of coverage of various floral types present for the dominant EVC of a site was measured and tabulated in various grades, as seen in Table 4.17a. For correlation statistics of the absence or presence of each type: graminoids; shrubs; herbs; sedges; ferns; and grasses were compared to absence or presence with high and very high-value assessments. The correlations for shrubs, herbs, ferns and sedges are statistically significant with $p < 0.01$, and each of these, and other relationships, were picked up by the cross-tabulation analyses in the previous chapter. However, only sedges had a correlation value of any strength ($\rho = 0.399$). Between vegetation types, there is only one correlation greater than or equal to 0.400 ($\rho = 0.444$) describes the relationship between the absence/presence of shrubs with absence/presence of graminoids for individual sites.

For the number of floral species at a site used in assessing vegetation intactness– critical lifeforms, site records vary from 0 (20 sites) up to more than 20 species (2 sites). Cross-tabulation analyses noted that low species counts tended to have very low or low assessments. The correlations between number of floral species at a site to high or very high-value assessments were reported as statistically significant with $p < 0.01$, but not with ρ greater than 0.400. There is also a statistically significant negative correlation (ρ = –0.447) between site modification and high and very high Environmental values, that is, sites where there are no modifications tend to be high or very high-value wetlands, and this association was also seen in the cross-tabulation analyses.

Finally, values recorded for vegetation intactness– width of vegetation fringe at sites varied from 0 to over 1000 metres. There is a statistically significant moderate correlation (ρ = 0.384) between vegetation absence/presence value with high and very high-value assessment, which was observed in the cross-tabulation analyses.

There are a plethora of possible correlations that could be computed for combinations between 16 attributes and their subattributes of the seven Environmental values described above (Table 4.12). All possible combinations of pairings were checked for correlations, and a positive correlation indicates an association where the presence of one attribute in the pair is a good indicator for the presence of the other. A negative correlation indicates a pairing of attributes where the presence for one attribute is often associated with the absence of its pair. The positive correlations greater than or equal to 0.400 are:

- A strong correlation with a ρ value of 0.772 exists between the vegetation intactness– critical lifeforms herbs absence or presence and vegetation intactness– critical lifeforms number of species present;
- There is a moderately strong correlation (ρ = 0.568) between wetland type permanent open water and the habitat value of permanent deep pools at a site;
- A moderately strong correlation was found between the vegetation intactness– critical lifeforms number of species present and the habitat value shoreline vegetation subattribute of shrubs with a ρ value of 0.510;
- Also a moderate correlation (ρ = 0.489) exists for vegetation intactness– critical lifeforms number of species present and vegetation intactness– vegetation width being present;

- there is an moderate association (ρ = 0.417) between the habitat value of the presence of permanent deep pools and hydrology attribute disposal of water;
- Coincidently with the same rho value (ρ = 0.417), there is a moderate association between habitat value shoreline profile subattribute of shrubs presence and vegetation intactness– critical lifeforms herbs; and,
- An association exists between habitat value shoreline profile subattribute of herbs presence and vegetation intactness– width of vegetation fringe presence of vegetation (ρ = 0.480).

In order of strength, negative correlations between attributes less than or equal to –0.400 are:

- A habitat value, shoreline profile subattribute of shrubs presence and vegetation intactness– width of vegetation fringe presence of vegetation (ρ = –0.588);
- A moderately negative correlation exists between vegetation intactness– width of vegetation fringe and vegetation intactness– critical lifeforms substantially modified (ρ = –0.435);
- The habitat value, shoreline profile subattribute of shrubs presence is negatively correlated with vegetation intactness– critical lifeforms' substantially modified (ρ = –0.423); and,
- Vegetation intactness– critical lifeforms' number of species present is negatively correlated to vegetation intactness– critical lifeforms' attribute of substantial modification (ρ = –0.400).

5.4.2 Environmental value – logistic regression models

For Environmental values listed in Table 4.12, there are 16 attributes and many additional subattributes. When designing binary logistic regression models, consideration needs to be given to the appropriate number of input variables to avoid over-fitting of data. Accepted statistical practice is to apply the rule of thumb method of ensuring that the number of input variables is no more than the number of data cases divided by 10. With approximately 160 inventoried wetlands for Environmental value, there should be no more than 16 input variables to any model. The appropriate choice of input variables is best guided by practicality and some measure of a meaningful relationship of input variables to output variable in the real world. Therefore the cross-tabulation analyses of Chapter 4 and the correlation analyses between, and across Environmental values reported above inform selection here. Binary linear regression models were built using the attributes and subattributes that showed correlations to high and very high-value and those attributes correlations to other attributes. The performances of these models were compared to the baseline case of Block 0, shown as Table 5.5a, where no input variables were used. The interpretation of each of the different models' Wald and Nagelkerke's R^2 statistics, led to the selection of two models for Environmental value: Model A uses seven input variables with 86% prediction rate; and, Model B with 15 input variables has a 91% prediction accuracy. Classification tables for Model A and Model B are given in Tables 5.5b and 5.5c respectfully.

Model A

The binomial logistic regression model with seven input variables is given in Equation 5.12. This model has good predictive power of 86% and a Nagelkerke's R^2 value of 0.641. To help navigate the variety of Environmental values, attributes and subattributes for the reader, the Environmental value for each attribute or subattribute is shown in brackets in Equation 5.12, and the equations following.

ln (odds of a high or very high Environmental value assessment) =

*ln (16.056)**flora VROT (significant flora) +

*ln (10.627)**sedges (vegetation intactness– critical lifeforms) +

*ln (8.567)**rocks (habitat value, terrestrial zone habitat) +

*ln (5.523)**shrubs (vegetation intactness– critical lifeforms) +

*ln (4.558)**shoreline shrubs (habitat value, shoreline vegetation) +

*ln (2.741)**vegetation intactness– width of vegetation fringe +

*ln (0.128)**redirection (hydrology) + *ln (0.017)*

[Equation 5.12]

Equation 5.13 results when all natural logarithms are computed in the Equation 5.12.

ln (odds of a high or very high Environmental value assessment) =

*2.776**flora VROT (significant flora) +

*2.363**sedges (vegetation intactness– critical lifeforms) +

*2.148**rocks (habitat value, terrestrial zone habitat) +

*1.709**shrubs (vegetation intactness– critical lifeforms) +

*1.517**shoreline shrubs (habitat value, shoreline vegetation) +

*1.008**vegetation intactness– width of vegetation fringe +

*–2.054**redirection (hydrology) + *–4.084*

[Equation 5.13]

Model B

The binomial logistic regression model with 15 input variables is given in Equation 5.14. The model has 91% prediction accuracy and a Nagelkerke's R^2 value of 0.738. With the exception of the hydrology attribute of redirection, this model shares each of the inputs of Model A

ln (odds of a high or very high Environmental value assessment) =

*ln (42.256)**fauna VROT (significant fauna) +

*ln (18.734)**flora VROT (significant flora) +

*ln (16.111)**sedges (vegetation intactness– critical lifeforms) +

*ln (13.160)**rocks (habitat value, terrestrial zone habitat) +

*ln (9.499)**vegetation intactness– width of vegetation fringe +

*ln (7.802)**herbs (vegetation intactness– critical lifeforms) +

*ln (7.596)**shoreline shrubs (habitat value, shoreline vegetation) +

*ln (3.305)**shoreline dead trees (habitat value, shoreline vegetation) +

*ln (2.810)**shrubs (vegetation intactness– critical lifeforms) +

*ln (2.715)**permanent deep pools (habitat value, terrestrial zone habitat) +

*ln (0.519)**submerged or

free-floating vegetation (habitat value, terrestrial zone habitat) +

*ln (0.311)**obstruction (hydrology) +

*ln (0.196)**ferns (vegetation intactness– critical lifeforms) +

*ln (0.122)**drainage (hydrology) +

*ln (0.025)**permanent open water (wetland type) + $ln\ (2.384 * 10^{-4})$

[Equation 5.14]

Equation 5.15 results when all natural logarithms are computed in the Equation 5.14.

ln (odds of a high or very high Environmental value assessment) =

*3.744**fauna VROT (significant fauna) +
*2.930**flora VROT (significant flora) +
*2.779**sedges (vegetation intactness– critical lifeforms) +
*2.577**rocks (habitat value, terrestrial zone habitat) +
*2.251**vegetation intactness– width of vegetation fringe +
*2.054**herbs (vegetation intactness– critical lifeforms) +
*2.028**shoreline shrubs (habitat value, shoreline vegetation) +
*1.195**shoreline dead trees (habitat value, shoreline vegetation) +
*1.033**shrubs (vegetation intactness– critical lifeforms) +
*0.999**permanent deep pools (habitat value, terrestrial zone habitat) +
*–0.655**submerged or
free-floating vegetation (habitat value, terrestrial zone habitat) +
*–1.169**obstruction (hydrology) +
*–1.628**ferns (vegetation intactness– critical lifeforms) +
*–2.102**drainage (hydrology) +
*–3.702**permanent open water (wetland type) + *–8.341*

[Equation 5.15]

The appearance of significant flora and types of vegetation (particularly sedges) amongst the attributes that most strongly influence high and very high-value assessments in Model A and Model B is noted here. In the next subsection, the inputs and performances of both Models are compared to each other and checked against the inputs reported by the WGCMA as being significant in predicting high-value wetlands. A comparison of all Environmental value models, including those with threat input, is made in Section 5.5, where the relevance of inputs predicting high-value assessments is discussed.

5.4.3 Environmental value – models evaluations

The validity and efficacy of Model A and Model B in deciding Environmental value assessments was manually checked by randomly sampling the Inventory Database for wetland records of very low, low, moderate, high and very high assessments and substituting absence or presence of input variables into Equation 5.13 and Equation 5.15. For the checked wetlands known to have high or very high assessments, the Models gave high probability values, and as would be expected, they gave very low probabilities for wetlands known to be very low, low or moderate assessments.

As with Economic and Social value models, the sign and magnitude of the w_i coefficients expressed in $ln(w_i)$ form equations can be used to gauge the significance and relative impact on a model's predictive ability. It is important to realize comparisons of the magnitudes of coefficients can be made within a model, but there is no meaning in making direct comparisons of coefficient size across models. Model A's Equation 5.12 shows that significant flora presence has a proportionally higher influence than other variables in deciding whether a wetland is of very high or high value. In Model B's Equation 5.14, the presence of significant fauna has an even greater (within the model) coefficient in than significant flora, which has the second largest impact.

The presence of sedges, shrubs and ferns appear as significant inputs in the Models and these were used as measures of vegetation intactness and habitat value. A comparison of input variables in Model A and Model B to those reported by the WGCMA (2007) shows considerable agreement. The WGCMA noted the highest value wetlands scored well for vegetation intactness, habitat value and wetland significance whilst wetlands assessed as low in value scored poorly for significant flora, habitat value and wetland rarity, and in some cases hydrology. In Model A, there are five input variables relating to either attributes of vegetation intactness or habitat value; the highest coefficient in the Model is for significant flora and the remaining variable is an attribute of hydrology with a strong negative coefficient. For Model B, five of the fourteen input variables relate to attributes of vegetation intactness and five inputs are for various habitat value attributes; there is a strong positive coefficient for significant flora and two negative coefficients for hydrology attributes. Model B also incorporates presence or absence input for significant fauna and whether or not a wetland is classified as permanent open water Corrick and Norman (1980) type.

Table 5.5a: Classification table for Environmental value shows the proportion of cases correctly classified prior to binary logistic regression model building.

Environmental value baseline		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low + moderate	102	0	100
	High + very high	56	0	0
		Overall percentage correctly classified		65

Table 5.5b: Classification table for Environmental value shows the proportion of cases correctly classified after the binary logistic regression model A, Equation 5.11, has been built.

Environmental value Model A		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	91	14	87
	High + very high	8	49	86
		Overall percentage correctly classified		86

Table 5.5c: Classification table for Environmental value shows the proportion of cases correctly classified after the binary logistic regression model B, Equation 5.13, has been built.

Environmental value Model B		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	93	9	91
	High + very high	6	50	89
		Overall percentage correctly classified		91

5.4.4 Environmental value – logistic regression model using threats

To understand the contribution of threat assessments in deciding high and very high Environmental value assessments, experimentation using 156 wetland records found the highest performing model with 91% prediction accuracy and a Nagelkerke's R^2 value of 0.857. The classification table for this model is given as Table 5.6. This model is shown as Equation 5.16, where there are 10 inputs: three for Environmental value attributes: fauna VROT, width of vegetation fringe and sedges; four inputs are for three threat attributes listed in Table 3.1: water source, pest plants and altered hydrology; and, the remaining threats of resource utilization, lack of reservation and drainage into the wetland. The three Environmental value attributes of Equation 5.16 are found in Environmental value's Model B with large positive coefficients underlining their influence in calculating the odds of high or very high Environmental value.

ln (odds of a high or very high Environmental value assessment) =

*36.849**fauna VROT (significant fauna) +
*35.671**vegetation intactness– width of vegetation fringe +
*31.710**resource utilization + *17.240**water source– other +
*3.18**sedges (vegetation intactness– critical lifeforms) +
*–1.039**pest plants + *–2.274**water source– rainfall +
*–3.013**altered hydrology + *–3.410**lack of reservation +
*–31.487**drainage into wetland + *–28.396*

[Equation 5.16]

Equation 5.17 shows the computed natural logarithms of Equation 5.16, and examination of its coefficients reveals that presence of fauna VROT value and the presence of width of vegetation fringe strongly influence high and very high Environmental value outcomes, and that the presence of drainage into a wetland strongly reduces the odds of the wetland being classified as high or very high Environmental value. The presence of sedges, as an indication of vegetation intactness at a site, is also a good predictor of high-value assessments. Like the threat models for Economic and Social values, resource utilization appears as a strongly influencing threat value although in practice it was not used for subcatchment wetlands assessments.

ln (odds of a high or very high Environmental value assessment) =

ln $(1.007 * 10^{16})$*fauna VROT (significant fauna) +

ln $(3.102 * 10^{15})$*vegetation intactness– width of vegetation fringe +

ln $(5.911\ 10^{13})$*resource utilization +

*ln (30692541.86)**water source– other +

*ln (24.188)**sedges (vegetation intactness– critical lifeforms) +

*ln (0.354)**pest plants + *ln (0.103)**water source– rainfall +

*ln (0.049)**altered hydrology + *ln (0.033)**lack of reservation +

ln $(2.116 * 10^{-14})$*drainage into wetland $+5.209 * 10^{-15}$

[Equation 5.17]

The coefficients of the terms in Equation 5.17 reveal the relative strengths of inputs in deciding the odds of high and very high-value assessments. The presences of significant fauna, width of vegetation fringe, resource utilization, water source and sedges have a strong positive effect on the prediction for high-value, whereas the threat of drainage into a wetland has a strongest negative influence.

Table 5.6: Classification table for Environmental value and threat input values showing the proportion of cases correctly classified after the binary logistic regression model, Equation 5.16, has been built for 156 wetlands. Table 5.5a shows the classification table prior to model building.

Environmental value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	92	8	92
	Moderate + high	6	50	89
		Overall percentage correctly classified		91

5.5 Synthesis and discussion

Each model presented in this chapter was built using binary logistic regression, a multivariate statistical technique, in order to predict Economic or Social or Environmental wetland values, with and without threat values. The predictive effectiveness of the models can be measured by comparing their % correct number of classifications with no input variables (Block 0 output in SPSS software) to their % correct number of classifications after model building, as presented in Table 5.7. Models had greater than 90% predictive ability for all wetland values, whether threat values have been incorporated or not. Such high prediction rates come at the cost of increasing the number of input variables, as a comparison of Model A and Model B of Environmental value shows. Given the predictive abilities of all models, the important questions are:

- How many variables are enough?
- What do the model input variables tell us about wetland evaluations?

These two questions are discussed next with reference to the three sets of analyses presented in Section 5.2, Section 5.3 and Section 5.4.

Economic value

Analyses in this chapter (Section 5.2.3) revealed that it is possible to correctly predict over 90% of Economic value assessments using absence/presence data for five variables: conservation forestry; diverted or farm runoff; food production; stock water supply; and, water storage, without the need to incorporate threat data (Table 5.1b and Table 5.7). The coefficient values of these variables in the model (Equation 5.4) indicate that presences of diverted or farm runoff, stock water supply and water storage at site increase the likelihood that a wetland will be classified as having a higher Economic value and presences of food production and conservation forestry reduce the odds. The inclusion of stock water supply in the model is supported by the univariate analyses reported in the previous chapter (Section 4.2.2). And, although there are no statistically significant associations for the remaining four variables, evidences of their influences can be found in the contingency table for conservation forestry, other land usage and diverted or farm runoff (Table 4.3a) where a large majority of higher-valued wetlands (Moderate and High assessments) have an absence value for conservation forestry and other land uses, while the single wetland record (wetland № 877461) evaluated as being high in Economic value has in addition a presence of diverted or farm runoff (Table 4.3a). Furthermore correlations using Spearman's rank coefficient, ρ, showed that diverted or farm runoff and water storage were moderately associated with higher-valued assessments, and there were strong negative correlations between food production and conservation forestry ($\rho = -0.587$), and between conservation forestry and stock water supply ($\rho = -0.438$). Collectively, these associations confirm that diverted or farm runoff, stock water supply, water storage, food production and conservation forestry are important attributes to decide Economic value assessments and these five input variables are quite sufficient and efficient in predicting the Economic value assessment for a surveyed site without the need to incorporate threat category data at over 90% accuracy.

The last sentence bears more reflection. Consider the baseline Block 0 statistic of 83% prediction rate, when no input variables are used (Table 5.1a). This percentage comes about as 133 of the 161 records were for low and very low assessments, and so classifying all inventoried wetlands as not high or moderate in value results in a high prediction rate. As only one wetland of 161 assessed was scored to be of high Economic value, and relatively few (only 27) were of moderate value, this is an argument for <u>not</u> undertaking Economic value assessments in the West Gippsland region. The exercise of collecting 12 input attributes for Economic value and 14 threat components to compute hundreds of risk assessments per wetland site required considerable expenditure in effort, time and money. The reality is that the effort to identify the single high Economic value wetland is likely to have been unnecessary. On the presumption that the high Economic value wetland is of sufficient monetary worth, then it is likely that the community will attempt preserve its status quo without the need for the WGCMA to identify it. If Economic assessments are to be undertaken, then onsite sampling can be reduced to five attributes: diverted or farm runoff; stock water supply; water storage; food production; and, conservation forestry, knowing that these are sufficient to achieve 91% prediction rate for moderate or high-value assessments. Again, it is not necessary to undertake the costly data collection for threat values, or the complicated risk assessment computation and collation exercise as described in Chapter 3 to assess Economic value.

For completeness in this investigation, a model using both Economic value attributes and threat value inputs showed that nine inputs (eight different variables) can achieve 97% prediction rate. It is important to question the improved prediction rate of the with-threats model when compared to the no threats model. Is it a function of the number of inputs used? Is the improved accuracy due to the inclusion of threat categories? Checking each model's entry in Table 5.7 under the column labelled 'average % increase in correct classifications per input', it is seen that both models have the same value, meaning the accuracy of prediction is simply a function of the number of inputs used, whether they are economic value attributes or threat categories. Again, this is further argument for <u>not</u> undertaking collection of threat categories data and for <u>not</u> completing the complicated risk assessments to evaluate Economic value.

Nevertheless, the Economic value with-threats model is of interest for its selection of predictive variables, which are two Economic value attributes: diverted or farm runoff and stock water supply, and six threat attributes: erosion; water source; urban development; resource utilization; sedimentation; and, lack of reservation were incorporated. The reappearance of diverted or farm runoff and stock water supply within this model further underlines the strong predictive influence of these two attributes to Economic value assessments, which is also evidenced in their large coefficients in the logarithmic version of model (Equation 5.6). For threats categories, urban development and water source- groundwater are strongly influential. The inclusions of resource utilization, sedimentation and a lack of reservation are interesting since these threat variables were not used by the WGCMA to assess subcatchment wetlands. Given the strong predictive power of these three attributes coupled with their usage in threats assessments at significant and nationally important wetlands in the region, consideration should be given to their incorporation in any future Economic value assessments.

Social value

For the Economic value assessment model, knowing how many variables are enough is more difficult to decide. As reported in Section 5.3.3, absence/presence data for nine Social value inputs are needed to correctly predict 92% site assessments when threat category data are not included (Table 5.3b and Table 5.7). The contributing attributes are: bird watching; park value; camping; hunting; recreational fishing; boating; motorized 4WD; swimming; and, education. Presence values for bird watching and park value strongly increase the odds of prediction of a higher Social value, as do the presences of camping, hunting, recreational fishing and boating to a lesser degree, while presence values for education, motorized 4WD and education reduce the odds of prediction (Equation 5.9). Several findings of the cross-tabulation analyses of the previous chapter (Section 4.3.2) and correlation investigations reported in this chapter (Section 5.3.1) provide strong supporting evidence for the inclusion of most attributes found in this model. In summary, statistically significant associations to higher-valued assessments could be found for (in order of strength): park value; recreational fishing; education; camping; swimming; boating; and motorized 4WD; there are correlations ($\rho > 0.4$) for: park value; recreational fishing; bird watching; education; and, boating with higher-valued assessments. As described in Section 5.3.3, passive recreation is removed from the model as it has little impact on overall predictive ability, despite passive recreation being the attribute having the highest χ^2 value of all Social value inputs for its association with higher-valued wetlands. In fact, passive recreation has twice as many recorded presences at sites than would be expected due to chance, and this strong association is also indicated by the correlation statistics for passive recreation to higher Social value assessments ($\rho = 0.573$). Correlation statistics between input variables explain why it was possible to cull passive recreation from the Social value binary logistic regression model; passive recreation is strongly correlated to park value, bird watching and education and the inclusion of these in the model captures the essence of the contribution made by passive recreation to decide Social value.

When models including threat inputs are created to predict Social value assessments, data are needed for absence/presence values of five Social value attributes: bird watching; park value; camping; education; and, motorized 4WD and five threat categories: water source; salinity; erosion; (inappropriate) recreation; and, resource utilization (Equation 5.10) to achieve the model prediction rate of 95%. A comparison of models with and without threat values helps answer the question about what does the models' input variables tell us about Social value wetland evaluations, For the no threats model, the input variables and their coefficients (the w_i value in *ln* (w_i)) show the two most significant variables influencing correct prediction rates are bird watching, where presence greatly increases the odds ratio of prediction by 10^8, and park value, where a value indicating that the site is protected gives a nearly 600-fold odds ratio increase. Equally, when threat values are included in model building, bird watching and park value have extraordinarily high values confirming their strong influence on Social value classifications. Likewise camping, education and motorized 4WD are found in models whether or not threats are included. Regarding the threat categories, the inputs that most strongly influence the odds of prediction are data values for water source, (inappropriate) recreation and resource utilization. Similar to the Economic value with-threats model, resource utilization appears, yet this attribute was not used by the WGCMA for subcatchment wetlands assessments; and thus, it should be considered for future Social value assessments.

Comparing the performance of Social value models with and without threat input can also be done through examination of Table 5.7. The average % increase in correct classifications per variable for each model remains the same, and it is the addition of another variable that effects the improved accuracy of with the threats model over the no threats version. This raises the question: Is necessary to collect threat values in the field and undertake the complicated process of risk assessments for Social value classifications? For Social value, considerable savings could be made by ignoring threat values entirely and concentrating efforts on evaluating the absence or presence of bird watching; park value; camping; hunting; recreational fishing; boating; motorized 4WD; swimming; and, education. Practitioners wishing to reduce the number of attributes for which data must be collected infield can be guided by Equation 5.9 that indicates if any input attributes should be removed on a cost-benefit analysis of their collection, they should be targeted in the following order: motorized 4WD; swimming; boating; recreational fishing; and, hunting.

Environmental value

By far and away, the most complicated, time consuming and expensive assessment undertaken by the WGCMA was for Environmental value. This has been reflected in the complexity of the individual values, attributes and subattributes used in the assessment and the considerable space taken in this thesis to describe them and discuss their interactions. Answering the question for Environmental value of 'how many variables are enough?' is difficult and the answer is covered in caveats. Before answering, it is best to first note that some input variables were not included in any model, and these absences point to a list of several attributes and subattributes that need <u>not</u> be collected in the field. These include Environmental value attributes of:

- Wetland rarity: All Corrick and Norman (1980) classified wetlands classes do not impact assessment predictability, with the exception of knowing if a wetland is classified as permanent open water, or not, for the Model B version. However if threat values are used, there is no need to assess this attribute;
- Significant flora: It is not necessary to check if a flora VROT if threat input data is used in the model;
- Significant fauna: It is not necessary to check if a faunal species is FFG registered species, as this attribute is highly correlated to faunal species VROT attribute, which appears in Model B and threat input model. If Model A is used, there is no need to collect data on either contributing attribute to significant fauna;
- Habitat value: Sedges is the only attribute of habitat value needed in the threat input Environmental value model. However, many subattributes of attribute terrestrial zone habitat type used to assess habitat value are found in both Models A and B but the following may not be collected as they do not appear in either calculation: logs; emergent vegetation; exposed substrate; shallow to medium depth water; water edge; and, other attribute. The two subattributes of permanent deep pools and submerged or free-floating vegetation appear only in Model B. Similarly with shoreline vegetation profile used to assess the shoreline profile subattribute of habitat value, alive trees were not found in either Model, while the absence or presence of dead trees was only used in Model B. All subattributes of shoreline shape used for shoreline profile assessment did not impact assessments, so it is not necessary to collect data on irregular or regular shaped shoreline shapes, nor on the absence or presence of islands;
- Hydrology: As cross-tabulation analyses and Spearman's rho correlation statistics showed very strong associations between all hydrology attributes

(Section 5.2.1), it is not necessary to collect all of the subattributes of hydrology. There is some variation between Model A and B in the hydrology attributes used; Model A uses redirection only and Model B uses obstruction and drainage in its computation. On both counts, there is no need to collect data for water storage and water disposal. No hydrology attributes assessed as Environmental attribute values contribute to the threat input model, although two threat values: altered hydrology (found in Table 3.1) and drainage into wetland are used; and,

- Vegetation intactness– critical lifeforms: Using the floral types of the dominant EVC at a site, it is not necessary to check for graminiods or grasses and a check for herbs and ferns need only be done if Model B is being used. Sedges appear in all Environmental value models with and without threats. Nor is it necessary to do a count of floral species at each site, as this subattribute does not feature in the calculations for any model, despite there were strong correlations and cross-tabulations of species numbers to high and very high-value assessments.

Threat attributes <u>not</u> used in any model which do not need to be collected include:

- Loss of wetland connectivity;
- Stock access;
- Pest animals;
- Urban development;
- Native vegetation decline;
- Land use;
- Physical alteration;
- Erosion;
- Fire regime;
- Recreation; and,
- Salinity.

As mentioned earlier, there is good agreement between patterns of attributes for high and very high-value wetlands noticed by the WGCMA and the cross-tabulation analysis, correlation statistics and inputs identified for the building of all Environmental value models. The WGCMA (2007) reported that high and very high Environmental value sites scored well for vegetation intactness, habitat value and wetland significance, while poorer Environmental value sites were characterized by low scores for significant flora, habitat value and wetland rarity. The inputs to the binary logistic regression models, with and without threat categories, reflect these broad patterns, and more specifically, underline the importance in deciding Environmental values assessments of the data values (absence/presence) of: flora VROT (*significant flora*); fauna VROT (*significant fauna*); sedges, ferns and herbs (*vegetation intactness-critical lifeforms*); shoreline shrubs, shoreline dead trees, rocks, permanent deep pools, permanent open water, submerged or free-floating vegetation (*habitat value*); shrubs (*vegetation intactness-critical lifeforms*); drainage and redirection (*hydrology*) and width of vegetation fringe (*vegetation intactness-width of vegetation fringe*).

Much previous research has indicated that classification schemes have a far greater impact upon wetland assessments than is indicated here, e.g. Fitzsimons and Robertson, 2005, and Robertson and Fitzsimons, 2004. For Corrick and Norman classified wetlands, only two statistically significant associations were found in the cross-tabulation analyses (Section 4.4.2): proportionally more permanent open water wetlands were assessed as moderate value; and, more freshwater meadows were assessed as low value, than would be expected due to chance. Supporting analyses were found using Spearman's rank correlation coefficient (Section 5.4.1), in that, there are negative associations of permanent open water wetlands ($\rho = -0.205$) and freshwater meadows ($\rho = -0.166$) to high-value assessments, and although the magnitude of the correlations was quite low, the value means both wetland types were more likely to have very low, low or moderate assessments.

So for Environmental value, what do the model input variables tell us about wetland evaluations and the impact of the Corrick and Norman wetland classification scheme? For binary logistic regression models without threat data, only Model B incorporated a wetland type, permanent open water (Section 5.4.2). The coefficient of this variable in Model B is *ln (0.025)* indicating a 40 to 1 odds impact on the calculation of not indicating a high or very high-value wetland, when a wetland is a permanent open water type. Therefore in the case study, this is the only evidence that any particular Corrick and Norman (1980) wetland type is more, or less, likely to be evaluated as high or very high in value. But it is more complicated than that! Examination of Table 2.1, which details the Corrick and Norman scheme, shows that wetland type is decided upon indicators of water depth for each of the seven types, and with subcategories of dominant vegetation types for deep freshwater marshes, shallow freshwater marshes and freshwater meadows. The vegetation types include shrubs, herbs and sedges, and as an examination of the input variables of Models A and B shows, high and very high evaluations are more strongly correlated to these vegetation types, indicating it is their physical presence, rather than their use in wetland classification, that precipitates high and very high Environmental value assessments.

The other wetland classification scheme used in Victoria is on the basis of EVCs, which were used in the case study as one of the attributes needed to assess the Environmental value of vegetation intactness. For each site, the dominant EVC was recorded and a measure of percentage of floral types present for that EVC was estimated. Cross-tabulation analyses found statistically significant associations between the absence of herbs and low value assessments, and the presence of shrubs, sedges and ferns with high and very high-value assessments (Section 4.4.2). These associations were confirmed by correlation analyses, which indicated that the strongest relationship was between the presence of shrubs and high and very high Environmental values (Section 5.4.1). The only EVC component needed to evaluate the threat input model is the absence or presence of sedges. However for Models A and B where no threat values were assessed, shrubs, sedges and the presence of shoreline shrubs are inputs to both models and their respective coefficients indicate that they impact significantly on the odds of predicting high and very high Environmental value assessments. For Model B, herbs and ferns are additional inputs, with coefficients for herbs increasing the odds likelihood and for ferns decreasing it.
Given that it is possible to build Models of strong prediction rates of over 90% (86% for Model A) without considering threat input, it poses the question: Is it necessary to collect threat data and undertake the arduous risk assessment to identify high and very high Environmental value wetlands? Again, Table 5.7 holds the answer by comparing

the values for each Model under the ‘average % increase in correct classifications per input’ column. For no threat Models, the improved prediction values for Model B over Model A is simply a function of eight additional inputs into the calculation, although there is a drop in efficiency per input. Thus, the choice between using seven or 15 inputs is to be decided by an analysis of the cost of collection for each input attribute versus its contribution to the assessment. Where threat categories are incorporated into the model, the ‘average % increase in correct classifications per input’ value is similar to the seven input version (Model A). This supports the need to incorporate threat data input into deciding Environmental value. Lynch (2011) relates the historical use of threat categories in various frameworks to assess wetlands, including the Millennium Ecosystem Assessment Framework and Ramsar Convention guidelines, and she argues the need to incorporate threat categories in wetland assessments and management. The evidence presented here suggests doing so only for Environmental value, and not for Economic and Social value assessments in West Gippsland.

This question is discussed further in Chapter 6 after the novel application of neural networks to wetland assessment described in the next chapter. Neural networks, a data-mining technique, are used to identify factors predicting high-value wetlands and to mimic the human-decision making processes of wetland assessments, and their efficacy in both regards is also discussed in Chapter 6.

Table 5.7: A summary of all binary logistic regression models showing the number of input variables used, the initial % correct classifications and final % correct classifications made by each model. The calculation of average % increase in correct classifications per input was made by taking the difference between initial % value and final value of the model, divided by the number of input variables.

Model		**Number of inputs**	**% Correct classifications**		**Average % increase in correct classifications per input**
			Block 0	**Final**	
Economic value	No threat input (n = 161)	5	83	91	1.6
	With threat input (n = 151)	9		97	1.6
Social value	No threat input (n = 149)	9	72	92	2.3
	With threat input (n = 144)	10		95	2.3
Environmental value– Model A	No threat input (n = 163)	7	65	86	3
Environmental value– Model B	No threat input (n = 158)	15		91	1.7
Environmental value	With threat input (n = 156)	10	64	91	2.7

Lakes Entrance. Victoria, September 2010.
Image courtesy of Paul Boon

Chapter 6

Artificial neural networks analyses

In Chapter 5, the multivariate statistical method of binary logistic regression was used to construct models of wetland assessments. These models, some incorporating threat data and others not, were able to correctly predict over 90% wetland classifications. Analyses of model inputs and model performances indicated that data for many attributes were not required, and more importantly, the effort to assess threat values and undertake risk assessments was not always necessary in order to decide wetland values. It was argued in the discussion of the previous chapter that for Economic value, assessments <u>not</u> be undertaken at all for any wetlands; for Social value, threat data should <u>not</u> be collected and risk assessments should <u>not</u> be done; and, for Environmental value, it <u>may</u> <u>not</u> be necessary to collect threat data and do risk assessments.

To shed further light on these preliminary conclusions and on the identity of the most appropriate attributes needed for wetland assessments, this chapter explores the application of artificial neural networks (ANNs) to the problem. As data-driven and self-adaptive tools, ANNs have been increasingly applied to complex classification problems in a wide variety of disciplines. First, the computing mechanisms of ANNs are explained and important design considerations are discussed. ANNs for Economic, Social and Environmental values are then built, trained and tested using WGCMA inventory data. The performances of these ANNs in conducting wetland evaluations are assessed for accuracy and efficiency in comparison with the traditional process and the multivariate statistical models presented in Chapters 5. The major contributing inputs in deciding each ANN's 'decisions' are identified through sensitivity analyses and these are contrasted to those found via the univariate and multivariate statistical approaches described in Chapters 4 and 5. A discussion of the usefulness of ANNs in undertaking wetland assessments concludes the chapter.

6.1 Introduction

An artificial neural network (ANN) is a computing strategy most often used to find solutions for complex real-world problems, where the relationship between data types is not obvious, or explicit (Zhang, 2000). Modelled on the way the human brain is connected, ANNs are able to infer function from observation. Thus, they excel in pattern recognition and classification problems, and they can be trained to learn desirable patterns found within one dataset and classify unseen data according to what has been learnt previously (Negnevitsky, 2011). As a non-linear data-mining technique, they are investigated here on two accounts: first to further explore salient data inputs into wetland assessments, and contrast the artificial neural network outcomes with the univariate and multivariate statistical analyses of the previous two chapters; and second, to examine their suitability as a mechanism to mimic and automate wetland assessments.

Artificial neural networks are often chosen for handling complex ecological and biological data problems (Brosse, et al., 2001; Lek & Guegan, 1999; Noble & Tribou, 2007; Recknagel et al., 2006; Shanmuganathan et al., 2006; Whigham et al., 2006). Amongst other applications, they have been used to predict the presence of algal blooms (Khanna et al., 2005; Muttil & Chau, 2007), lake water temperatures (Liu & Chen, 2012), river levels (Leahy et al., 2008), and long term drought forecasts (Barros & Bowden, 2008). As an indication of their widespread application to environmental assessment and management, Maier and Dandy (2000b) identified 43 papers published up to 1998 where ANNs were used to predict water-resource variables. In a later review across the same research domain, Maier et al. (2010) found the number had increased after 1998 to 210 academic papers across 18 international journals. These papers reported the application of neural networks to forecasting water quantity and quality variables of rivers.

The widespread popularity of ANNs is due in part to their ability to cope well where other statistical approaches, such as multiple regressions, may fail due to non-linear relationships between variables, the presence of unusual but ecologically relevant outliers, and other problems with handling uncertainty (Brosse et al., 2001; Findlay & Zheng, 1999; Lek & Guegan, 1999; Olden et al., 2006; Zhang, 2000). Most importantly, ANNs make no assumptions regarding the statistical distribution of input data and are able to handle multiple disparate variables; moreover, they cope with noisy data and uncertainty to find complex relationships amongst the inputs, and moreover once correctly set up and trained, an ANN can be relied upon to make predictions similar to those upon which it has been trained with good predictive ability (Negnevitsky, 2011).

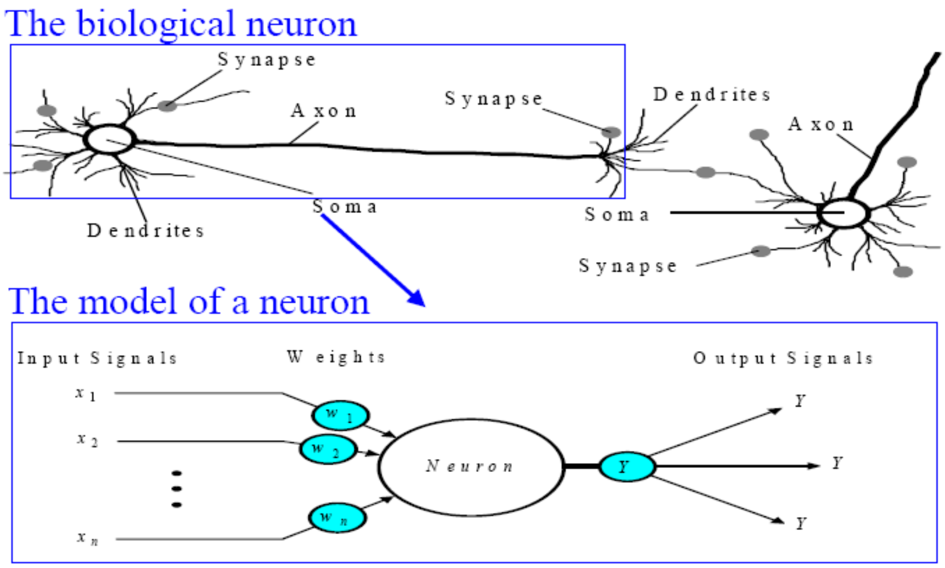
6.1.1 Artificial neural networks

Artificial neural networks consist of computing neurons, which are modelled on the biological neuron; a comparison of both is made in Figure 6.1. The components of a computing neuron are strongly analogous to biological neurons, since stimuli or inputs enter the neuron to be collectively evaluated in deciding whether output will be sent onto the next neuron. The seminal work describing computing neurons was done by McCulloch and Pitts (1943), who explained that a single neuron collects each of its inputs (x_i) and individually multiplies these by a corresponding weight (w_i). The neuron sums all $x_i * w_i$ calculations and compares the result to a threshold amount or hard limiter decided by an activation function, be it a step, sign, sigmoid or linear function. The result of this calculation determines the output signal of the neuron. Using this strategy, the computing neuron illustrated in Figure 6.1 is capable of solving simple problems that are linearly separable functions, such as logical AND and logical OR calculations. How this is done is described in the worked example following[4].

More generally, neurons are gathered in groups to build layered neural networks, as shown in Figure 6.2. Here the neural network consists of three layers: an input layer, a hidden middle layer and an output layer. Each neuron in the input layer receives its input signals from the outside world and transmits it as output to neurons in the middle layer. The neurons of the middle layer collect inputs, process weights, calculate sums and make comparisons to activation functions to decide the output they will pass onto the next layer. The neurons of the output layer repeat the process described for middle layer neurons to decide their output signals to be passed out of

[4] Note from this point on, computing neurons will be referred to as neurons and artificial neural networks will be referred to as neural networks, as is the practice in the computing literature.

the ANN. The neural network architecture of Figure 6.2 shows one middle layer, although there may be several middle or internal layers in a design. Middle layers are labelled as “hidden”, as they are not readily observable nor directly accessible; they have indirect contact with the outside world.



Analogy between biological and artificial model neuron

Biological neuron	*Artificial or model neuron*
Soma	Neuron
Dendrite	Input
Axon	Output
Synapse	Weight

Figure 6.1: Diagram of a biological neuron and a model of a computing neuron, together with a listing of analogous components. Source: Negnevitsky (2011).

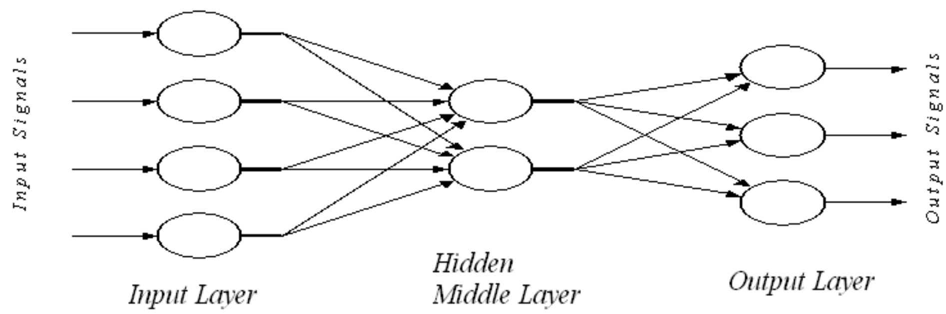


Figure 6.2: Architecture of a typical artificial neural network where the network consists of an input layer of neurons which receive data, at least one hidden middle layer of computational neurons and an output layer of computational neurons. Source: Negnevitsky (2011).

Whether it be the single neuron of Figure 6.1 or a multilayer ANN shown in Figure 6.2, the ability of any ANN to learn and solve problems is done through an adjustment of input weights in a process called training. For every directional arrow between neurons in Figure 6.2, there is an adjustable weight which is modified during the training process, as first introduced by Rosenblatt (1958). To illustrate how this is achieved, a simple neuron with two inputs, x_1 and x_2, and one output, Y, will be taught the logical AND operation. The neuron structure is shown in Figure 6.3. The logical AND operation is a binary operation with inputs, x_1 and x_2, each may take the value of either 0 (false) or 1 (true). The logical AND operation examines the values of both inputs and returns 1 (true) only when both x_1 and x_2 have a value of 1 (true), otherwise the result should be 0 (false), as shown in Table 6.1.

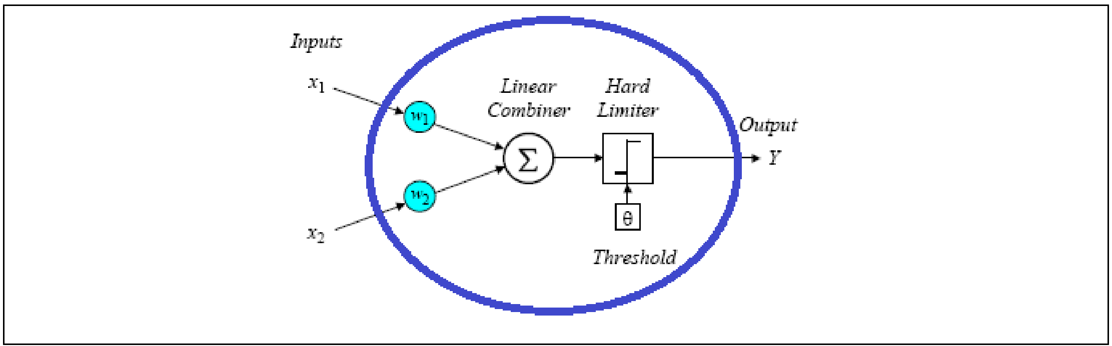


Figure 6.3: A simple two input neuron, with inputs x_1 and x_2 and weights w_1 and w_2. Diagram modified from Negnevitsky (2011).

Table 6.1: An outcome table for the binary logical AND operation of inputs x_1 and x_2.

Input x_1	Input x_2	Desired outcome Y
0	0	0
0	1	0
1	0	0
1	1	1

When a computing neuron is set up, values for weights, hard limiter function, threshold value and learning rate are all assigned. For the neuron in Figure 6.3, the weights w_1 and w_2 are randomly set as 0.2 and 0.1 respectively, along with a learning rate α of 0.1. The hard limiter is the step function shown in Figure 6.4 with a threshold θ of 0.2. This example has been taken from the text by Negnevitsky (2011).

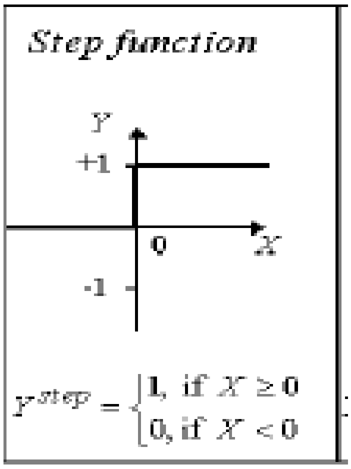


Figure 6.4: Mathematical step function, where an input of less than 0 results in output of 0, and an input greater than or equal to 0 is assigned as 1.

Training is done in epochs, where the neuron is presented with one batch of training data; in this instance it is the set of all possible inputs for x_1 and x_2. For the first set of inputs in row 1 of Table 6.1, the neuron computes

$$x_1 * w_1 + x_2 * w_2 = 0 * 0.2 + 0 * 0.1 = 0.$$

The neuron then subtracts the threshold value, $\theta = 0.2$, from the result and applies the step function of Figure 6.4 where an input of –0.2 results in an output value of Y equals 0. Checking the desired outcome for the given inputs of x_1 and x_2 in Table 4.1 also gives 0, meaning that the computing neuron is giving the desired solution and it does not need to be corrected for this set of input.

Proceeding with the second data input of the training set, where $x_1 = 0$ and $x_2 = 1$, the neuron computes

$$x_1 * w_1 + x_2 * w_2 = 0 * 0.2 + 1 * 0.1 = 0.1.$$

After subtracting θ and applying the step function, the output value of Y is computed as 0. This is also the desired outcome for the given inputs, so the next training data of where $x_1 = 1$ and $x_2 = 0$ is presented to the neuron. The first step in the calculation is

$$x_1 * w_1 + x_2 * w_2 = 1 * 0.2 + 0 * 0.1 = 0.2.$$

Next the subtraction of θ from *0.2* results in a value of 0 to be used as input to the step function. This results in a Y value of 1, which is not the desired outcome for this data input. 0 is required. So the computing neuron has made an error of –1 in its calculation. Error is calculated using Formula 6.1.

$$error = desired\ outcome - actual\ outcome$$

[Formula 6.1]

When a neuron computes an outcome other than desired, it needs to undertake learning through an adjustment of its weights. The formula given for the adjustment is presented as Formula 6.2, where the change in weight Δw_i is the learning rate α multiplied by the error and the value of x_i.

$$\Delta w_i = \alpha * error * x_i$$

[Formula 6.2]

In this case, the adjustment needed for w_1 is calculated as

$$\Delta w_1 = 0.1 * -1 * 1 = -0.1$$

The value of Δw_1 is added to w_1 to produce the new weight of w_1 for use in subsequent training. In this case, w_1 becomes 0.1 as a result of 0.2 + –0.1. Likewise, Δw_2 is computed using Formula 6.2, which results in Δw_2 equalling 0 and no change is made in w_2. Finally, the fourth training data in the epoch is presented to the neuron which uses the newly computed weights of w_1 and w_2. The calculation becomes

$$x_1 * w_1 + x_2 * w_2 = 1 * 0.1 + 1 * 0.1 = 0.2.$$

After subtraction of the threshold and application of the step function, the result is the desired Y value of 1. No additional adjustment to weights needs to be made for this pair of x_1 and x_2 values. Training commences again with the first dataset of $x_1 = 0$ and $x_2 = 0$ and it continues until the desired outcome Y is calculated correctly for the entire dataset or epoch without the need for learning. On the second pass, the neuron performs correctly for all sets of input, so training stops. The neuron with weights $w_1 = 0.1$ and $w_1 = 0.2$, a threshold value θ of 0.2 and a learning rate α of 0.1 is now capable of reliably computing the logic AND operation into the future.

From this example, it is evident that the ability of the neuron to be trained, and the speed at which it is done is affected by the randomly generated initial weights, the threshold value selected, and the learning rate. The learning rate regulates the size of the steps taken by the neuron to approach its solution; too small a size means more epochs of training data are presented to the neuron to reach its optimal weights, and too large a size may mean that the neuron calculations seesaw either side of the best weights as they are unable to zero-in due to their stride size. Additionally, there are several possible combinations of different values of w_1, w_2, θ and α for the neuron to solve the logic AND problem, and different runs using a neuron or neural network to solve a problem will result in various versions for the task at hand.

The practical implications of randomly chosen components of a network are twofold: every time a network is generated, the performance statistics will be similar, but rarely identical, necessitating multiple runs over which to find general predictive abilities; and, the once a suitably performing ANN is found, its final weights must be saved to a file and the activation functions known for constructing the same network in the future.

6.1.2 Considerations in applying neural networks to the study

In all ANNs, neurons are assigned randomly generated weights, which are altered during the training process to learn solutions to a specific problem. These weight values have no intrinsic meaning, but collectively they are used to compute appropriate output, and for this reason, neural networks are considered black-boxes (Olden & Jackson, 2002). As seen in the worked example, simple computing neurons are capable of solving linearly separable functions, like logic AND and logic OR, whereas anything more complicated needs a set of neurons, like the layered artificial neural network shown in Figure 6.2.

The ANN design of Figure 6.2 is known as a feed-forward neural network (FFNN) with one hidden layer, and they have been shown mathematically capable of representing any continuous function to any degree of accuracy given suitable numbers of hidden neurons (Cybenko, 1989; Hornik et al., 1990). As pointed out by Maier and Dandy (2000b), the use of more than one hidden layer adds greater flexibility and often makes computationally more efficient solutions for many situations, and deciding the most appropriate design of an ANN is as much art as it is science (Negnevitsky, 2011).

Often FFNNs are referred to as feed-forward back propagation networks, in reference to their training approach. In training, FFNNs need to back-propagate errors from the output layer back through to its internal hidden layers (Rumelhart et al., 1986). To mathematically accommodate back propagation, a sigmoidal function, rather than step function, is most often used. Sigmoidal functions, such as the hyperbolic or logistic functions, are easily differentiated to derive the rate of error used to calculate Δw_1 and modify the weights of hidden layer neurons during the learning process (Negnevitsky, 2011). For neural networks using categorical data, the softmax function is best applied as it gives the logit probabilities for each output category (IBM Corporation, 2011; Zeng, 1996).

Other important design issues relate to data requirements. Unlike the logic AND example, where the entire dataset was presented to the computing neuron, for real-life situations it is accepted practice for the data pool to be partitioned into three sets: a training set for training the neural network; an unseen testing set to check on errors during training and avoid over-fitting; and, a holdout sample to assess the resulting trained network for performance (IBM Corporation, 2011; Negnevitsky, 2011). Each of the sets should be representative of the patterns present in the data and have the same statistical properties (Maier & Dandy, 2000b).

It is known that ANN prediction accuracy improves with growing data numbers and it is desirable to have 200 cases as a minimal dataset size (Detienne et al., 2003; Sug, 2010). For the WGCMA dataset, the number of wetlands inventoried was controlled by the need to gain statistical representation of all wetland types within the West Gippsland catchment region; it is limited to, at best, 163 records. As it was not practical to undertake additional surveys to generate more training data, two approaches have been taken to resolve the problem. The first approach was training networks with the entire dataset to enable direct comparisons of these ANNs with Chapter 5 analyses. Maier & Dandy (2000b) noted that ANN models can be computationally equivalent to some statistical approaches and ANNs trained using the softmax activation function can compared with binary logistic regression models, assuming the same dataset has been used (Sarle, 1994). The second approach was taken when assessing an ANN's predictive abilities; the dataset was divided into training and testing sets, forgoing the luxury of a holdout sample dataset. This was the strategy taken by Milne (1995) when faced with a similar situation during a study of the NSW Nullica State Forest.

Other data concerns relate to sensitivity of neural networks to the magnitudes and ranges of scaled variables. To improve network performance, it is important to rescale these variables to small, predictable ranges (IBM Corporation, 2011; Noble & Tribou, 2007). This transformation will be largely unnecessary in this investigation as most of the data were categorical. Categorical data, however, present their own issues; they necessitate the use of dummy variables to represent each possible category as was discussed in considerations for the logistic regression analysis in Chapter 5. To avoid the need for dummy coding, I handled this problem in the same manner with the use of dichotomous variables of absence and presence categories only.

Finding the nature and appropriate number of input variables for constructing neural networks is a topic of much academic interest (Bowden et al., 2005; Maier & Dandy, 2000a & 2000b; Maier et al., 2010; Muttil & Chau, 2007; Piramuthu, 2004; Zhang, 2000). Neural networks are lauded by many practitioners as the best strategy to use when the appropriate number of inputs is unknown and inherent relationships between input data and output are not easily described (Detienne et al., 2003; Zhang, 2000). As non-linear, adaptive and data-driven tools, ANNs cope with noisy data, outliers and irrelevant data within input; however unnecessary input variables add computational complexity, they increase the need for more training data, and they make interpretations more difficult (Bowden et al., 2005). Superior and simpler models are generated when irrelevant input data are identified and removed (Muttil & Chau, 2007).

The benefit and the disadvantage of using an ANN is that it is a black-box approach. It is only possible to observe the inputs fed into a network and see the outcomes they produce. The weights of each interneuron connection can be read, but they are a computational slight-of-hand with no real-world meaning. Each ANN construction commences with a set of randomly chosen weights for its interneuron connections, and it is usual for different runs, using the same neural network architecture and input data, to not result in the same exact output. For each ANN construction described in the following sections, a minimum of 20 runs were completed to gauge ANN performance. Also, the use of multiple runs helped overcome the known difficulty of ANNs of sometimes converging on local, rather than global, minima due to their descent search strategy (Stager & Agarwal, 1997).

Much has been written on guiding appropriate ANN design and a plethora of advice has been given. Maier and Dandy (2000a & 2000b) and Maier et al. (2010) make valuable comments on ANN design for water-resource problems, which I have heeded in this investigation. In particular, they discuss the importance of performance criteria for evaluating models, the appropriate division of datasets, the need for data pre-processing steps, the determination of suitable inputs, decisions relating to appropriate ANN architecture, training algorithms, and validation.

Until recently, to create an ANN required either programming ability or detailed knowledge on how to customize specialist software. As the application of neural networks has become more of a mainstream practice, the statistical SPSS software offers a customizable point-and-click interface for ANN generation. As in Chapter 4 and 5 analyses, the IBM® SPSS® 20 Statistics package (http://www.spss.com/) has been used. The advantages of this software are its provision of algorithms to optimize and automatically decide the most appropriate neural network architecture and design, including the number of hidden layers, the number of neurons in each layer, and the relevant activation functions between layers. The automation of these functions relieves the user of design decisions, where poor choices may adversely influence ANN function. As well, SPSS has a sensitivity analysis tool to identify the most significant inputs during an ANN run. This tool was used extensively to identify significant inputs of the ANNs described in the following sections.

6.2 *Economic value of wetlands*

6.2.1 Economic value – ANN constructions

Data were prepared for ANN building as for binary logistic regression models reported previously. All attributes of Table 3.1, other than commercial fishing (with only two records), were partitioned into absence and presence groups. The output variable, Economic value assessment, was separated into two groups: moderate and high-value cases together, of which 27 were moderate assessments and one high assessment; and, low and very low assessments, with 109 low value and 24 very low value wetlands. To enable comparisons with the performances of binary logistic models to be made, the dataset was not partitioned into training, testing and holdout sets, and 161 wetlands records of Economic value attributes were used to build the ANNs.

The first step in finding the most suitable set of inputs was the construction of an ANN using all 11 input attributes of the WGCMA Economic value assessments: conservation forestry; drainage; disposal of water; diverted or farm runoff; food production; obstruction; other land usage; redirection; stock water supply; tourism; and, water storage. The ANNs architecture was 22-5-2, meaning there were 22 input neurons (an absence neuron plus a presence neuron for each input attribute), five neurons in the hidden layer (automatically calculated by the software as optimal), and twos neurons in the output layer (the first neuron for very low and low assessments calculations, and the second neuron for moderate and high assessments). All ANNs described in this chapter were built using the hyperbolic tangent as the activation function for the hidden layer and softmax as the activation function of the output layer.

The next step was to repeatedly run the software so that 20 ANNs with 11 inputs were built. As different initial weights were randomly chosen for interneuron connections, the prediction performances of the 20 ANNs varied with the number of hidden neurons calculated as optimal. The classification tables for the ANNs were examined and the classification table that occurred most often is shown as Table 6.2a. This classification table is referred to, from here forward, as the ceiling ANN for Economic value with 11 inputs. For the ceiling ANN, the overall percentage correct classification rate was 96%, correct classifications for very low and low assessments were at 98% and for moderate and high assessments at 79%. However, given the number of input variables and the very high prediction rates (Zhang, 2000), it is likely to be over-fitting the dataset, particularly for very low and low Economic value assessments.

Next, checks were made of the outputs of sensitivity analysis for each of the 20 ANNs. The inbuilt SPSS sensitivity analysis tool computes a normalized importance for each predictor; this indicates how much each ANN model changes with different values of each input variable, and it ranks the inputs in order of magnitude from most significant to the least. For each ANN construction, the sensitivity analyses were marginally different, and the rankings of inputs are strongly influenced by the learning performance of the set of randomly chosen initial weights. To determine the most influential inputs across the 20 runs, I assigned a rank number to each input for every sensitivity analysis. For instance in the first run, conservation forestry was found to be the most significant input, so it was assigned 1; the second most important input was redirection, and it was set as 2; and continuing in this manner until the least significant input tourism, which was designated as 11. Next, each input's rankings were summed across the 20 sensitivity analyses; those with the lowest scores were consistently assessed by the sensitivity analyses as influential, and those with the highest scores usually were ranked as least significant.

The sensitivity analyses found that conservation forestry, with a score of 29 out of a possible 220, was the most significant input variable for Economic value assessment. The listing of inputs in order of most influential to least across the 20 runs are, with the input's score in brackets, conservation forestry (29); diverted or farm runoff (67); stock water supply (72); redirection (99); water storage (106); food production (146); obstruction (147); other land usage (152); drainage (154); disposal of water (171); and, tourism (177). Note the scores give an indication of the magnitude of input variable effect only; the sensitivity analyses do not indicate whether the impact is positive or negative effect.

Commencing with the most influential input identified in the sensitivity analysis, an ANN was then built using conservation forestry as its only input. Again, 20 runs were done and the resultant ANNs were examined for their abilities to identify both output groups and contrasted to the ceiling ANN. The classification table for these ANNs is given as Table 6.2b, and it is referred to as the baseline ANN for Economic value. All conservation forestry only ANNs were able to correctly identify very low and low Economic value assessments, but were unable to discern any moderate and high wetland assessments. Next, 20 ANNs were constructed using conservation forestry and the next highest magnitude input, diverted or farm runoff, and these were able to correctly classify very low and low assessments and identify 39% of moderate and high-value assessments, with an overall correct prediction rate across both groups of 89%. Continuing in this manner, ANNs were progressively built by adding inputs one at a time and in order of their influence, and a check was made of improvements to overall prediction rates and the number of correct classifications of moderate and high-value assessments. When using this one-at-a-time approach to build ANNs, incremental improvements in the classification of moderate and high assessments came at the expense of losing some prediction accuracy of very low and low assessments, resulting in the same overall performance rate across groups.

Experiments suggest that the five-inputs ANN, using conservation forestry; diverted or farm runoff; redirection; stock water supply; and, water storage, are the most suitable for generalizing Economic value assessments without over-fitting the data. The classification table for this five-inputs ANN is shown as Table 6.2c. Further experimentation building ANNs using various permutations of subsets of these five inputs found that the best classification performance occurred when they were all present. Further, taking a subtraction-from-the-total strategy, that is commencing with the ceiling 22-5-2 ANN and progressively removing the least significant input variables also arrived at the five-inputs ANN, with architecture of 10-6-2, as the most appropriate for predicting Economic value assessments.

Table 6.2a: Classification table for the ceiling Economic value ANN inputs using all 11 input attributes. The table shows the proportion of cases correctly classified for 161 wetland records.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	132	1	99
	Moderate + high	6	22	79
			Overall percentage correctly classified	96

Table 6.2b: Classification table for baseline Economic value ANN using conservation forestry as the only input. The proportion of cases correctly classified for 161 wetland records is shown.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	133	0	100
	Moderate + high	28	0	0
			Overall percentage correctly classified	85

Table 6.2c: Classification table for the Economic value ANN built using five inputs. The proportion of cases correctly classified for 161 wetland records is shown.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	127	6	96
	Moderate + high	9	19	68
			Overall percentage correctly classified	91

6.2.2 Economic value – ANN evaluations

In their advice for creating neural networks to solve water resource problems, Maier and Dandy (2000a) and Maier et al. (2010) pointed out that it is important to decide a priori suitable performance criteria by which to evaluate ANNs. In this instance, the ability of the five-inputs ANN was compared to performance of the five-inputs Economic value binary logistic regression (BLR) model (Table 5.1b); it is possible to compare both as they were built using the same dataset. The overall ability to correctly predict Economic value was compared and the ability to discern moderate and high-value assessments were contrasted.

Comparing Table 5.1b, the classification table of the five-inputs BLR model with Table 6.2c of the five-inputs ANN, it is noticed that the overall percentage correctly classified is the same for BLR model and the ANN as 91%. It is more productive to compare the ability of each approach to separate each outcome group, and in particular, to correctly classify moderate and high-value assessments and in this regard, the BLR model and the ANN differ. Table 5.1b shows that the five-inputs BLR model is able to predict 99 % of very low and low Economic value assessments, but the model finds difficulty in discerning moderate and high-value assessments with only 57% correct. The five-inputs ANN outperforms the BLR model in correctly classify 68% moderate and high assessments, and very low and low assessments at 96%. On this inspection, the ANN appears to be the better choice of approach for deciding Economic value assessments.

Comparing the inputs of the five-inputs BLR model with five-inputs ANN, there are four inputs in common: conservation forestry; stock water supply; water storage; and, diverted or farm runoff. This commonality is further evidence of the efficiency of these inputs to describe Economic value assessments, and this point will be discussed further in the concluding section of this chapter. The additional input in BLR model was food production, an attribute of the Economic value production, and the extra input for the ANN was redirection, a subattribute of the drainage disposal Economic value.

6.2.3 Economic value – Threat ANNs

As the WGCMA assessment process incorporated risk assessments of how threats impacted on Economic values at all sites, ANNs were built and tested that incorporated threats as inputs. The dataset contained 151 wetlands where there were entire records for every Economic value attribute and threat factors. To create 20 ceiling ANNs, all 11 inputs for Economic value plus 26 threat inputs were used, resulting in a 74-2-2 architecture. The threat inputs were those used to assess 14 threat attributes listed in Tables 4.27a and 4.27b. With such a high neuron count in the input layer, all 20 ANNs created were expected to dramatically over-fit the dataset, and it is no surprise that the majority correctly classified 100% of all Economic values and 100% of the moderate and high assessments. Table 6.3a shows the most commonly occurring classification table.

The sensitivity analyses of the ceiling ANNs were examined and each analysis listed the 19 most influential inputs. Within each analysis, the reported 19 inputs were assigned numbers according to their rankings; the most important input in a run was given 1 as its score, and the least significant was assigned 19; and, any inputs not mentioned were assigned a score of 20. Next, every input's rankings scores were summed across the 20 sensitivity analyses; those with the lowest scores, such as diverted farm runoff with a total of 86 out of a possible 400, were consistently assessed by the sensitivity analyses as being most influential. The 10 most often significant inputs across the sensitivity analyses, with each input's score in brackets, are diverted or farm runoff (86); stock water supply (197); salinity (224); erosion (235); resource utilization (242); loss of connectivity (246); conservation forestry (267); eutrophication (154); urban development (276); and, water storage (286). The input of least significance was "change since European settlement" (385). Again the scores give an indication of the magnitude of input variable effect only, and no indication of positive or negative aspect of using the input. Of the 10 most significant inputs, four are Economic values: diverted runoff; stock water supply; conservation forestry; and, threats; and, six are threat values: salinity; erosion; resource utilization; loss of connectivity; eutrophication; and, urban development.

Using the one-at-a-time method to build ANNs and commencing with diverted or farm runoff as the first input, 20 ANNs were constructed and checked for prediction abilities. These baseline neural networks had an overall correct prediction rate across both groups of 87%, as seen in Table 6.3b. These ANNs were able to correctly classify very low and low assessments at 97% correct predictions rate and identify 39% of moderate and high-value assessments. By adding inputs in the order indicated by sensitivity analysis, progressively ANNs were built and their predictive abilities checked. For Economic value and threat inputs ANNs, the six-inputs ANN, as seen in Table 6.3c, has an acceptable overall classification rate of 94%, 96% recognition of very low and low assessments and 78% correct classifications for moderate and high-value wetlands. The architecture of the ANN was 12-6-2 and the inputs used to build this ANN were diverted or farm runoff; stock water supply; salinity; erosion; resource utilization; and, loss of wetland connectivity.

Two attributes of the six-inputs for the Economic value with-threats ANNs, diverted or farm runoff and stock water supply, were also significant inputs of the five-inputs Economic value ANNs. The remaining inputs are threat values; two are listed in Table 3.1 (salinity and erosion) as being used by the WGCMA to assess subcatchment wetlands, and two (resource utilization and loss of wetland connectivity) are threat values used by the WGCMA for significant wetlands and not for subcatchment wetlands assessments. This matter is discussed further in the final section of this chapter.

It is useful to see common inputs between the nine inputs (of eight different variables) BLR model, of Equation 5.5, and six-inputs ANN. Common to both are two Economic values (diverted or farm runoff and stock water supply) and two threat values (erosion and resource utilization). The appearance of these four inputs across solutions for binary logistic regression models and ANNs is testament to their potencies in predicting wetland assessments. The significance of this is also discussed in the concluding section of this chapter.

To assess the performance of the six-inputs Economic values with-threats ANN, its classification table, shown as Table 6.3c, can be compared with the classification table of the nine-inputs BLR model, given in Table 5.2. The overall percentage correctly classified is higher for the BLR model, being 97% compared with 94% correct, and it is assumed that the improved performance is due to the inclusion of three extra inputs in the multivariate model over the neural network. This assumption is supported by two pieces of evidence. First, Table 5.7 shows there is an average 1.6 increment per input variable in correct classifications for the BLR model. The additional three variables of the BLR model would account for the improved accuracy performance when compared to the ANN. Second, the experiments building eight-inputs ANNs resulted in the same overall prediction rate as the nine-inputs BLR, 97%, and the nine-inputs ANNs consistently gave 99% overall accuracies.

As in the previous section, it is more productive to compare the abilities of the nine-inputs BLR models and the six-inputs ANN in separating each classification group. The BLR model (Table 5.2) outperforms the six-inputs ANN (Table 6.3c) in discerning both groups: it correctly classifies 99% of very low and low assessments, compared to the ANN at 96%; and, 86% of moderate and high-value assessments against 78% for the ANN. Again the better performance of the BLR model is likely a function of its extra inputs over the six inputs of the ANN. Improvements were seen in the recognition of moderate and high-value wetlands during ANN building by increasing the number of inputs to seven, eight, and nine inputs. The additional inputs correctly classified percentages for moderate and high-value assessments at around 80%, 90% and 96%. In fact, from this experimentation, it is possible to conclude that for the same number, and types of inputs, the ANNs are better than binary logistic regression models at identifying Economic value wetlands overall and better at discerning moderate and high-value assessments.

Table 6.3a: Classification table for ceiling ANN built using all Economic value attributes and threats as inputs. The table shows the proportion of cases correctly classified for 151 wetland records.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	129	0	100
	Moderate + high	0	22	100
			Overall percentage correctly classified	100

Table 6.3b: Classification table for baseline Economic value and threats ANN using diverted runoff as the only input. The proportion of cases correctly classified for 161 wetland records is shown.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	129	4	97
	Moderate + high	17	11	39
			Overall percentage correctly classified	87

Table 6.3c: Classification table for the Economic value with-threats ANN built using six inputs. The proportion of cases correctly classified for 155 wetland records is shown.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	127	5	96
	Moderate + high	5	18	78
			Overall percentage correctly classified	94

6.2.4 Economic value – Predicting wetlands assessments

The widespread popularity of the application of neural networks to classification problems is in part due to their ability to be trained to learn patterns within datasets and to recognize these patterns in unseen data. This ability is only useful if the ANN can generalize broader data relationships and does not over-fit the dataset (Detienne et al., 2003; Negnevitsky, 2011; Zhang, 2000).

To evaluate the predictive abilities and suitability of Economic value ANNs in mimicking wetland assessments decision making, the dataset was separated into training and testing sets; 70% of data was used for training and 30% for testing. The difficulty in dividing the data is that there are fewer than 120 cases of wetlands for training data, barely half what is recommended as desirable (Detienne et al., 2003; Sug, 2010). As a result of the fewer training examples coupled with the random selection of data into either pool, there is much greater variation in performance statistics over the 20 ANNs built without threat data and the 20 ANNs using threat data.

Without threat inputs

A typical classification table for Economic value ANNs with no threat inputs is seen in Table 6.4a, where five inputs (conservation forestry; diverted or farm runoff; food production; stock water supply; and, water storage) were used. In this case, the architecture was 10-8-2. The trained network is able to classify unseen data with the same overall correct statistics. As well, the trained ANN has statistics comparable to the Economic value ANN network trained on the full dataset (Table 6.2c).

The point of difference between the network trained on 105 wetlands compared to the network trained on the entire dataset is their abilities to discern moderate and high-value assessments; the network trained on the entire dataset is able to better distinguish moderate and high classifications at 68% compared to 56% for the training sets. Both networks have similar figures 98% and 96% for very low and low value wetlands. The conclusion I draw is that it is possible to train a network using Economic value alone to correctly classify 91% wetlands when presented with unseen data, but the greater the number of wetlands in the training data, the better the discernment of moderate and high Economic value wetlands.

With threat inputs

Table 6.4b gives a typical classification table for an ANN built using Economic attributes and threat data; the six inputs used were diverted or farm runoff; erosion; loss of connectivity; resource utilization; salinity; and, stock water supply. The ANN's architecture was 12-6-2 and the overall prediction rate during training and the predictions in testing are very similar, although these performances are strongly influenced by the small amount of data and the randomness of selection of which wetlands are assigned to training data or test data.

Table 6.3c shows the classification table of the comparable network to Table 6.4b; both networks trained using threat input have quite similar overall correct classification rates, 94% and 93% respectively. As with no threat Economic value networks, there are marked differences in each network's ability to recognize moderate and high Economic value assessments; those trained on 155 wetlands were far better at 78% (Table 6.3c) compared to the ANN trained on 111 wetlands with 50% (Table 6.4b).

These experiments show that ANNs built with less than optimal training data can still reliably classify Economic value wetland assessments and be used to classify unseen data, and in particular, the more data available for training, the better the identification rates for moderate and high-value assessments.

Table 6.4a: Classification table for Economic value ANN built without threat data using five Economic value attributes as inputs, and trained using 105 wetland records and tested using data for 56 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Training (n= 105)	Very low + low	87	2	98
	Moderate + high	7	9	56
Overall percentage correctly classified				91
Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Testing (n= 56)	Very low + low	44	0	100
	Moderate + high	5	7	58
Overall percentage correctly classified				91

Table 6.4b: Classification table for Economic value ANN built with threat data using six inputs, and trained using 111 wetland records and tested using data for 44 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Training (n= 111)	Very low + low	95	0	100
	Moderate + high	8	8	50
			Overall percentage correctly classified	93
Economic value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Testing (n= 44)	Very low + low	36	1	97
	Moderate + high	3	4	57
			Overall percentage correctly classified	91

6.3 Social value of wetlands

6.3.1 Social value – ANN constructions

For building Social value ANNs, all input variable records were partitioned into absence and presence values. The attributes listed in Table 4.6 were used for inputs with the exceptions of water skiing and research, as they each had two records in the WGCMA database. There were 10 unknown records for the attribute park value in the database that could not be assigned as absence or presence within a reserve or protected area; this has reduced the number of available records for use in training ANNs. The output variable, Social value assessments, was separated into two groups, moderate and high-value cases together, of which 37 were moderate assessments and five high assessments; and, low and very low assessments, with 71 low value and 36 very low value wetlands. There was one unknown Social value record resulting in 149 records from which Social value ANNs could be built.

As the starting point, the 10 input attributes of Table 4.6 (recreational fishing; swimming; camping; hunting; boating; passive recreation; motorized 4WD; bird watching; education; and, park value) were used to build 20 ANNs. For the 20 ANNs built, the most often occurring classification table is shown as Table 6.5a, and it will be referred to as the ceiling ANN for Social value attributes. This classification table shows as an overall percentage correct classification rate of 95%, with very low and low assessments prediction rate of 96%, and moderate and high Social value assessments predictions at 93%.

Sensitivity analyses for 20 ceiling ANNs were collected and the inputs in each analysis were ranked according to their impact strengths. For each run, the identified inputs were scored as 1 for the strongest input, 2 was given for the next in strength, until the least significant input identified was assigned 10. Next, each input's rankings were summed across all analyses. Out of possible total score of 200, the listing of inputs from most influential to least (input's score in brackets) was found to be: park value (31); bird watching (51); camping (86); passive recreation (108); boating (114); motorized 4WD (132); recreational fishing (133); education (143); swimming (151); and, hunting (152). As with all sensitivity analyses, the scores give an indication of the magnitude of input variable effect only, not positive or negative influence.

Park value was the most influential attribute for predicting Social value assessments using the sensitivity analyses' rankings. Using park value as the only input, 20 ANNs were built, and their classification table is shown as Table 6.5b. It is referred to as the baseline case. With no other inputs, park value could correctly classify 84% of very low and low assessments and 88% of moderate and high Social value assessments, with an overall correct prediction rate of 85%. These statistics bear witness to the high correlation statistic between park value and Social value assessments ($\rho = 0.676$) previously identified in Section 5.3.1.

Using the one-at-a-time method, 20 ANNs were built by progressively adding inputs in the order identified by sensitivity analyses. The behaviours of the various inputs ANNs were rechecked using the subtraction-from-the-total method. From all experiments, I selected the six-inputs neural network as the most suitable to generalize Social value classifications; it has an overall correct prediction rate of 92%, as seen in Table 6.5c, and it was able to discern moderate and high-value assessments at 93% and classify very low and low value assessments at 92%, using a 12-7-2 architecture. The six inputs, in order of influence, were park value; bird watching; camping; passive recreation; boating; and, motorized 4WD.

Table 6.5a: Classification table for ceiling ANN built using 10 Social value attributes as inputs. The table shows the proportion of cases correctly classified for 149 wetland records.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	103	4	96
	Moderate + high	3	39	93
Overall percentage correctly classified				95

Table 6.5b: Classification table for baseline Social value ANN using park value as the only input. The proportion of cases correctly classified for 149 wetland records is shown.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	90	17	84
	Moderate + high	5	37	88
Overall percentage correctly classified				85

Table 6.5c: Classification table for the six-inputs Social value ANN built. The proportion of cases correctly classified for 149 wetland records is shown.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	98	8	92
	Moderate + high	3	39	93
			Overall percentage correctly classified	92

6.3.2 Social value – ANN evaluations

The ability of the six-inputs Social value ANN is compared with performance of the nine-inputs Social value BLR model, whose classification table is given in Table 5.3b. The BLR model correctly classified 93% across both categories of assessments, which is marginally higher than the ANN, at 92% correct. This negligible difference in overall performance is easily accounted for by considering two things. First, each approach is different in what it attempts to optimise; the binary logistic regression strategy elects the model with the highest overall predictive power, whereas in building neural networks, the overall prediction rate was weighed as equally important as correct classifications of moderate and high-value assessments. Second, the numbers of inputs are quite different; the BLR model incorporates three more inputs than the mere six needed for the ANN. In considering the impact of the number of additional variables for the BLR model, Table 5.7 shows there is approximately a 2% increase with the addition of each input variable, easily accounting for differences in overall performance between approaches. It was noted that nine-inputs ANNs built using the one-at-a-time and subtraction-from-the-total methods gave an overall correct classification value of 93%, supporting the notion that more inputs are expected to improve overall performance in both binary logistic regression models and neural networks.

As was done for Economic value, it is better to compare the BLR model and the ANN on their abilities to separate each outcome group of Social value assessments. The BLR model is superior in identifying very low and low assessments at 95% compared to 92%, and the ANN is better at classifying moderate and high-value assessments, 93% compared to 88%.

For building Social value binary logistic regression models and Social value neural networks, there was a pool of 10 possible inputs. So, it not surprising that all six inputs of the ANN are found in the nine-inputs BLR model. It is the inclusion of passive recreation as the fourth most significant input for ANN building that is noted as it is the one attribute not included in the BLR model. The inclusion in the ANN is supported by the statistically strong association of passive recreation with higher Social value assessments (Section 4.3.2) and the strong correlation statistic of passive recreation's relationship to higher-valued assessments (Section 5.3.1), and its absence from the BLR model is explained by the strong correlations between passive recreation to park value, bird watching and education, as discussed in Section 5.5

6.3.3 Social value – Threat ANNs

There were 144 cases within the dataset containing entire records for all inputs: 10 Social value attributes and 26 threat inputs, covering the threat attributes listed in Tables 4.27a and 4.27b. Twenty ANNs were built using all inputs and the most commonly occurring architecture seen was 72-2-2, resulting in extremely high prediction performances for Social value assessments, as seen in Table 6.6a. As before, the classification table is referred to as the ceiling ANN. The accuracy of the ceiling ANN was expected due to the high number of neurons in the input layer, resulting in over-fitting of the data as the neural networks learnt almost every item in the dataset.

For given set of inputs and architecture, the various ANNs produced slightly different results due to the randomly generated initial weights for interneuron connections. To try and judge overall patterns of influence, the sensitivity analyses of the 20 ceiling ANNs were examined and scored. For each run, the software ranked the 18 most influential inputs for Social value using threats assessments. Inputs were scored according to their rankings; the input identified as the strongest was given a score of 1, the next most important was assigned a score of 2, until the last identified input was allocated 18. Inputs not identified by the sensitivity analysis for a particular run were given the score of 20. The most influential input was pest animals, scoring the lowest at 198 out of a possible score of 400. In order of influence, strongest first, the 10 most significant inputs for deciding Social value assessments (input's score in brackets) were pest animals (198); camping (200); salinity (227); bird watching (230); lack of reservation (251); boating (262); swimming (264); passive recreation (265); motorized 4WD (271); and, stock access (276). The sensitivity analyses do not indicate whether the impact is positive or negative on the assessments.

Social values account for six of the 10 most significant inputs: bird watching; boating; camping; motorized 4WD; passive recreation; and, swimming. The remaining threat values are lack of reservation; pest animals; stock access; and, salinity. Of the threat values pest animals, stock access and salinity can be found in Table 3.1, and these were used in assessments for subcatchment wetlands by the WGCMA, whereas lack of reservation was not used. The significance of this is discussed in the last section of this chapter.

Taking the 10 most significant inputs, ANNs were built using the one-at-a-time method. As before, baseline ANNs were built using the most significant input identified in the sensitivity analyses, pest animals in this instance, and the resulting classification table is given as Table 6.6b. The table shows that the presence or absence of pest animals at a site can decide 80% of very low and low Social value classifications, 66% of moderate and high-value assessments, averaging to 76% accuracy overall. ANNs were built by incrementally adding input variables in the order indicated by the sensitivity analyses, and the eight-inputs ANN was selected as the most suitable for generalizing Social values assessments using threat data, as seen in Table 6.6c. This ANN has a 95% overall prediction rate, with 96% recognition very low and low assessments and 91% for moderate and high-value wetlands. The eight-inputs ANN was selected as the most suitable for two reasons. The first reason is convenience of comparisons: it has the same overall prediction ability as the Social value with threat inputs BLR model described in Table 5.4. The second, and more genuine reason, is that the eight-inputs ANNs showed marked improvements in being able to classify moderate and high-value assessments when compared to lower number of inputs models. A counterargument against the selection of the eight-inputs ANN for generalizing Social value assessments is the high prediction rates seen across all rows in Table 6.6c. These are likely evidence of the ANNs over-fitting the data, rather than generalizing it. On these grounds, there is equally good support for selecting the six-inputs version with an overall rate of 91%. This matter will be discussed further in the next section, where neural networks were used as predictors of Social value assessments.

The most common architecture for the 20 eight-inputs ANNs generated was 16-6-2, and amongst the eight inputs were only three which were threat values: pest animals; salinity; and, lack of reservation. Unlike pest animals and salinity, lack of reservation, is not listed in Table 3.1 as one of the threat values used by the WGCMA to assess subcatchment wetlands. The remaining five inputs are Social attributes: camping; bird watching; boating; passive recreation; and, swimming. Of these, the first four were also found in the Social attributes without threats ANNs. A noticeable absence from these Social values is the attribute park value, which alone had 85% overall correct prediction rate as the baseline Social attributes ANN. As well, park value was one of the most significant inputs to the 10-inputs BLR Social value plus threats model, described as Equation 5.11.

There are three inputs in common between the eight-inputs Social value with-threats ANN and the 10-inputs BLR threat model. The presence of bird watching, camping, and salinity in the results of both methods, is an indication of their strength in predicting Social value wetland assessments. The strength of camping and bird watching as important inputs is further indicated by their appearances in all BLR and ANN solutions, whether threats are included or not.

To assess the performance of the eight-inputs Social value with-threats ANN, its classification table, shown as Table 6.6c, needs to be compared with the classification table of the 10-inputs BLR model, given in Table 5.4. The overall percentage correctly of both models is the same at 95%, and they perform nearly identically in discernment of both groups of assessments, very low and low values, and moderate and high values. The major difference between the binary logistic regression and neural networks approach is in the number of inputs needed to achieve these results, with the neural network appearing the more efficient.

Table 6.6a: Classification table for ceiling ANN built using 10 Social value attributes and 26 threat values as inputs. The table shows the proportion of cases correctly classified for 144 wetland records.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	100	3	97
	Moderate + high	0	41	100
			Overall percentage correctly classified	98

Table 6.6b: Classification table for baseline Social value ANN using the threat pest animals as the only input. The proportion of cases correctly classified for 152 wetland records is shown.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	86	22	80
	Moderate + high	15	29	66
			Overall percentage correctly classified	76

Table 6.6c: Classification table for the eight-inputs Social value with-threats ANN built. The proportion of cases correctly classified for 150 wetland records is shown.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Observed value	Very low + low	102	4	96
	Moderate + high	4	40	91
			Overall percentage correctly classified	95

6.3.4 Social value – Predicting wetlands assessments

To evaluate the predictive abilities and suitability of Social value ANNs in mimicking wetland assessments decision making, the dataset was separated into training and testing sets; 70% of data was used for training and 30% for testing. Twenty Social value ANNs were built without threat data and 20 ANNs using threat data.

Without threat inputs

The inputs used for the 20 Social value ANNs with no threat input were: bird watching; boating; camping; motorized 4WD; park value; and, passive recreation. A typical classification table for one of these ANNs is given as Table 6.7a, and the trained network architecture was 12-7-2. It is interesting to note that the trained network performs similarly on test data in overall correct classifications and in separating moderate and high Social value wetlands from very low and low value assessed wetlands. This suggests that the dataset is relatively consistent in respect to data patterns that predict Social values. This premise is borne out when a comparison is made of the ANN statistics of Table 6.7a with the comparable network trained on the full dataset of 149 wetlands (Table 6.5c). The percentage correct statistics of both networks are identical, supporting further the notion of consistency within the dataset. This consistency definitely supports the hypothesis that ANNs without using threat data as input can be trained and then used to consistently classify wetlands at quite high correct classification rates where the data is unseen.

With threat inputs

Table 6.7b gives a typical classification table for an ANN built using Economic attributes and threat data with eight inputs: bird watching; boating; camping; lack of reservation; passive recreation; pest animals; salinity; and swimming. The ANN's architecture was 16-4-2 and the overall prediction rates during training and testing are very similar however there is variation between training and testing for the types of wetland assessments. The neural network is able to more accurately predict moderate and high values for the unseen data than it did during training. Of course, to achieve the same overall correct prediction rate during testing and training, there is a lower percentage correct for very low and low values for the unseen data testing. This better-than-expected performance on unseen data for moderate and high values, and poorer results for very low and low values, illustrates two points. First, neural networks are able to learn and generalize data patterns during the training phase, and use these patterns to classify unseen data to near equal ability. Second, the fluctuations in ANN performances between training and testing can in large part be attributed to the limited number of wetlands for which data was available; it is well short of the 200 minimum desired for consistency (Detienne et al., 2003; Sug, 2010).

Evaluating the performance of the eight-input ANN trained on 116 wetlands (Table 6.7b) with its comparable network trained using the full dataset (Table 6.6c), there is quite a considerable drop in overall prediction rates for the network trained on 116 records, due mostly to poorer discernment of moderate and high Social value wetlands, 91% compared with 77%. This is the same pattern observed as for Economic value, in that, the more training data available, the better the identification rates for moderate and high-value assessments, and this pattern also underlines the need to use as much training data as possible for good classification rates.

More remarkable is the better performance statistics in every category of the six-inputs ANN without threats (Table 6.7a) compared to the eight-inputs ANN that used threat inputs (Table 6.7b). These results support the argument made in the previous chapter that it is not necessary to incorporate threat input to achieve high predictions for Social value assessments. In either case, ANNs can be relied upon to classify Social value wetland assessments even when there is a scarcity of training data.

Table 6.7a: Classification table for Social value ANN built without threat data using six Social value attributes as inputs, and trained using 101wetland records and tested using data for 48 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Training (n= 101)	Very low + low	67	6	92
	Moderate + high	2	26	93
Overall percentage correctly classified				92
Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Testing (n= 48)	Very low + low	31	3	91
	Moderate + high	1	13	93
Overall percentage correctly classified				92

Table 6.7b: Classification table for Social value ANN built with threat data using eight inputs, and trained using 116 wetland records and tested using data for 34 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Social value		Predicted value		
		Very low + low	Moderate + high	Percentage correct
Training (n= 116)	Very low + low	79	2	98
	Moderate + high	8	27	77
Overall percentage correctly classified				91
Social value		**Predicted value**		
		Very low + low	Moderate + high	Percentage correct
Testing (n= 34)	Very low + low	23	2	92
	Moderate + high	1	8	89
Overall percentage correctly classified				91

6.4 Environmental value of wetlands

6.4.1 Environmental value – ANN constructions

The building of ANNs for Environmental value assessments is complicated by the large number of input variables involved, 16 contributing attributes, and several subattributes, of seven individual Environmental values (see Table 4.12). There are a variety of scales and ranges used across the assessment of attributes and subattributes, so data preparations involved partitioning all 35 input variables' records into absence and presence values. The output variable, Environmental value assessments, was separated into two groups: very high and high-value assessments, of which eight were high assessments and 47 very high assessments; and, moderate, low and very low assessments, with 72 moderate value, 24 low and one very low value wetlands. There were 152 entire records in the database used to build ANNs. In order for comparisons to be made with binary logistic models, the dataset was not partitioned into training, testing and holdout sets, which allowed the neural networks to be trained on as much data as was available.

As before, ceiling Environmental values ANNs were created using all input variables. The most commonly occurring architecture seen amongst the resulting 20 ANNs was 70-2-2, with the classification table shown as Table 6.8a. With so many input neurons, the ceiling ANNs are seen to over-fit the data with overall correct Environmental value classifications of 99%, very low, low and moderate values predicted at 99%, and high and very high Environmental value assessments predictions at 98% for the ceiling ANNs.

Sensitivity analyses were undertaken for these ANNs to identify the 18 most significant inputs influencing Environmental classifications. For individual analyses, each input was scored; 1 was assigned to the strongest input, 2 was given for the next most influential, until 18 was assigned to the least significant input. Inputs not listed in an analysis were assigned 20 as their rank. The rankings of each input were summed across the sensitivity analyses, with 400 being the maximum possible value, and the inputs were ranked from most influential to least. The fifteen most significant inputs are listed below, where for each input, the Environmental value attribute and subattribute are listed in the first bracket and the summed rankings score are given in the second bracket. As with all sensitivity analyses, the scores give an indication of the magnitude of input variable effect only; the positive or negative influence is not known. The inputs were:

- sedges (*vegetation intactness– critical lifeforms*) (20);
- vegetation width (*vegetation intactness– width of vegetation fringe*) (198);
- fauna FFG (*significant fauna*) (223);
- flora VROT (*significant flora*) (226);
- disposal of water (*hydrology*) (232);
- shoreline shrubs (*habitat value– shoreline vegetation*) (245);
- rocks (*habitat value– terrestrial zone habitat*) (250);
- drainage (*hydrology*) (254);
- emergent vegetation (*habitat value– terrestrial zone*) (264);
- obstruction (*hydrology*) (265);
- deep freshwater marsh (*wetland rarity*) (272);
- redirection (*hydrology*) (282);
- semipermanent saline wetlands (*wetland rarity*) (288);

- permanent open water wetlands (*wetland rarity*) (291) ; and,
- fauna VROT (*significant flora*) (293).

In all 20 sensitivity analyses, the input variable sedges was selected as the most significant input, accounting for its very low summed score. Using the one-at-a-time method, a set of 20 baseline ANNs were built using sedges as the single input. The most common classification table for these ANNs is displayed as Table 6.8b, where it is seen that absence or presence of sedges correctly classifies 77% of very low, low and moderate Environmental value assessments, 63% of high and very high assessments, averaging to 73% overall correct classifications. Further ANN building incorporating input variables in the order listed above identifies the eight-inputs ANNs, with an architecture of 16-6-2, as a suitable candidate for identifying higher Environmental value wetlands. Table 6.8c shows the most common classification table for the eight-inputs ANNs, where very low, low and moderate assessments have a correct classification rate of 90%, and 83% of the high and very high Environmental value assessments are correct identified.

Further experimentation creating various inputs shows that 12-inputs ANNs have a 91% overall correct classification rate. The classification table for 12-inputs ANNs is given in Table 6.8d, where very low, low and moderate assessments are correctly identified 94% of the time, and high and very high assessments have 82% correct predictions. The 12-inputs ANN is presented here for comparisons to the BLR Model B, and its most commonly observed architecture was 24-4-2. Subsequently, the subtraction-from-the-total method was used to recheck the selection of the eight-inputs and 12-inputs ANNs as having the most suitable predictive behaviours.

Comparing the performance of the eight-inputs ANNs (Table 6.8c) with the 12-inputs versions (Table 6.8d), the improvement in overall classification performance from 87% to 91% is solely the result of improved identifications of very low, low and moderate wetlands assessment. The addition of absence/presence data for the additional four inputs (deep freshwater marshes; emergent vegetation; obstruction; and, redirection), did not improve recognition of high and very high wetlands. On these grounds, the eight-inputs ANN is adequate for generalizing Environmental value assessments. The WGCMA noted that high-value wetlands scored well for vegetation intactness and habitat value. The four of eight inputs selected by the ANNs tie directly with these attributes; sedges and vegetation width were used as measures of vegetation intactness, and shoreline shrubs and rocks were subattributes of habitat value.

Table 6.8a: Classification table for ceiling ANN built using 35 Environmental value attributes as inputs. The table shows the proportion of cases correctly classified for 152 wetland records.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	96	1	99
	High + very high	1	54	98
Overall percentage correctly classified				99

Table 6.8b: Classification table for baseline Environmental value ANN using sedges as the only input. The proportion of cases correctly classified for 162 wetland records is shown.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	81	24	77
	High + very high	21	36	63
Overall percentage correctly classified				73

Table 6.8c: Classification table for the eight-inputs Environmental value ANNs. The proportion of cases correctly classified for 162 wetland records is shown.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	94	11	90
	High + very high	10	47	83
			Overall percentage correctly classified	87

Table 6.8d: Classification table for the 12-inputs Environmental value ANNs. The proportion of cases correctly classified for 158 wetland records is shown.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	96	6	94
	High + very high	10	46	82
			Overall percentage correctly classified	91

6.4.2 Environmental value – ANN evaluations

To evaluate the performance of Environmental value ANNs against the models generated using logistic regression (BLR) models, the classification behaviours of eight-inputs ANN are compared those of Environmental value BLR Model A and the 12-inputs ANN behaviours are compared those of BLR Model B from Chapter 5.

The eight-inputs ANNs' overall correct classification of 87% (Table 6.8c) is similar the classification made by the seven input BLR Model A, with 86% (Table 5.5b). They differ in their abilities to discern each outcome group of Environmental value assessments. For very low, low and moderate values, the ANN is superior at 90% compared to 87% of the BLR Model A, but Model A is better at identifying high and very high assessments, 86% compared to 83%.

The 12-inputs ANNs have an overall classification rate of 91% correct (Table 6.8d), which is the same as achieved by the 15-inputs BLR Model B (Table 5.5c). There are differences in classifications for very low, low and moderate assessments with the ANN correctly identifying 94% compared to Model B with 91%, however Model B is better at deciding high and very high assessments, 89% compared to 82% for the ANN.

There are five inputs in common between the seven-inputs BLR model and eight-inputs ANN; they are flora VROT (*significant flora*); rocks (*habitat value– terrestrial zone habitat*); sedges (*vegetation intactness– critical lifeforms*); shoreline shrubs (*habitat value– shoreline vegetation*); and, width of vegetation fringe (*vegetation intactness– width of vegetation fringe*). Both analytic approaches incorporated hydrology attributes, however they are not did not incorporate the same subattributes. The ANN selected drainage and disposal of water as inputs and the Model A used redirection. Earlier correlation analyses of Chapter 5 indicated strong associations between hydrology subattributes, therefore the differences between the selections made by each technique to incorporate a measure for hydrology are not thought to be significant.

Checking the inputs of the 12-inputs ANNs and the 15-inputs BLR Model B, eight of the inputs were found to be in common. They include the five inputs listed in the previous paragraph plus drainage (*hydrology*); fauna VROT (*significant flora*); and, permanent open water wetlands (*wetland rarity*). The commonalities of inputs found between ANNs and BLR Models A and B indicate the importance of these inputs to describe Environmental value assessments, and this point will be discussed later in this chapter.

6.4.3 Environmental value – Threat ANNs

The addition of 26 threat inputs to the 35 inputs needed to cover attributes and subattributes of Environmental value, resulted in the creation of ANNs requiring 122 input neurons, 61 for the absence of each value and 61 for the presence of each. Given that there were 144 cases within the dataset with entire records for all inputs, the exceptionally high number of input neurons guaranteed that the data was over-fitted since there is almost one computing element per record. Nevertheless, 20 ANNs were created using all inputs and the most common architecture decided by the software was 122-2-2. The classification table for these ceiling ANNs is given in Table 6.9a, where, not unsurprisingly, all groups have been correctly classified.

The sensitivity analyses for each of the 20 ANNs returned the 19 most significant inputs of each run. For each sensitivity analysis, the identified inputs were scored using the method described previously and inputs not listed scored as 20. The ranking scores of every input were totalled, to a maximum possible value of 400. The lower the value, the stronger the input impacts the number of correct Environmental value wetlands classifications, although the impact cannot be judged as either positive or negative. The fifteen most significant inputs are listed below. For each input, the Environmental value attribute and subattribute are listed in the first bracket and the summed input's score is given in the second bracket. The inputs were:

- sedges (*vegetation intactness– critical lifeforms*) (78);
- sedimentation (227);
- rocks (*habitat value– terrestrial zone habitat*) (263);
- lack of reservation (268);
- fauna VROT (*significant flora*) (277).
- water source– groundwater fill (280);
- semipermanent saline wetlands (*wetland rarity*) (286);
- shoreline islands (*habitat value– terrestrial zone habitat*) (291);
- vegetation width (*vegetation intactness– width of vegetation fringe*) (299);
- freshwater meadows (*wetland rarity*) (304);
- altered hydrology (305);
- permanent open water wetlands (*wetland rarity*) (306);
- resource utilization (309);
- water source– other (315); and,
- urban development (318).

Of the fifteen most significant inputs, eight are threat values: altered hydrology; lack of reservation; resource utilization; sedimentation; water source (groundwater fill and other); and, urban development. Importantly, three of these eight inputs (lack of reservation; sedimentation; and, resource utilization) were not used by the WGCMA in their assessments of subcatchment wetlands. The importance of this omission is discussed in the final section of this chapter.

Using the one-at-a-time method and the above listing to build ANNs, 20 baseline ANNs were built using sedges as the single input; their classification table is the same as given in Table 6.8b, where the overall correct classifications was 72%. Incrementally, 20 ANNs were created by adding inputs in the order given above, up to 15 inputs. The results were checked using subtraction-from-the-total method commencing with ANNs built starting with 15 inputs. The nine-inputs ANN was the most suitable for generalizing Environmental values assessments using threat data. With architecture of 18-6-2, the nine-inputs ANNs are able to correctly identify 95% of very low, low and moderate assessments, 90% of high and very high-value wetlands, resulting in an overall correct classification rate of 93% as seen in Table 6.9b. The nine-inputs were six Environmental values: fauna VROT (*significant flora*); rocks (*habitat value–terrestrial zone habitat*); sedges (*vegetation intactness–critical lifeforms*); semipermanent saline wetlands (*wetland rarity*); shoreline islands (*habitat value–terrestrial zone habitat*); and, vegetation width (*vegetation intactness–width of vegetation fringe*). Of these Environmental values, rocks; sedges; and, width of vegetation fringe were common to the eight- and 12-inputs Environmental value ANNs, indicating the importance of these attributes to the assessment of Environmental value. Water source– groundwater fill is the only threat incorporated in risk assessments for subcatchment wetlands, whereas the threats of sedimentation and lack of reservation were not used in WGCMA assessments. The significance of sedimentation and lack of reservation to wetland assessments, and their omission from the WGCMA process, is discussed in the final section of this chapter.

The performance of the nine-inputs Environmental value with-threats ANNs (Table 6.9b) is compared against the 10-inputs BLR model (Table 5.6). Overall percentage wetlands correctly assessed is 93% for the nine-inputs ANNs and 91% for the 10-inputs BLR model. For each group of assessments, the nine-inputs ANNs are better at classification than the 10-inputs BLR model. The ANNs correctly predict 95% of very low, low and moderate assessments and the BLR model is able to identify 92%; the ANNs predict 90% of high and very high assessments and the BLR model correctly classifies 89%. The neural network appears more efficient as it requires one less input than the BLR to achieve improved results.

It is noted that there are three common inputs between the 10 inputs (of nine different variables) BLR model, of Equation 4.16, and all Environmental value ANNs (eight-inputs Environmental value ANNs; twelve inputs Environmental value ANNs and nine-inputs Environmental value and threats ANNs). The common inputs are: fauna VROT (*significant flora*); sedges (*vegetation intactness– critical lifeforms*); and, vegetation width (*vegetation intactness– width of vegetation fringe*) and their appearances across all solutions is testament to their potencies in predicting wetland assessments.

Lack of reservation was the only threat value found in the 10-inputs BLR model and the nine-inputs Environmental value and threats ANNs; this threat was not used by the WGCMA for subcatchment wetlands assessment but its appearance in both model as a strong predictor suggests that it should have been used.

Table 6.9a: Classification table for ceiling ANN built using 35 Environmental value attributes and 26 threats as inputs. The table shows the proportion of cases correctly classified for 144 wetland records.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	90	0	100
	High + very high	0	54	100
			Overall percentage correctly classified	100

Table 6.9b: Classification table for nine-inputs Environmental value with-threats ANN. The proportion of cases correctly classified for 146 wetland records is shown.

Environmental value		Predicted value		
		Very low + low + moderate	High + very high	Percentage correct
Observed value	Very low + low + moderate	87	5	95
	High + very high	5	49	90
			Overall percentage correctly classified	93

6.4.4 Environmental value – Predicting wetlands assessments

The dataset was separated into training and testing sets; 70% of data was used for training and 30% for testing to evaluate the predictive abilities and suitability of Environmental value ANNs in mimicking wetland assessments decision making. 40 Social value ANNs were built without threat data, being 20 ANNs with 8 inputs and 20 ANNs with 12 inputs. An additional 20 ANNs were created using threat data.

Without threat inputs: eight inputs

A typical classification for an eight-inputs Environmental value ANN without threats is given as Table 6.10a for a 16-2-2 architecture, and the eight inputs incorporated are: drainage; fauna FFG; flora VROT; disposal of water; rocks; sedges; shoreline shrubs; and, width of vegetation fringe. The overall correct classification performance of the trained network in testing phase is marginally lower at 85% compared with 87% due to a reduced ability to discern very low, low and moderate wetlands; the trained network performs equally well on high and very high-value assessments.

A comparison of the trained network with the comparable network trained on the full dataset of 149 wetlands for the same eight inputs (Table 6.8c) shows quite similar overall classification rates and discernment of very low, low and moderate wetlands. However the network trained on 104 wetlands does not quite perform to the same ability on distinguishing high and very high assessments, at 81%, as the network trained using the full dataset of 162 records with 83%.

Without threat inputs: 12 inputs

The 12 inputs used for the 20 Environmental value ANNs with no threat input were the same as the eight-inputs ANN plus deep freshwater marsh; emergent vegetation; obstruction; and, redirection. Table 6.10b shows a typical classification for one of the 12-inputs Environmental ANNs without threat inputs for a network with 12-1-2 architecture. The trained network has an overall correct classifications rate of 90% during training, however its percentage correct classifications drops to 80% due to a 10% reduction in the discernment of high and very high wetlands on the unseen data.

The comparable network to the one shown in Table 6.10b is the 12-inputs Environmental value ANN without threats with a classification table given in Table 6.8d. A check of both tables shows similar overall statistics, 90% (Table 6.10b trained on 107 wetlands) and 91% (Table 6.8d trained on 158 wetlands), with 93% and 94% for very low, low and moderate identifications respectively, a 2% difference in the networks' classifications for high and very high wetlands, 82% and 84% in the same order. It appears here, as in all Economic value ANNs and Social ANNs with threats, that the more training data available, the better the identification rates for moderate and high-value assessments.

The effect of the increasing the number of inputs from eight to 12 can be seen by comparing the overall percentage correctly classified statistics of Table 6.10a and Table 6.10b, respectively, where during training 12-inputs ANN is able to correctly classify 90% of assessments compared to 87% correctly classified for the eight-inputs ANN. Interestingly, the performance of the 12-inputs network on unseen data is actually poorer than the eight-inputs ANN on its testing data! This is evidence that the 12-inputs ANN has been over-fitting the training data; it has been learning specific data details and not generalizing and recognizing general data patterns.

With threat inputs

A typical classification table for a nine-inputs ANN built using Economic attributes with threat data is given in Table 6.10c; the nine inputs were: fauna VROT; lack of reservation; rocks; sedges; sedimentation; semipermanent saline wetlands; shoreline islands; water source- groundwater fill; and, width of vegetation fringe. The ANN's architecture was 18-2-2. The overall prediction rates during training and testing are very similar, but performances on the different groups of wetland assessments differ by quite an amount; during training the network identified very low, low and moderate assessments at 99% but on unseen data at 92%. The opposite behaviours occurred for high and very high wetlands with classifications during training of 82% and 94% for the unseen data. These results indicate that the neural network learnt the generalities of high and very high assessment data during training and it was not over-fitting the training data.

For the nine-inputs Environmental value ANN with threats, a comparable Environmental value network with threat inputs is found in Table 6.9b. Both networks have the same overall correct classification rate of 93% of wetlands, however the effect of the number of wetlands used in training is seen in the abilities of the networks to discern high and very high-value wetlands. The network trained on 107 records is only able to detect 82% of high and very high-value wetlands during training, whereas the network trained on 146 wetlands can detect 90%.

The performance results of all Environmental ANNs add support to the argument that threat data need to be incorporated to be able to more accurately classify high and very high-value wetlands.

The next section discusses the results of this chapter in more detail. The discussion is concerned with the nature, and importance, of input variables that predicting high-value wetland assessments as discovered by neural networks analyses. A comparison of these inputs is made with those uncovered by the multivariate statistical analyses of Chapter 5, and to those mentioned by the WGCMA as significant in their reports.

Table 6.10a: Classification table for eight-inputs Environmental value ANN built without threat data and trained using 104 wetland records and tested using data for 58 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Environmental value		Predicted value		
		Very low + low + moderate	High + very high	Percentage correct
Training (n= 104)	Very low + low + moderate	61	7	90
	High + very high	7	29	81
		Overall percentage correctly classified		87
Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Testing (n= 58)	Very low + low + moderate	32	5	87
	High + very high	4	17	81
		Overall percentage correctly classified		85

Table 6.10b: Classification table for 12-inputs Environmental value ANN built without threat data and trained using 107 wetland records and tested using data for 51 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Training (n= 107)	Very low + low + moderate	65	5	93
	High + very high	6	31	84
		Overall percentage correctly classified		90
Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Testing (n= 51)	Very low + low + moderate	27	5	92
	High + very high	5	14	74
		Overall percentage correctly classified		80

Table 6.10c: Classification table for Environmental value ANN built with threat data using nine inputs, and trained using 107 wetland records and tested using data for 39 wetlands. The table shows the proportion of cases correctly classified for training and testing.

Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Training (n= 107)	Very low + low + moderate	67	1	99
	High + very high	7	32	82
		Overall percentage correctly classified		93
Environmental value		**Predicted value**		
		Very low + low + moderate	High + very high	Percentage correct
Testing (n= 39)	Very low + low + moderate	22	2	92
	High + very high	1	14	93
		Overall percentage correctly classified		92

6.5 Synthesis and discussion

Artificial neural networks were created in order to predict either Economic or Social or Environmental wetland values, with and without threat values. The predictive effectiveness of the networks was gauged by their overall percentage correct classifications, by their ability to discern moderate and high Economic and Social values assessments, and by their ability to correctly identify very high and high Environmental values assessments for wetlands. Table 6.11 presents a summary of the ANNs devised in this chapter, the number of inputs used and the percentage overall correct number of classifications. For comparison, Table 6.11 also includes a summary of BLR models presented in the previous chapter. For ANNs and BLRs, the percentage of correctly identified moderate and high wetlands are given in brackets for Economic and Social value, and for Environmental value the number in brackets is the percentage correctly identified high and very high-value wetlands assessments.

Table 6.11 shows that ANNs and BLR models had greater than 90% predictive ability for all wetland values, regardless of threats being included or not. It is possible to create networks with near 100% correct classification rates by using the maximum number of inputs, as in all the ceiling ANNs (e.g. see Table 6.2a, Table 6.3a, Table 6.5a, Table 6.6a, Table 6.8a and Table 6.9a), where the large number of input neurons learnt the entire dataset. The 'art' in ANN building is in finding the number of inputs and their identities that allow good generalization capabilities without over-fitting the data (Detienne et al., 2003; Maier & Dandy, 2000; Zhang, 2000). Sensitivity analyses over 20 runs indicated the pool of most significant inputs for subsequent consideration, while the appropriate number of inputs was decided in deference to overall classification performance and the ability of networks to discern moderate and high Economic and Social value assessments or high and very high Environmental value wetlands.

Having built ANNs capable of equal, and in some cases better, performances than their more traditional multivariate equivalents, the important questions for wetland assessments remain as:

- How many variables are enough?
- What do neural networks' input variables tell us about wetland evaluations?
- Can neural networks be used to predict wetland assessments?

The first two questions are discussed next with reference to the three sets of analyses, and the third question is explored afterwards.

Economic value

An inspection of the summary statistics of all ANNs and BLRs models (Table 6.11) reveals that it is possible to correctly predict over 90% of Economic value assessments using absence/presence values for a subset of the inputs used in the WGCMA assessment process. As identified and discussed earlier (Section 5.5), the most efficient Economic value BLR models were those built with no threat category data and absence/presence data for five input variables of Economic value. There is also an equivalent five-inputs ANN that is quite efficient and sufficient at predicting overall Economic value assessments without the need to incorporate threat data (Table

6.11). A listing of inputs for all ANNs and BLR Economic value models is given in Table 6.12a, for versions with and without threat data. For the no threat ANN and BLR model, there are four input variables in common being: diverted or farm runoff; conservation forestry; stock water supply; and, water storage. As mentioned previously (Section 5.5), there is strong statistical association between stock water supply with moderate and high Economic value assessments, as evidenced with chi-squared (χ^2) testing and correlation (ρ) statistics. There is also support for the inclusion of diverted or farm runoff; conservation forestry; and, water supply to be found in contingency table (Table 4.3a) and correlation statistics relating each variable to Economic assessments, and correlations between input variables (Section 5.2.1). As stated in Section 6.2.2, the five-inputs no threats ANN is better able to discern higher-value assessments than its BLR counterpart, and as four inputs are shared by the two approaches, the addition of redirection in the ANN gives better recognition of moderate and high Economic values, than does the fifth input, food production, used in the BLR model. On these grounds the ANN is the recommended approach for when no threat data is used.

When threat category data is included, the summary presented in Table 6.11 shows higher performances for the BLR model with nine inputs over the ANN with six inputs. The summary statistics for Economic value BLR models (Table 5.7) show for each input in the model, there is an increase in correct classifications of 1.6. As is argued earlier (Section 5.5 and Section 6.2.3), a quick calculation (1.6 * additional inputs) easily accounts for improvements in BLR model performance when compared to the network's abilities. For this reason, the ANN is recommended over the BLR model, in that, the network achieves very high overall classification rates and identifications of moderate and high wetlands on far fewer inputs.

An inspection of lists of inputs to BLR and ANN Economic value models with threats (Table 6.12a) reveal four common inputs across approaches, being two Economic value attributes: diverted or farm runoff and stock water supply, and two threat categories: erosion and resource utilization. In fact, testament to the predictive strength of stock water supply and diverted or farm runoff, is the appearance of these two attributes in <u>every</u> Economic value approach in Table 6.12a, and in all reported previous analyses, univariate and multivariate (Section 4.4.2, Section 5.2.1, Section

5.2.3, Section 5.2.4, Section 6.2.2 and Section 6.2.4). Diverted or farm runoff and stock water supply are important inputs for deciding Economic value and they should always be included in a minimal set as their presences increase the likelihood that a site will be assessed as moderate or high Economic value. Likewise, the predictive power of the two common threats, erosion and resource utilization, found in threat ANNs and the corresponding threat BLR models, underlines the need for these threat attributes to be collected whenever risk assessments are undertaken, even though resource utilization was not used by the WGCMA for subcatchment wetlands assessments.

Earlier in Section 5.5, an argument was presented for not undertaking Economic value assessments in the West Gippsland region on the grounds that only one wetland identified was high Economic value. Given the likelihood of this wetland receiving protection within the local community in order to maintain its monetary worth, the effort in identifying it and the relatively few (27) moderate Economic value seems incommensurate with the result. The collection of 12 input attributes and 14 threat components to compute and synthesize 168 risk assessments per 161 wetland sites is surely a waste of resources. Political considerations may dictate that future assessments of the Economic value of West Gippsland's wetlands need to be done. In this event, the high prediction rates the Economic value BLR without threats models and ANNs without threats (Table 6.11) challenge the need to incorporate threat data in Economic value assessments, as a collection of absence/presence data for five inputs is adequate to describe the majority of higher Economic value sites.

Social value

All approaches used to evaluate Social value (Table 6.11) show greater than 90% prediction rates, whether threat category data was included or not. From these statistics, it is evident that the performances of ANNs are generally superior to that of their equivalent BLRs. In illustration, where no threat values are included, the six-inputs ANN is recommended over the BLR model as it better classifies moderate and high-value wetlands (93% versus 88%) and it has equivalent overall correct classification statistics without the need of an additional three inputs. The six inputs for this ANN are listed in Table 6.12b, are: park value; bird watching; boating;

camping; motorized 4WD; and, passive recreation. With the exception of passive recreation, these inputs are also found in the corresponding Economic value BLR model of nine inputs, and as discussed earlier (Section 5.5), there is strong statistical support for the inclusion of each of these inputs, including passive recreation (cross-tabulation analyses of Section 4.3.2 and correlation investigations in Section 5.3.1). As mentioned in Section 5.5, it was not possible to reduce the number of inputs needed by Social value BLR models without threat data to fewer than nine, without detrimentally impacting overall model performance. The sensitivity analyses of ceiling ANNs helped to overcome this obstacle, in that, the most significant inputs were identified in order of importance, and subsequently it was shown that six inputs were sufficient in building an ANN with the same overall correct classifications as the nine-inputs BLR model.

The inputs of all Social value approaches are listed in Table 6.12b. Four of the most significant inputs for ANNs without threats were shared by the ANN where threat category data is included, being: bird watching; boating; camping; and, passive recreation. These inputs should be included in a minimal set to evaluate Social value as they appear consistently throughout the statistical analyses undertaken in this research (Section 4.3.2, Section 5.3.1, Section 5.3.3 and Section 5.3.4), and their presences improve the odds of a moderate or high Social value assessment (Section 5.5). Of note, is the omission of park value from the inputs of ANNs with threat values, despite park value being the most significant input to ANNs without threats. The inclusion of park value in the minimal set is supported by the coefficients of both BLR models, with and without threat input, which additionally indicated that bird watching and park value were strongly contributing inputs.

In the previous chapter when threat data was included in Social value BLR modelling, the improvement in the prediction rate was simply a function of additional inputs, rather than some intrinsic information stored in threat category as compared to a Social value input (Table 5.7 and Table 6.11). At this point, it was argued that there was no merit in collecting threat data and undertaking risk assessments to decide Social value assessments (Section 5.5). Additional evidence for this viewpoint is seen in the interesting anomaly presented when the ANN with no threats is contrasted to the ANN where threat categories were incorporated. Both ANNs have remarkably similar predictive performances, but only six Social value inputs are needed for the without threats version, whereas eight inputs are needed when threats were included. This is supporting evidence indicating that Social value attributes are better predictors of wetland condition, and thus assessment, than are threat categories. It also bolsters the argument for not collecting threat data and for not undertaking risk assessments to decide Social value assessments in the West Gippsland region. Again, the WGCMA's effort in collecting 11 input attributes and 14 threat components to calculate 154 risk assessments per wetland sites is pragmatically unnecessary when over 90% of 37 moderate and five high Social value wetlands can be identified using only absence/presence data for six Social value attributes. If however, it is necessary to incorporate threat values in the assessment, Table 6.12b shows that the only common threat value found in threat ANNs and the corresponding threat BLR models was salinity, and given its strong predictive abilities, salinity always be included when threat values are collected and risk assessments done.

Environmental value

The results of ANN building experiments and their BLR model equivalents are summarized in Table 6.11. Of the BLR models, Model A and Model B were created using only Environmental value attributes and without threat input. As pointed out earlier (Section 5.5), the improved prediction values of Model B compared to Model A are a function of eight additional inputs, whilst the best BLR model to correctly predict the Environmental value is the version that uses threat inputs. Similarly, the summary statistics for ANNs given in Table 6.11 reveal that the with-threats ANN outperforms in every regard the two no-threats ANNs (eight and 12 inputs). More importantly, the threats-included ANN has slightly better prediction statistics than does the with-threats Environmental value BLR model built using one more input and, comparing across approaches, ANNs are consistently better at deciding Environmental value assessments for fewer inputs than their analogous BLR model.

The inputs of all Environmental value ANNs and BLR models are given in Table 6.12c. Before examining these more thoroughly, it is important to note that there are several input variables not included in any approach, which leads to the recommendation that these need not be collected in the field. Taking the inputs of

Environmental ANNs and BLRs together, unnecessary Environmental value attributes are:

- Significant flora: For BLR models and ANNs where there is threat input, it is not necessary to check if a flora VROT;
- Significant fauna: For ANNs built with threat data it is not necessary to check if a faunal species is FFG registered species, as this attribute is highly correlated to faunal species VROT attribute. The strong correlation of these two attributes accounts for the appearance of Fauna FFG as input, rather than Fauna VROT for ANNs without threats;
- Habitat value: Habitat value was assessed by the WGCMA using attributes of: terrestrial zone habitat type; shoreline profile; and, wetland rarity (Table 4.12), and their component subattributes (Section 4.4). Many subattributes of attribute terrestrial zone habitat type are not used as inputs for any BLR Models or ANNs, and the following may not be collected: exposed substrate; logs; other attribute; shallow to medium depth water; and, water edge. The two subattributes of permanent deep pools and submerged or free-floating vegetation appear only in Model B BLR. Similarly for shoreline vegetation, alive trees were not used in any BLR model or ANNs, and the absence or presence of dead trees was only used in Model B BLR. All subattributes of shoreline shape used for shoreline profile assessment did not affect assessments, so it is not necessary to collect data on irregular or regular shaped shoreline shapes, however the absence or presence of islands is needed for the nine-inputs ANN with threats;
- Hydrology: Hydrology attributes appear only in Environmental value BLR models and ANNs, where threat values are not used. I suggest that drainage, disposal of water, water storage, obstruction and redirection capture data features similar to those captured by the threat values: altered hydrology and water source. In fact, the hydrology attributes seem to act as surrogates for these threat data; and,
- Vegetation intactness– critical lifeforms: Using the floral types of the dominant EVC at a site, it is only necessary to check for sedges as they appear in all Environmental value approaches, with and without threats. It is not

necessary to check for graminoids, grasses, herbs and ferns for any ANNs, and a check for herbs and ferns need only be done if Model B BLR is being used. Nor is it necessary to do a count of floral species at each site, as this subattribute does not feature in the calculations for any approach.

There is good agreement between patterns of attributes for high and very high-value wetlands noticed by the WGCMA and inputs identified by the sensitivity analyses of Environmental value ANNs and the inputs selected in BLR modelling (Table 6.12c). Of particular interest are the inputs of the with-threats BLR model and the with-threats ANN, where it is noted three Environmental values selected in BLR modelling: fauna VROT (*significant flora)*; sedges (*vegetation intactness-critical lifeforms*); and, width of vegetation fringe (*vegetation intactness-width of vegetation fringe*), are also found in the ANN together with: rocks (*habitat value-terrestrial zone habitat*); semipermanent saline wetlands *(wetland rarity*); and, shoreline islands (*habitat value-terrestrial zone habitat*). This overlap is support for WGCMA reports (2007) that mentioned high and very high Environmental value sites scored well for vegetation intactness, habitat value and wetland significance/rarity. In regard to threat categories for the with-threats ANN and with-threats BLR listed in Table 6.12c, the one threat category shared by both is lack of reservation, despite this category not being used in the WGCMA assessments for subcatchment wetlands. Further, shared inputs within approaches also point to the importance of habitat values in deciding Environmental value; rocks, sedges, shoreline shrubs and width of vegetation fringe appear in all ANNs versions as significant inputs. The importance of sedges cannot be overemphasized as it is the only Environmental value attribute needed by all BLR models and ANNs. This is a testament to its importance in predicting wetland assessments. In conclusion, the absence/presence of sedges and lack of reservation should always be included in Environmental value assessments because of their strong abilities to predict high and very high assessments.

Threat categories

For the WGCMA, the selection of the most appropriate threat values for use in risk assessment was problematic. In preparation for inventory and assessment, the WGCMA sought expert opinion and consulted with stakeholders in deciding a listing of suitable threat categories (Table 3.1). Initial lists of threats were progressively altered, and this is evidenced by changes to threat listings in different documentations of the assessment process (WGCMA 2006b, 2007). Further, the difficulty of the decision is borne out in the usage of two different sets of threat categories in the assessments, one for significant wetlands (Table 4.26a) and another for subcatchment wetlands (Table 4.26b).

This research offers some guidance as to the threat categories that may be abandoned in future assessments based on their absences from all BLR models and ANNs; the need to collect data for the following needs to be revisited:

- Loss of wetland connectivity;
- Stock access;
- Urban development;
- Native vegetation decline;
- Land use;
- Physical alteration;
- Fire regime; and,
- Recreation (inappropriate use for).

Given the amount of conversation devoted to the selection of suitable threat categories for use in risk assessments, it is indeed surprising that above eight attributes were not helpful in predicting high-value assessments. Moreover, there are reporting obligations at state, national and international levels that require wetland monitoring as to condition, and the threats present likely to impact condition. Lynch (2011) points out there is a need for more succinct reporting of threats and disturbances, and using the Queensland Wetlands Program as a case study, she argues for the development of a threat topology to record information on processes and disturbances, and resulting environmental impacts. More dialogue on this matter is needed for future assessments in West Gippsland, particularly in light of the findings of this research.

The influence of classification schemes

Earlier research of Fitzsimons and Robertson (2005) and Robertson and Fitzsimons (2004) on Victorian wetlands indicated that classification schemes significantly impact wetland assessments. The analysis of binary logistic regression models showed little evidence of this, with the exception of Model B that used absence/presence data for permanent open water wetlands. As pointed out in the discussion of Section 5.5, shrubs, herbs and sedges are used in the Corrick and Norman (1980) wetlands classification scheme to decide the subcategories for deep freshwater marshes, shallow freshwater marshes and freshwater meadows (Table 2.1); it is their physical presence at a site, rather than their use in wetland classification, that precipitates high and very high Environmental value assessments. This is evidenced by the appearance of vegetation types as the inputs for all binary logistic regression models.

In respect of wetland types, ANNs without threat inputs showed similar behaviours to their BLR model counterparts; there are no wetland types in the inputs for the eight-inputs ANNs, while the 12-inputs ANNs used absence/presence data for deep freshwater marshes. Again the lists of inputs for these ANNs, seen in Table 6.12c, support the premise that it is the appearance of vegetation types at a site that are more likely to be associated with higher value assessments.

For ANNs where threat values were used as inputs, there is some difficulty in dismissing the effect of the classification scheme on Environmental value assessments as the sensitivity analyses for ceiling ANNs identified semipermanent saline wetlands as the seventh most significant input. The Corrick and Norman (1980) subcategories for semipermanent saline wetlands are listed in Table 1.1 as 6.1 Salt pan; 6.2 Salt meadow; 6.3 Salt flats; and, 6.4 Sea rush-dominant. These subcategories cannot be separated on the appearance of vegetation characteristics listed amongst the significant inputs, and the appearance of semipermanent saline wetlands cannot be explained away in this manner as done previously for deep freshwater marshes, shallow freshwater marshes and freshwater meadows.

Is the absence or presence value for semipermanent saline wetlands a strong predictor of high or very high Environmental value? I suggest not, as there is no supporting evidence amongst all the analyses of Chapters 4, 5 and 6. As discussed in Section 5.5, correlations showed statistically significant negative associations of permanent open water wetlands (ρ = –0.205) and freshwater meadows (ρ = –0.166) and high-value assessments, meaning both wetland types were marginally more likely to have very low, low or moderate assessments. How can the appearance of semipermanent saline wetlands in significant inputs for ANNs with threats be reconciled?

Semipermanent saline wetlands make up 10% of wetland types found in public and private landholdings in Victoria (Traill & Porter, 2001). In mirroring these percentages, 16 semipermanent saline wetlands were inventoried and assessed by the WGCMA, and the assessments they generated were two low, eight moderate, five high and one very high Environmental value wetlands (Table 4.20a). A check of the component attributes of each Environmental value assessed (Table 4.12) shows that many inputs are more descriptive of freshwater, rather than, saline wetlands, such as, all of the hydrology attributes. Given there were six high or very high Environmental value wetlands of saline type, I suggest that the SPSS software had no other choice than to select the absence/presence of semipermanent saline wetlands as an attribute that could capture the 'saline' characteristics of these wetlands when building ANNs with threats. Note permanent saline wetlands were not part of the analyses due to their low count in the inventory.

The other wetland classification scheme used in Victoria is EVCs and for each site, the dominant EVC was recorded and a measure of percentage of floral types present for that EVC was estimated. The single EVC component needed to evaluate the threat input model is the absence or presence of sedges, and in fact, sedges are a prominent input for all Environmental BLR models and ANNs. The only other components used were herbs and ferns, but they are only found as input to the 15-inputs BLR model without threats. As mentioned above, the absence/presence value for sedges is strongly correlated to high and very high Environmental value assessments and it should also be included in any wetland assessment in West Gippsland.

For Environmental value, is it necessary to collect threat data and undertake the arduous risk assessment to identify high-value wetlands? At the end of the previous chapter, I noted that binary logistic regression models were somewhat ambivalent in their support for collecting threat data and undertaking risk assessments for Environmental value. It was possible to achieve comparable classification performances to the 10 BLR with-threat model by adding up to 15 inputs of Environmental attributes for the Model B version. In consideration of the neural networks analyses, it is necessary to incorporate threat data for Environmental value assessments; the use of Environmental value attributes alone is insufficient to describe the data and capture all of its nuances. This was seen in the poorer performances of the eight-inputs ANN without threat data (Table 6.8c) and 12-inputs ANNs without threat data (Table 6.8d). It is further supported by the experiments in building Environmental value ANNs without threat data that used up to the 15 of the significant inputs identified by the sensitivity analyses of ceiling ANNs. The 15-inputs ANNs showed no difference to classification performances over the 12-inputs versions. The inclusion of extra inputs for attributes describing Environmental value did not improve prediction rates; improvements were only seen when threat input was used, indicating that threats attributes, in of themselves, better describe wetland condition than other inputs. Threat category data needs to be incorporated to assess Environmental value of a wetland.

Using neural networks to predict wetland assessments

Historically, there has been widespread application of artificial neural networks to environmental assessment and management problems, as evidenced in their application to water resource variables (Maier & Dandy, 2000a & 2000b; Maier et al., 2010). Their broad appeal is on two counts. Firstly, ANNs make no assumptions of statistical distributions and are able to cope well with non-traditional data sets. Secondly, ANNs are able to reliably predict outcomes when given unseen data, provided they have been trained on similar dataset (Brosse et al., 2001; Findlay & Zheng, 1999; Lek & Guegan, 1999; Olden et al., 2006; Zhang, 2000). In this study, ANNs were constructed and sensitivity analyses were conducted to identify important contributing inputs to wetland assessments. Additionally, ANNs were investigated as to their suitability for predicting wetland assessments on unseen data that had been collected by Greening Australia staff for the same purpose. Optimally, there should be at least 200 cases in the training datasets (Detienne et al., 2003; Sug, 2010). Despite lower than optimal numbers of wetlands used in training datasets, the experiments, where 30% of the available data was set aside for testing, show that for all wetland values, neural networks can be trained on one set of wetland records and perform very well on unseen data.

For all Economic values ANNs, the effect of a smaller training set size was to reduce the ability of networks to recognize moderate and high Economic value wetlands. For Social values ANNs, there is little performance difference noticed for the ANN trained using 70% of available data. For all Environmental value ANNs, more training data results in better recognitions of high and very high Environmental value wetlands. Comparisons of the classification performances of Environmental ANNs with and without threat data support the need for threat inputs to be incorporated to be able to more accurately classify wetlands overall, and in particular, high and very high-value wetlands.

In conclusion, the application of neural networks to wetland assessment has in many ways supported the conclusions of Chapter 6; for Economic value, <u>no</u> assessments need be done; threat data is <u>not</u> needed and risk assessments should <u>not</u> be done for Social value assessments. Neural networks have clarified the need for threat data to be included in Environmental value assessments. In this chapter, I have shown the potential for neural networks trained using one set of wetland records to perform consistently well in making wetland assessments on unseen wetland data. In the next chapter, the major findings of this research are presented and I discuss the implications for wetland assessments in West Gippsland, and more broadly in Australia.

Table 6.11: A summary of all artificial neural networks and binary logistic regression approaches showing the number of records, the number of input variables, and the % overall correct classifications. For Economic and Social values, the % correct moderate and high-value classifications is given in brackets and for Environmental value, the number of high and very high-value correct classifications is given in brackets.

<table>
<tr><th colspan="2" rowspan="2">Approach</th><th colspan="2">ANNs</th><th colspan="2">BLR models</th></tr>
<tr><th>Number of inputs</th><th>%
Correct classifications</th><th>Number of inputs</th><th>%
Correct classifications</th></tr>
<tr><td rowspan="2">Economic value</td><td>No threat input
(n = 161)</td><td>5</td><td>91
(68)</td><td>5</td><td>91
(57)</td></tr>
<tr><td>With threat input</td><td>6
(n = 155)</td><td>94
(78)</td><td>9
(n = 151)</td><td>97
(86)</td></tr>
<tr><td rowspan="2">Social value</td><td>No threat input
(n = 149)</td><td>6</td><td>92
(93)</td><td>9</td><td>92
(88)</td></tr>
<tr><td>With threat input</td><td>8
(n = 150)</td><td>91
(93)</td><td>10
(n = 144)</td><td>95
(91)</td></tr>
<tr><td rowspan="5">Environmental value</td><td rowspan="2">No threat input</td><td rowspan="2">8
(n = 162)</td><td rowspan="2">87
(83)</td><td colspan="2">Model A</td></tr>
<tr><td>7
(n = 163)</td><td>86
(86)</td></tr>
<tr><td rowspan="2">No threat input
(n = 158)</td><td rowspan="2">12</td><td rowspan="2">91
(82)</td><td colspan="2">Model B</td></tr>
<tr><td>15</td><td>91
(89)</td></tr>
<tr><td>With threat input</td><td>9
(n = 146)</td><td>93
(90)</td><td>10
(n = 156)</td><td>91
(89)</td></tr>
</table>

Table 6.12a: A summary of Economic value inputs for all artificial neural networks and binary logistic regression approaches showing the number of inputs in common within, and between approaches. Threats with * were not used in the WGCMA assessments for subcatchment wetlands.

	Approach	Number of inputs	Input		Common inputs	
			Economic value attributes	**Threat**	**Within approach**	**In ALL approaches**
Economic value	**BLR**	5 No threats	Conservation forestry Diverted or farm runoff Food production Stock water supply Water storage	Not applicable	Diverted or farm runoff Stock water supply	**Economic value attributes** Diverted or farm runoff Stock water supply **Threats** Erosion Resource utilization*
		9 With threats	Diverted or farm runoff Stock water supply	Erosion Lack of reservation* Resource utilization* Sedimentation* Urban development Water source– groundwater fill Water source– rainfall		
	ANN	5 No threats	Conservation forestry Diverted or farm runoff Redirection Stock water supply Water storage	Not applicable	Diverted or farm runoff Stock water supply	
		6 With threats	Diverted or farm runoff Stock water supply	Erosion Loss of connectivity Resource utilization* Salinity		

Table 6.12b: A summary of Social value inputs for all artificial neural networks and binary logistic regression approaches showing the number of inputs in common within, and between approaches. Threats with * were not used in the WGCMA assessments for subcatchment wetlands.

	Approach	**Number of inputs**	**Inputs**		**Common inputs**	
			Social value attributes	**Threat**	**Within approach**	**In ALL approaches**
Social value	**BLR**	9 No threats	Bird watching Boating Camping Education Hunting Motorized 4WD Park value Recreational fishing Swimming	Not applicable	Bird watching Camping Education Motorized 4WD Park value	**Social value attributes** Bird watching Camping **Threats** Salinity
		10 With threats	Bird watching Camping Education Motorized 4WD Park value	Erosion Recreation Resource utilization* Salinity Water source– other		
	ANN	6 No threats	Bird watching Boating Camping Motorized 4WD Park value Passive recreation	Not applicable	Bird watching Boating Camping Passive recreation	
		8 With threats	Bird watching Boating Camping Passive recreation Swimming	Pest animals Salinity Lack of reservation*		

Table 6.12c: A summary of Environmental value inputs for all artificial neural networks and binary logistic regression approaches showing the number of inputs in common within, and between approaches. Threats with * were not used in the WGCMA assessments for subcatchment wetlands.

	Approach	Number of inputs	Inputs		Common inputs	
			Environmental value attributes	**Threat**	**Within approach**	**In ALL approaches**
Environmental value	**BLR**	7 Model A: No threats	Flora VROT Rocks Redirection Sedges Shrubs Shoreline shrubs Width of vegetation fringe	Not applicable	Sedges	**Environmental value attributes** Sedges
		15 Model B: No threats	Drainage Fauna VROT Ferns Flora VROT Herbs Obstruction Permanent deep pools Permanent open water wetland Rocks Sedges Shoreline shrubs Shoreline dead trees Shrubs Submerged or free-floating vegetation	Not applicable		

Environmental value	**BLR**	10 With threats	Fauna VROT Width of vegetation fringe Sedges	Altered hydrology Drainage into wetland* Lack of reservation* Pest plants Resource utilization* Water source– other Water source– rainfall		**Threats** Lack of reservation*
	ANN	8 No threats	Drainage Fauna FFG Flora VROT Disposal of water Rocks Sedges Shoreline shrubs Width of vegetation	Not applicable	Rocks Sedges Shoreline shrubs Width of vegetation	
		12 No threats	As 8 inputs ANN + Emergent vegetation Deep freshwater marsh Obstruction Redirection	Not applicable		
		9 With threats	Fauna VROT Rocks Sedges Semipermanent saline wetlands Shoreline islands Width of vegetation fringe	Lack of reservation* Sedimentation* Water source– groundwater fill		

Powlett River, Victoria, July 2008.
Image courtesy of Paul Boon

Chapter 7

General discussion and conclusions

The overarching objective of the research outlined in this thesis was to increase understanding of the process of wetlands assessment by examining its practice in Gippsland, south-eastern Australia through the application of three complementary approaches:

- *a statistical exploration of the relationships between the values of different input factors and the classification of high-value wetlands using univariate and multivariate statistics, described in Chapters 4 and 5, respectively;*
- *an investigation of the impact of two wetland classification schemes in evaluating and ranking of wetland sites, addressed in Chapters 4, 5 and 6; and,*
- *the application of neural networks, a data-mining technique, to mimic the wetland assessment process, detailed in Chapter 6.*

This chapter summarizes the results of the research and discusses the findings in relation to the research's objective above. In the first section of this concluding chapter, an overview of the WGCMA approach to wetland assessment is given, the findings of the 2006 assessment are summarized, and the lessons learnt from this detailed examination of the case study are discussed. This is followed by a discussion which relates to the objective's individual approaches. Next, there is a summation of significant findings of the research and their implications for the study, assessment and wise management of wetlands. Recommendations for future wetland assessments are given in the concluding section of this thesis.

7.1 Overview of WGCMA approach and their findings

A group of prominent Australian environmentalists (Morton et al., 2009) identified one of the important “big ecological questions inhibiting effective environmental management in Australia” as “How can datasets be rigorously gathered, analysed and reported to establish environmental trend, critical thresholds, and feedbacks to management?” In this thesis, I have analysed the WGCMA Wetlands Inventory Database using three approaches: univariate statistics, multivariate statistics and neural networks to discover and report upon pertinent relationships between the values of different site characteristics and the classification of high-value wetlands. The Database (7.61 Megabytes) was the depository of biological, chemical, hydrological and physical data for 163 wetlands, which was collected specifically for the rapid assessment undertaken by the WGCMA in autumn 2006. The impetus for the assessment was the need to identify and prioritize wetlands within the catchment according to the value of services each wetland provides (Section 3.1, Section 3.3 and Appendix A).

Various public documents of the WGCMA assessment detail the context, guiding principles, priorities, scope of the process and the development of Wetlands Plan (WGCMA, 2006a, 2006b, 2006c & 2007). The WGCMA assessment commenced with the establishment of a Wetlands Plan Steering Committee, who garnered technical expert advice, established stakeholder workshops and consulted with the community. The Committee’s first task was to decide the set of economic, social and environmental values and threat categories (Table 3.1) to be used to assess wetland value and condition. The conceptual models used by the Committee to decide the set of appropriate indicators to assess these values and categories have not been publicly detailed, however the Greening Australia report (2006) mentions that contemporaneous work being done across Victoria to establish an Index of Wetland Condition (DSEE, 2005b) guided indicator selection, and this is evidenced particularly in attributes selected to assess environmental value. A very broad range of indicators were decided to assess 21 wetland values (five economic + nine social + seven environmental) and 14 threat categories (Table 3.1, Table 4.1, Table 4.6 and Table 4.12) for which large quantities of data were collected during inventory, before collation and storage in the Database (Section 3.3.3). For transparency, the WGCMA used a set of scoring matrices to calculate hundreds of risk assessments per wetland site (Section 3.3.2). Each site's risk assessments were the basis of the rankings of all sites within the West Gippsland region for their Economic, Social and Environmental values (Section 3.4). The outcome was the Wetlands Plan for the West Gippsland region that reported the assessment, and for individual wetlands it documented a description of important values and a listing of risks present, together with an outline of a management proposal designed to maintain values and reduce risk for each wetland (WGCMA, 2006a & 2006b).

For the WGCMA, the assessment task was onerous; it was time consuming, labour intensive, and expensive (Section 3.5). Limited effort and attention was given to a systematic appraisal of the data amassed during the 2006 wetlands assessment. This was an opportunity lost by the organisation to better understand the nature and composition of wetlands in the region, particularly in regard to identifying the characteristics of high-value wetlands. Such understanding could have been easily gained through the application of readily available computing tools to data already amassed for the assessment. Rather, the WGCMA (WGCMA, 2007) broadly noted that some data inputs were associated with high Economic, Social and Environmental value assessments (Section 2.4). My univariate statistical analyses checked these reported associations, of which only a few were confirmed (Section 4.2, Section 4.3 and Section 4.4), and any management decisions made on the basis of these associations would have been flawed. In particular, the data analysis undertaken by Greening Australia (2006) for the WGCMA was inadequate in identifying the characteristics of wetlands that predicted moderate and high Economic and Social values (Section 4.6, Section 5.5 and Section 6.5).

This research has shown that simple univariate statistics (Chapter 4) can reveal associations between input data values and high-value assessments, while multivariate statistics (Chapter 5) and neural networks (Chapter 6) can succinctly describe relationships between input attributes and assessment outcomes. The relevance and possible applications of this research are discussed in upcoming sections. Firstly, a review is undertaken of the most important factors identified as significant in assessing wetland values in West Gippsland, and the broader implications of these findings are discussed. Secondly, the impact of wetland classification schemes in the

WGCMA assessment is considered and implications for other jurisdictions are indicated. Thirdly, the effectiveness of statistical analyses and the neural network approaches for use in wetland assessments, locally and more generally, is explored. Fourthly, a set of recommendations for future West Gippsland wetland assessments and monitoring efforts is made. Finally, concluding remarks relate the applicability of the novel approaches, multivariate statistical analyses and neural networks, to wetland assessments more widely.

7.2 Variables needed to assess wetlands

There are a variety of wetland assessment methods that are used to identify high value wetlands and give some measure of the economic, social and ecological services that wetlands supply (DEC, 2008; DSE, 2005b). In practice, wetland assessments rely on a suitable set of inputs that collectively describe the gamut of wetland types and possible conditions in a region, and for which data can be reliably and consistently collected infield. Examples, such as the hydrogeomorphic (HGM) wetland classification system adopted in the United States, illustrate the requirement for assessment methods to be broadly applicable, whilst being customizable to local conditions (Cole, 2006; U.S.D.A., 2008). As mentioned in the previous section, the selection of indicator variables for the WGCMA assessment came about after much expert and community consultation to arrive at the five economic + nine social + seven environmental attributes and their many sub-attributes together with 14 threat categories (Table 3.1, Table 4.1, Table 4.6 and Table 4.12) for which inventory data was collected. In effect, the WGCMA used a scattergun approach to assess wetland values. By examining the data values for input attributes and sub-attributes and relating them to assessment outcomes, my research has distilled the most significant factors that strongly predict high-value, or not, wetlands in the West Gippsland region. The identification of these significant factors will allow future inventory, assessment and monitoring efforts in the region to be better targeted.

7.2.1 Specific application to West Gippsland wetlands

The analyses reported in this research indicate the most appropriate and useful inputs of a minimal set for the assessment of economic, social and environmental wetland values in West Gippsland. In deciding inputs, there are two important data issues which need consideration. As mentioned above, the WGCMA orchestrated a large data collection across a great variety of attribute types attempting to assess hydrological, chemical, biological and physical characteristics of over 160 wetlands. The broad nature of their attempt has afforded my research a large set of possible inputs from which to select significant factors. Secondly in Chapters 4, 5 and 6 analyses, data were aggregated into absence or presence groups for statistical convenience, where previously there had been various grades of presence values. For instance, all Social value attributes, except park value, were assessed in the field as either none, occasional, seasonal or frequent (Table 4.7a) and in conducting cross-tabulation analyses (Section 4.3.2), logistic regression modelling (Section 5.3.2) and neural network construction (Section 6.3.1), occasional, seasonal and frequent data were combined as the presence value of the Social value attribute under study. By binning presence data in this manner, it is possible that any finer grained relationships between shades of presences for inputs and assessment outcomes would be smoothed and more subtle relationships masked. This possibility could be statistically investigated only if there were more inventoried wetlands and data to meet the pre-conditions for such analyses. In this research, absence/presence values alone were used for input variables and it is a testament to the strengths of the relationships between these variables and high-value assessments that over 90% correct classifications could be made. This, in, itself, is an argument for not recording finer quantitative grades of presence values, which in turn, would save considerable collection time in the field and effort at the desk in data checking, validations and in calculating assessments.

Economic value

The strategy taken to decide a minimal set of significant inputs for Economic value was to look at the inputs for the best performing approach and compare and contrast these against a listing of inputs of all of the approaches to predict Economic value assessments. As previously discussed (Section 6.5), the neural network without threats was chosen as highest performing approach for its ability to classify moderate and high Economic value wetlands for the least number of inputs. Table 7.1 lists the attribute values of this neural network, and when these are inspected, they indicate to

Economic values of drainage disposal, production value and water supply, as seen in the summary table, Table 7.2. To check attributes of all approaches, Table 6.12a gives a summary of Economic value inputs, and within approaches and across approaches comparisons. The range of attributes and values listed in Table 6.12a further support the use of drainage disposal, production value and water supply, as the most significant input for assessments for Economic value in West Gippsland. Importantly it is these three, rather than the five, Economic values listed by the WGCMA (Table 3.1) that decide overwhelming a wetland's Economic value assessment. No evidence was found in my analyses that the absence or presence values for the values of tourism (present at 25% of sites) or commercial fishing activities (2 sites only) were of any significance in determining Economic value.

On the grounds that only one wetland was identified as having high Economic value, discussions in Section 5.5 and Section 6.5 argue that Economic assessments need not be conducted at all, thereby eliminating the need to collect data on any of the attributes used to measure Economic value or data on threat levels. It is acknowledged that political considerations may decide otherwise in the future. In this event, there is strong evidence provided by the high prediction rates of the Economic value BLR without threats models and ANNs without threats (Table 6.11) assessments to dispute the need to incorporate threat data in Economic value assessments, and support for the use of inputs to quantify drainage disposal, production value and water supply.

Social value

Similarly, a minimal set of significant inputs for Social value can be decided by looking at the inputs for the best performing approach and considering each in light of those found within and across all of the approaches deciding Social value assessments (Table 6.12b). Earlier in Section 6.5, it was noted that the performances of ANNs are generally superior to that of their equivalent BLRs, with the six-inputs neural network with no threats input is the best predictor of Social value assessments. Therefore, the six attributes of this approach are listed in Table 7.1 with the five Social values, which the attributes were used to quantify, being: bird watching; boating; camping; passive recreation; and, park value. As discussed in Section 6.5, there is strong statistical support for the inclusion of each of these inputs, including passive recreation and park value, and in particular, for bird watching and camping, which appear in all Social value approaches (Table 6.12b). Table 7.2 lists these five, most significant Social values for use in predicting high value assessments.

For Social value assessments, it is five, rather than the nine, values listed by the WGCMA (Table 3.1) that decide overwhelmingly a wetland's Social value assessment as indicated particularly by the sensitivity analyses used in building Social value ANNs. Education was a common attribute in both BLR models (present at nearly 35% of sites), but it is not included in the minimal set since it was absent from the higher performing ANNs. Nor is hunting (present at over 50% of sites), or recreational fishing (present at over 30% of sites), or swimming (present at less than 10% of sites) included since there is no statistical support for the inclusion of these values. Here, I repeat my earlier argument (Section 5.5 and Section 6.5) to not collect data for threat values or undertake risk analyses for Social value assessments since inputs for Social values achieved remarkably high classification rates without threat data.

Environmental value

Deciding a minimal set for Environmental value assessments, is less clear cut than for Economic and Social value assessments. The first step is to note attributes not needed in assessments; this was done for attributes not used in BLR modelling (Section 5.5) and later updated in regard to ANN constructions (Section 6.5). It is the complement of this list, those data types not mentioned, that is the starting point to describe a minimal set of inputs for Environmental value.

The next step in defining a minimal set is to decide whether threat categories should be included or not in the assessment of Environmental value. This matter was discussed at length earlier (Section 5.5 and Section 6.5) and the conclusion reached was that threats should be incorporated. This recommendation is cognizant of the WGCMA difficulties surrounding the choice of threat categories often noted in this thesis. A guide to which threat categories should be included is given in the next subsection.

The presence or absence of sedges, an attribute of vegetation intactness- critical lifeforms, should definitely be included in the minimal set, as this attribute is found in all Environmental value analyses undertaken in this research (Table 6.12c). The best performing approach, the nine-inputs ANN with threat categories, includes six attributes for the five Environmental values used by the WGCMA, being: wetland rarity; significant fauna; habitat value; vegetation intactness- critical lifeforms and vegetation intactness- width of vegetation fringe. These values also encompassed all contributing inputs found across all approaches (Table 6.12c), with the exception of flora VROT that was used to measure significant flora. Significant flora has not be included in the minimal set on two accounts; it does not appear in the BLR with threats model or in the ANN with threats, and floral aspects and types are encompassed by the attributes used to measure vegetation intactness- critical lifeforms. Therefore, Table 7.2 lists the five values, rather than seven, needed to assess Environmental value in West Gippsland

Threat categories

There is a necessity to include threats as part of wetland assessments, particularly as the Ramsar definition for wetland assessment is "*the identification of the status of, and threats to, wetlands as a basis for collection of more specific information through monitoring activities*" (Ramsar, 2005, point 17). As pointed out on several occasions (Section 3.4 and Section 4.5), the assessment of threat has been problematic for the WGCMA in that two different sets of threat categories were reported; one set for significant wetlands and another set for inventoried wetlands, whilst data on all threat categories was collected in the field and stored in the Database for all sites.

On the basis of this investigation, I have argued (Section 5.5 and Section 6.5) that there is no need (statistically speaking) for threat category data to be used for the assessment of Economic or Social value and this data is only required to make Environmental value assessments in West Gippsland. Should this approach be adopted, Table 7.3 provides the minimal set of threat categories needed to assess Environmental value only, being: water source; a lack of reservation; and, sedimentation. Note: the lack of reservation and sedimentation were categories not used by the WGCMA in the assessment of inventoried wetlands. Table 7.3 also lists a larger set of threat categories, incorporating erosion and resource utilization which are shared by Economic 'with threats' approaches (Table 6.12a), and salinity found to be in common in Social value 'with threats' analyses (Table 6.12b). The remaining threat categories, altered hydrology, pest plants and altered hydrology are included for their appearances within various BLR and ANN analyses in this thesis.

Examination of the larger listing in Table 7.3 shows that only five of the fourteen of threat categories published by the WGCMA (2006b) are of statistical influence and importance in their wetland assessments. Rather, the additional threat categories of: drainage into wetland; lack of reservation; resource utilization; and, sedimentation are better classifiers of wetland condition, or not, and these should be used in future assessments for subcatchment wetlands as well of those of international and national importance and significance.

7.2.2 Broader application to wetlands assessment

The lessons learnt from this study of the 2006 WGCMA wetland assessment can be applied also to wetlands assessments more broadly. There is no doubt that priorities for protection and restoration of wetlands should target wetlands deemed to be highest in value, and that assessment needs to take into account a broad range of factors to assess the character and value of a wetland and to incorporate a risk assessment of the various threats likely to downgrade wetland values (Breckenridge et al., 1995; Lui et al., 2006; Ticehurst et al., 2007). There is much discussion and argument in the literature as to the best attributes to collect to assess the character and value of a wetland, and a recognition that attribute selection is likely to locale-specific (Cowardin & Golet, 1995; DEC, 2008; DSE, 2007; Fitzsimmons & Robertson, 2005, Gitay et al., 2011; Spencer et al., 1998). By collecting attribute data across a very broad range of indicators in order to assess 21 wetland values and 14 threat categories, the WGCMA approach to assess wetland values could have been better targeted, despite considerable effort spent by the Wetlands Plan Steering Committee to decide the set of economic, social and environmental values and threat categories (Table 3.1). This research questions the necessity to collect data across such a broad range of attributes in the field to undertake an assessment of wetland values as the 13 values listed in Table 7.2 can collectively correctly predict at least 90% of assessments for Economic, Social and Environmental values, where previously 21 values were used by the WGCMA (Table 3.1). Equally, the listings of threats in Table 7.3 point to a smaller set of threat categories that are statistically significant and illustrate the complexity of deciding which threat categories to use.

My research has shown that data analyses can identify redundancies within data collected and used in the WGCMA 2006 assessment. Checking these redundancies, it is seen that the absence/presence values for tourism or commercial fishing activities were of no significance in determining overall Economic value, and there is no suspicion that their influence is captured elsewhere since neither of these attributes was highly correlated with any other Economic value attribute (Section 5.2.1). Similarly the absence/presence values for the attributes of recreational fishing, swimming, hunting and education were of little use in deciding Social value. However in this case, these attributes are correlated with those identified in the minimal set (Table 7.2), indicating the collection of minimal set data does in fact capture similar characteristics to these attributes in predicting Social values.

Greening Australia (2006) noted that the autumnal timing of the data collection meant that access to wetlands was much easier due to minimal water flows, whilst noting that evidence of plant and animal species was more difficult to find. The degree to which the timing of the rapid assessment affected representative data collection is difficult to gauge. Data for several attributes used to assess hydrology is significant in deciding the Economic value of drainage disposal but the same attributes have limited influence on the assessment of Environmental value. In fact, it is seen that data collected to quantify of hydrology and significant flora is unnecessary as some of the data characteristics are captured by the inclusion of attributes for habitat value and vegetation intactness- critical lifeforms for Environmental value assessment (Section 6.5).

At a local level, there is little need to collect any more data than is indicated in Table 7.2 and Table 7.3. This may not be the case for other assessment efforts further afield. For the HGM method used in the U.S., where wetlands are classified primarily on their physical characteristics and hydrodynamics (Cole, 2006), it would expected and necessary to collect data on all attributes used to assess hydrology, even if these attributes were highly correlated with one another, as is the case in West Gippsland. Other assessment methods, such as the Millennium Ecosystem Assessment (2005) focus more on the impact of humans on wetlands' functions, and it would be unwise to summarily discount attributes such as tourism, recreational fishing, swimming, hunting and education in this type of assessment. Furthermore, as succinctly detailed by Lynch (2011), there is a rich history of wetland assessment methods which attempt to take account of "pressures" and "stressors" resultant from human activities and there is a need to better identify, describe and incorporate measures of their influence in assessment methods, particularly in Australia.

This research has illustrated that a systematic and concerted effort in analysing data collected during the inventory stage of a wetland assessment is a worthwhile investment in identifying the salient predictors for the assessment at hand. A practical and pragmatic approach would be to collect data across a broad range of factors for a smaller, representative sample of wetlands and then analyse the collected data of the sample to find the salient predictors of high-value wetlands using the methods outlined in this thesis. Once these factors have been identified in the sample, a data collection using this reduced set of factors can be undertaken for many more wetland sites, than otherwise resources would have previously permitted. A more thorough data analysis is the key to identifying the most factors that strongly predict high-value wetlands in a region, and identification of these factors in of themselves would be insightful in guiding monitoring efforts.

Table 7.1: Minimal data inputs needed to correctly identify at least 90% of high-value wetlands for each wetland value in the West Gippsland region of south-east Australia. Data were chosen through matching the highest performing approaches with the least number of inputs for each value from Table 6.11 and the list of inputs from Tables 6.12a, 6.12b and 6.12c.

<table>
<tr><th rowspan="2">Wetland Value</th><th colspan="2">Value Inputs</th><th colspan="2" rowspan="2">Threat Inputs</th><th rowspan="2">Comments</th></tr>
<tr><th>Attribute</th><th>Value</th></tr>
<tr><td rowspan="5">Economic</td><td>Conservation forestry</td><td>Production value</td><td colspan="2" rowspan="5">None</td><td rowspan="5">In WGCMA assessment only one high-value wetland was identified.</td></tr>
<tr><td>Diverted or farm runoff</td><td>Drainage disposal</td></tr>
<tr><td>Redirection</td><td>Drainage disposal</td></tr>
<tr><td>Stock water supply</td><td>Water supply</td></tr>
<tr><td>Water storage</td><td>Drainage disposal</td></tr>
<tr><td rowspan="6">Social</td><td colspan="2">Bird watching</td><td colspan="2" rowspan="6">None</td><td rowspan="6">In WGCMA assessment, six inputs of Social values alone were sufficient to identify high-value wetlands.</td></tr>
<tr><td colspan="2">Boating</td></tr>
<tr><td colspan="2">Camping</td></tr>
<tr><td>Motorized 4WD</td><td>Passive recreation</td></tr>
<tr><td colspan="2">Park value</td></tr>
<tr><td>Passive recreation</td><td>Passive recreation</td></tr>
<tr><td rowspan="6">Environmental</td><td>Fauna VROT</td><td>Significant fauna</td><td>Attribute</td><td>Value</td><td rowspan="6">Significant inputs were attributes or subattributes of Environmental values, each of which included several other attributes used in the measure.

Two of the three threat inputs were not actually used by the WGCMA.</td></tr>
<tr><td>Rocks</td><td>Habitat value– terrestrial zone habitat type</td><td>Lack of reservation</td><td>None</td></tr>
<tr><td>Sedges</td><td>Vegetation intactness– critical lifeforms</td><td>Sedimentation</td><td>None</td></tr>
<tr><td>Semipermanent saline wetlands</td><td>Wetland rarity</td><td>Water source– ground fill</td><td>Water source</td></tr>
<tr><td>Shoreline islands</td><td>Habitat value– shoreline</td><td colspan="2" rowspan="2"></td></tr>
<tr><td>Width of vegetation fringe</td><td>Width of vegetation fringe</td></tr>
</table>

Table 7.2: Significant wetland values identified by collation of highest performing models from Table 5.11 with inputs from Tables 6.12a, 6.12b and 6.12c. This table is a modified version of Table 3.1 which listed values for the 2006 WGCMA assessment.

Economic Values	Social Values	Environmental Values
Drainage disposal	Bird watching	Wetland rarity
Production value	Boating	Significant fauna
Water supply	Camping	Habitat value
	Passive recreation	Vegetation intactness–critical lifeforms
	Park value	Vegetation intactness–width of vegetation fringe

Table 7.3: Significant threat categories identified for use in future WGCMA wetland assessments. This table is a modified version of Table 3.1 which listed threat categories for the 2006 WGCMA assessment. Threat categories not used in WGCMA assessments are indicated by *.

Threats categories identified in best performing approach	Threats categories identified across all approaches
Water source	Water source
Lack of reservation*	Lack of reservation*
Sedimentation*	Sedimentation*
	Altered hydrology
	Drainage into wetland*
	Erosion
	Pest plants
	Resource utilization*
	Salinity

7.3 *Wetland classification schemes*

7.3.1 Specific application to West Gippsland wetlands

My research found that selection of either the two wetland classification schemes, the Corrick and Norman (1980) scheme and Ecological Vegetation Classes (EVCs), made minimal impacts on the evaluations and rankings of wetland sites in West Gippsland. In regard to the Corrick and Norman (1980) scheme, cross-tabulation tables (Section 4.4.2) and correlations statistics (Section 5.4.1) indicated that permanent open water and freshwater meadows were marginally more likely to have very low, low or moderate assessments than would be expected due to their frequency in the inventory sample. Evidence from constructions of BLR models suggested that high and very high wetland evaluations were strongly correlated to the presence of shrubs, sedges and herbs, and, as discussed in Section 5.5, it is likely the physical presence of these vegetation types that precipitates high and very high assessments. This deduction was further supported by experimentation in building ANNs (Section 6.5).

Semipermanent saline wetlands were a significant input for Environmental value ANNs if threat categories were used (Section 6.4.3). As discussed in Section 6.5, the majority of attributes used to assess Environmental value seem skewed to measure freshwater wetland characteristics, and not those of saline types. Given the lack of attributes that would be useful to characterize saline wetland types, the SPSS software selected the wetland type of semipermanent saline wetlands as the mechanism to correctly classify the 16 semipermanent saline wetlands inventoried. Further, the threat category of salinity appears in ANNs with threats for Economic and Social values (Table 6.12a and Table 6.12b), which is also likely to have come as the ANNs try to incorporate features of the 16 semipermanent saline wetlands. For future wetland assessments, I suggest the possible inclusion of a salinity measure being incorporated into inventory sampling and the assessment process.

The dominant EVC vegetation type and a measure of percentage of floral types present for the EVC was recorded for each site in the WGCMA dataset. By far and away the most significant floral type influencing wetland classifications was the absence/presence value for sedges; sedges was a significant input for all BLR models and ANNs (Table 5.12c). To a much lesser extent, herbs, ferns and shrubs made smaller contributions; herbs and ferns were used in some of Environmental value BLR models, and shoreline shrubs was found in the no threat ANN versions. As already stated in Section 5.5 and Section 6.5, it seems that the physical presence of vegetation types at a wetland site that is associated with high-value assessments, more so than the classification of wetland type under the Corrick and Norman (1980) scheme.

7.3.2 Broader application to wetlands classification

As described above, there was no marked association with high-value wetland assessments for the Corrick and Norman (1980) scheme or EVCs. Fitzsimons and Robertson (2003 & 2005) have found to the contrary in their studies of the Wimmera bioregion in Victoria, where the use of EVCs for classification in reservation systems led to the conclusions that wetlands were more severely depleted than the amount of depletion indicated for the same wetlands than when the Corrick and Norman (1980) scheme was used. It is possible that the differences between the findings of my research and the conclusions of Fitzsimons and Robertson are related to three dissimilarities of the studies. First, Fitzsimons and Robertson (2005) were not concerned directly with the identification of high-value wetlands but rather with assessing wetland representation within reserve systems, where they found a bias, in that shallow freshwater marshes tended to be poorly represented in protected areas. Second, the Wimmera region is a markedly less-watered region of Victoria than is West Gippsland, and this may account in some part for poorer representations of shallow freshwater marshes in protected areas in the Wimmera. Finally, the WGCMA assessment included vegetation types and other attributes that more succinctly predicted high-value wetlands than did the Corrick and Norman (1980) or EVC schemes, and it is not evident that factors other than the these two classification schemes were considered in the Fitzsimons and Robertson study (2005). In light of these conflicting findings, there is a need for further studies across different regions within the State of Victoria, where the Corrick and Norman (1980) scheme and EVCs are applied, to help truly gauge the degree of influence that a particular classification scheme makes in predicating high-value wetlands.

Given the wide-ranging group of attributes for which data was collected in this case study, there is no surprise that there is considerable data redundancy. Particularly for freshwater wetland types, there is almost a ‘doubling up’ of information provided by the measures of habitat value (vegetation types of sedges, herbs, etc) and the Corrick and Norman (1980) scheme which partially categorizes on vegetation type. Equally, as mentioned, there is a paucity of information for saline type wetlands. The decision to use a specific classification scheme in a wetland assessment needs to be mindful of the scheme’s particular bias (towards vegetation for the Corrick and Norman scheme or hydrology for the HGM method) so that shortfalls in data capture can be met and unhelpful redundancies in data collection avoided.

7.4 The use of neural networks and a comparison of traditional analytical techniques

The application of artificial neural networks to the task of wetland assessments is novel to this research. In the first instance, ANNs were used as an alternative approach to binary logistic regression modelling, where the ANNs performed consistently better than traditional univariate and multivariate statistics at classifying high-value wetlands (Table 6.11). In the second instance, an exploration of the ability of ANNs to mimic the wetland assessment process using unseen data was done by dividing the data into 70% training and 30% testing sets. Despite the less than desirable number of training data available, the results were consistently encouraging and the networks were still able to identify high-value wetlands in the unseen data (e.g. see Section 6.2.4, Section 6.3.4 and Section 6.4.4).

The performance of all the ANNs, which were trained on 70% and 100% of the data, shows that neural networks are indeed an effective tool for predicting high-value wetlands with this dataset. Any trained ANN with good performance statistics can be saved and then be used reliably into the future given there are absence/presence values for its listed inputs collected using the same protocols and sampling regime.

For the ANNs built in this research, multiple runs and sensitivity analyses were needed to decide the most significant inputs for Economic, Social and Environmental values. Therein, lies the difficulty of using ANNs, which has been aptly elucidated by Curry & Morgan (2006, p.569) as "Model selection issues are still crucial. This is because of the rather neat irony that better approximation within the training naturally increases the risk of over-fitting. The very strength of (A)NNs, their ability to approximate, is also their principal weakness. Ultimately, it is the capacity of the network to generalize which is the most important."

The benefit of using a neural network approach over either traditional expert opinion or multivariate statistical approaches is that it is not necessary to understand input-to-output relationships to build an ANN, or to get it to learn how to solve a problem. The disadvantage is not being unable to directly 'look under the hood' and unravel the computations, nor see the relationships between inputs and their positive and negative influences on prediction. By comparison, BLR models are relatively transparent, in that, it is possible to identify the magnitudes of influence of each input, through examination of coefficients, w_i in $ln(w_i)$ format, and see the relationship amongst inputs in the equations produced. In either case, BLR models and ANNs can only reliably predict when supplied with similar input data to that used in their constructions.

What is the better approach, statistics or neural networks, for use in wetland assessments? Insights are offered in Karlaftis and Vlahogianni's review of instances where ANNs and statistics have been applied to data analysis problems in the transportation literature (Karlaftis & Vlahogianni, 2011). For classification problems, they found that feed-forward neural networks outperformed their statistical counterparts, being logit models, discriminant analysis, negative binomial regression and stepwise logistic regression in the majority of cases. Karlaftis and Vlahogianni (2011) commented that neural networks are inherently more flexible and adaptive, however a statistical method should be selected in preference to an ANN for a given problem only when one of the following four conditions is met:

- The statistical method solves the problem better than neural networks;
- There is a priori information on the functional relationship between variables;
- There is a need to verify the statistical properties of an underlying mechanism that produced the problem; or,

- Interpretation of results and their causalities is paramount.

For wetland assessments, the first three conditions do not apply and only the fourth condition could come into play. It is possible that the application of neural networks could be dismissed on the basis of their perceived novelty value in favour of statistical methods, which have broader acceptance and proven mathematical foundations. This research dispels this misconception; neural networks can successfully identify high-value wetlands and they can do so for unseen data despite being trained on a limited number of examples. To find causalities, that is the most significant inputs linked to high-value outcomes, sensitivity analyses were examined and trends across multiple runs analysed. Therefore, neural networks are a flexible and suitable tool for classifying high-value wetlands.

The application of neural networks to predict water-resource variables and in particular forecast water quantity and quality variables of rivers has been gaining momentum over the last fifteen years (Maier & Dandy, 2000a & 2000b; Maier et al., 2010). The more recent incorporation of neural networks into widely used statistical packages, such as SPSS, helps provide easy and cheap access to those willing to experiment with this computing algorithm. Govindaraju and Ramachandra (2000) argue that the earlier relatively slow adoption of neural networks, at least amongst hydrologists, can be accounted for by the limited record of earlier successful ANN applications, together with the predisposition of hydrologists to look for physics-based approaches that helped explain the hydrologic cycle, which has meant that hydrologists have tended to shy away from the black-box nature of neural networks. The more recent introduction of sensitivity analyses, and other like tools, to neural networks can account for their increased uptake amongst hydrologists, and biologists alike.

7.5 Overall findings and their implications

Undertaking wetland assessment is extraordinarily difficult. It is difficult to assess the character of a wetland and its value, and to take account of threats likely to negatively affect the services a wetland provides (Breckenridge et al., 1995; Lui et al., 2006;

Ticehurst et al., 2007). The first step is to identify suitable input variables that capture wetland characteristics, which at the same time are useful in discriminating between high-value wetlands and those less so (Goosen et al., 2007; Spencer et al., 1998). In my research, I examined wetland assessment practice in West Gippsland and investigated the contribution, and potencies, of component biological, chemical, hydrological and physical data inputs, individually and collectively, to the identification of high social, economic and environmental value wetlands, through analyses using univariate and multivariate statistics and neural networks.

Specifically, my research has shown that:

- Much can be learnt about the practice of assessment, and the nature of the wetlands being assessed, through the systematic application of statistical and computing techniques to inventory data collected during the assessment;
- Inventory datasets contain a wealth of useful information for organisations that collect them. Datasets, like the WGCMA Wetlands Inventory Database, rarely have their full potential explored or undergo thorough interrogation. This is an ongoing concern in Australia, where the public assumes that environmental data collection and monitoring activities provide effective feedback to natural resource managers, and the reality has been otherwise (Morton et al., 2009);
- In practice, relatively few attributes are needed to discern the value of a wetland, particularly high-value wetlands. For any wetland assessment, the identity of these critical attributes can be discovered by applying traditional univariate statistical approaches to inventory data. In the case of the assessment undertaken by the WGCMA in 2006, the use of simple absence/presence data for relatively small number of inputs were successful in deciding wetland values. The specific inputs of a minimal dataset to guide data collection, the attributes and their values, are given in Table 7.1 for Economic, Social and Environmental value assessments, and summarised in Table 7.2. Table 7.3 summarizes threat category inputs;
- More complex relationships between input data and the classification and value of a wetland can be uncovered using binary logistic regression, a traditional and often used multivariate statistics technique. This approach is

able to handle the types of data inputs used in wetland assessments (categorical and non-categorical) and it returns the likelihood probability that a wetland is high-value, or not, expressed as a function/equation of the inputs. Within the equation, the coefficient of each input is a measure of the degree to which the input decides the likelihood of a high-value assessment; the analysis of the magnitudes and signs of the coefficients of all inputs is a good indicator of potency of attributes used in the assessment. For the WGCMA assessment, binary logistic regression models were able to determine which inputs predicted high-value assessments. Overall it was seen that much of the infield data collected during inventory was superfluous to the core task of making the assessment of wetland value;

- The use of threat categories in assessments is, however, problematic. There are difficulties around deciding which particular threat categories are to be assessed in the field and how their measure is to be taken. As well, the decision to include a threat category has a multiplicative effect on the number of risk assessments that need to be calculated for each wetland assessment. This research has shown many threat categories used in assessment were not useful in recognizing high-value wetlands (Section 6.5 and Table 7.3) and in particular, it was unnecessary to collect threat data or undertake arduous risk assessments to ascertain Economic and Social values classifications, as argued in discussion (Section 5.5 and Section 6.5). Additionally, four threat categories, denoted with * in Table 7.3, were useful in recognizing high-value wetlands in this research but not used in the WGCMA assessments of subcatchment wetlands; these categories were used to assess wetlands already identified as significant. In hindsight, it seems incongruous that two different sets of threat categories were used, one set for significant wetlands and another set for subcatchment wetlands. This research supports the application of a common set of threat categories, based on the Table 7.3 listing, for use in future assessments of significant and subcatchment wetlands;

- Using only absence/presence values for data inputs in the statistical and computing techniques used in this research, I was able to correctly predict at least 90% of assessments for Economic, Social and Environmental values. Therefore, considerable time in inventory collection and desk processing could be saved by reducing the infield collection of attributes to absence/presence values rather than using various grades to indicate presence as was done by the WGCMA;

- In retrospect, it seems futile to have conducted Economic value assessments in the West Gippsland region, given the outcome of the 2006 assessment was a solitary high-value wetland. In the future, it is likely that political imperatives will dictate that Economic value assessments be undertaken as a component of the widely accepted triple-bottom-line method of ranking wetlands (Section 2.4.3). In this case, it is not necessary to undertake the costly data collection for threat values, rather onsite sampling should be restricted to the collection of three values listed in Table 7.3: drainage disposal; production value; and, water supply. The absence/presence values for contributing attributes for these values can achieve an overall 91% prediction rate for Economic value assessments without the need to incorporate threat values or undertake risk assessment computations (Table 6.11);

- The use of two contrasting wetland classification schemes, in of themselves, did not directly affect the West Gippsland wetland assessments. Instead, the physical presence of individual attributes, like specific vegetation types used in Corrick and Norman (1980) scheme and EVCs, were indicators of high-value assessments (Section 5.5 and Section 6.5). This is particularly true for the presence of sedges, as evidenced by their inclusion in all BLR models and ANN constructions (Tables 6.12a, 6.12b and 6.12c);

- The only exception to the previous conclusion is the special case for deciding high-value semipermanent saline wetlands and permanent saline wetlands. There is evidence that the current attributes used to evaluate Environmental value are biased towards freshwater types and they do not adequately capture the saline characteristics of these wetlands (Section 6.5 and Section 7.3);

- Neural networks are an effective tool for classifying wetland types, particularly for their ability to recognize high-value wetlands (Table 6.11 and Section 7.2). On equivalent data inputs, neural networks outperformed binary logistic regression models in most instances, with the main difficulty being selection of a network that did not over-fit the dataset (Section 6.5);

- If neural networks are to be used in the future, it is necessary to undertake multiple constructions and run sensitivity analyses for neural networks in order to establish the number and identity of the most suitable inputs for the wetland value being assessed (Section 6.1.2). In contrast, binary logistic regression models offer the comfort of a single and repeatable solution which is given as a best fit equation that describes the multiplicative relationship of input variables to the odds ratio of a high-value assessment (Section 5.1); and,
- The main benefit in using neural networks is their predictive ability; they can be trained on one dataset and perform to a similar ability on unseen data collected for the same purpose (Section 6.2.4, Section 6.3.4, Section 6.4.4 and Section 7.4). This potential means that assessments can be reliably carried out for wetlands not part of the inventoried sample or into the future as part of monitoring efforts for West Gippsland's wetlands.

7.6 Implications and recommendations for wetland assessments

Wetlands assessment is a complex procedure. It can be expensive, labour intensive and time consuming, and the process often must be tailored to its local context. Whilst acknowledging the inherent difficulty of the task, my research has identified a number of salient features of high potency for predicting high-value wetlands in the West Gippsland region. Other than for saline wetland types, I found little evidence that the Corrick and Norman (1980) wetland classification scheme or EVCs impacted the evaluation and ranking of wetlands during the WGCMA assessment. My research has shown that it is possible to quite accurately describe wetland assessments using binary logistic regression (BLR) modelling. Furthermore, as an alternative mechanism for classifying wetlands neural networks (ANNs) were better than BLR models in discerning high-value wetlands. The worth of ANNs to make wetland assessments for unseen data was demonstrated.

Many of the conclusions reached in this research have implications for future wetland assessments and monitoring efforts in West Gippsland. The recommendations are:

- Restrict infield data collection to assessing the absence or presence of attributes at a site;
- For Economic value assessment, forgo Economic value assessment if possible. If not, reduce data collection and assessment to production value, drainage disposal and water supply and their attributes listed in Table 7.1. Do not collect threat data values or undertake risk assessment evaluations;
- For Social value assessment, reduce data collection and assessment to bird watching, boating, camping, park value and passive recreation and their attributes listed in Table 7.1. There is no need to collect threat data or do risk assessments to evaluate Social value;
- For Environmental value, undertake risk assessment calculations and evaluations using absence/presence values for the following Environmental values of habitat value, significant fauna, vegetation intactness, wetland rarity, and width of vegetation fringe;
- For Environmental value, consideration should be given to deciding a suitable attribute or set of attributes to better describe semipermanent saline wetlands and permanent saline wetlands for future wetland assessments; and,
- For threat categories, collect absence/presence data for the following threat categories of: altered hydrology; drainage into wetland; erosion; lack of reservation; pest plants; resource utilization; sedimentation; salinity; and, water source. These threat categories should be used only in risk assessments for Environmental value assessment alone.

In conclusion, this research has shown that the use of sophisticated, yet cheap and easily accessible, statistical and computing approaches can offer valuable insights into the process of wetland assessments. For other wetland assessments, the value in undertaking analyses using multivariate statistics and neural networks, separately or in unison, is that these methods can be used to identify the unique combination of attributes that describe high-value wetlands, without being constrained by categorical data as inputs. A wetland assessment should commence on a representative subset of the targeted wetlands. Data should be collected for these sites across a broad range of attributes and the assessment carried out using traditional methods. Next, a systematic analysis of the outcomes using multivariate statistics, or neural networks, or both, can be used to elucidate the most significant inputs that align to high-value assessments. This strategic step will supply a minimal set for further data collection and assessments. Refining the assessment practice in this manner will indicate possible efficiencies in the assessment effort that may be applied across the entire wetlands set. Either the statistical models built or the resultant trained neural networks can be used to accurately decide wetland classifications for the remaining wetlands at reduced effort and cost. Additionally, the steps of this approach can also be incorporated as part of ongoing monitoring efforts.

In the thesis, the techniques of binary regression modelling and neural networks were described in considerable detail in order that others could follow in their use. For any locale, the application of this approach on inventory data would be extremely useful to resource managers. The mechanism would illuminate possible efficiencies to be made in undertaking wetland assessments and it would provide an important feedback on the contributions made by differing inputs to the wetlands assessments process.

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Appendix A
Wetland values

Wetlands are valuable for the variety of services they provide (Mitsch & Gosselink, 2000 & 2007). Amongst other things, wetlands protect water and food supplies, sustain indigenous groups and cultural values, provide flood and coastal protection, and harbour biodiversity (Finlayson & Weinstein, 2008; Williams, 1994). The combined physical, biological and chemical components of different types of wetlands, combined as a group, generate a number of products and provide for several functions. A description of some of the products that wetlands supply is given in Table A.1 and some of the functions supplied by wetlands are listed in Table A.2. Table A.3 gives details of attributes of wetlands. All tables are a summary of material supplied by Dugan (1990, p.15) and other authors.

Table A.1: Wetland products as described by Dugan (1990) and others.

Wetland Values: Products	**Description**
Forest resources	Includes fuel wood, timber, bark, resins and medicines.
Wildlife resources	Includes meat, honey, skins, eggs of birds and turtles, shelter for threatened and endangered species.
Fisheries	Two-thirds of the world's fish depend upon wetlands for some part of their life-cycle.
Forage resources	Important grasslands and trees are grazed by livestock.
Agricultural resources	Intensive agriculture e.g. rice paddies.
Water supply	Used for human consumption, agriculture, watering livestock and industrial supply.
Energy resource	Peat-lands and other products are harvested to provide energy on a regular basis.

Table A.2: Wetland functions as described by Dugan (1990) and others.

Wetland Values: Functions	**Description**
Groundwater recharge	Wetlands feed down into underground aquifers and purify the water.
Groundwater discharge	Underground water moves upward into wetland and becomes surface water.
Flood control	By storing precipitation and releasing runoff more evenly, diminish the effect of destructive floods.
Shoreline stabilisation and erosion control	Stabilise shorelines by reducing the energy of waves, currents and other erosive forces and holds sediment in place with roots.
Sediment and toxicant retention	Sediment can settle in wetland basins helping maintain quality of ecosystems downstream and toxicants adhere to suspended sediment so protect downstream. Dugan (1990) hypothesized that wetlands reduce sediment in streams by as much as 90% lower in river basins, and by 40% in lakes compared to areas without wetland habitats.
Nutrient retention	Nitrogen and phosphorus accumulate in sub-soil and wetland vegetation. Wetlands act as sinks and sources and the cycle between each has important implications for algal growth, water quality, fish production, and recreation downstream, as it prevents eutrophication conditions.
Biomass export	Biomass export through supporting dense populations of fish, forage resources for cattle or wildlife e.g. migratory waterfowl.
Micro-climate stabilisation	Particularly rainfall and temperatures on local climatic conditions.
Storm protection and windbreaks	Particularly mangroves and forested coastal wetlands help dissipate the force and lessen the damage of coastal storms.
Water transport	Carrying goods and public transport for local communities.
Recreation and tourism	Includes sport hunting, fishing, bird-watching, nature photography, swimming, and sailing.

Table A.3: Wetland attributes as described by Dugan (1990) and others.

Wetland Values: Attributes	**Description**
Biological diversity	Genetic reservoir as many wetlands support significant diversity of animals, of which many are endemic or endangered.
Uniqueness to culture and heritage	Scenic and wildlife values or cultural association attract peoples to a wetland region.
Historical records	Wetland archaeology provides evidence from which the palaeoenvironmental history of a wetland can be gleaned. Cultural evidence of human activities through artefacts and actual bodies is often found.

Further, it is possible to categorize the types of values of wetlands, as values which supply biological, hydrological, economic, and social services.

Biological services

Wetlands are credited as being amongst the "most biologically productive natural ecosystems in the world" (Vriesinga, 2008, p.174). Collectively, the set of natural habitats found in wetlands offer an immense variety of niches for both terrestrial and water-based wildlife, being molluscs, crustaceans, arthropods, reptiles, fish, frogs, birds and mammals, including dolphins and porpoises. In fact, there are approximately 10,000 freshwater fish species inhabiting wetlands (Millennium Ecosystem Assessment, 2005).

Wetlands have been likened to the world's rainforests, in that, they harbour great biodiversity, estuarine wetlands protect endangered species and they are estimated to be four times as productive as temperate grasslands (National Parks Association of NSW, 1988). In Australia, nearly 20% (117 of 656) bird species depend on wetlands, with some species relying on different wetlands for breeding and feeding (Kingsford, 1997). Australian wetlands form part of an international network of migratory bird habitat for millions of waterbirds and several waterbird species (mainly *Charadriiformes*, spoonbills and bitterns) migrate annually after breeding season from the Northern Hemisphere to Australia.

At a smaller scale, phytoplankton, attached and microscopic algae and macrophytes are the sources of primary production in Australian wetlands (Boon & Bailey, 1997) with microinvertebrates including protozoans (ciliates, flagellates and amoebae) and zooplankton (microcrustaceans and rotifers) occurring as well. Bacteria are an often not recognized important food source for other aquatic organisms, yetthey play a major role in metabolising dissolved organic carbon found in the detritus (Boulton & Brock, 1999). Macroinvertebrates are represented by mostly insects of the order Odonata (dragonflies and damselflies), Ephemeroptera (mayflies), Hemiptera (true bugs), coleopteran (true beetles), Diptera (two-winged flies) and Trichoptera (caddis flies) (Boulton & Jenkins, 1997; Boulton & Brock, 1999). The representations and proportions of types are dependent on whether the wetland under study is standing or running water, and more details are given in Boulton and Brock (1999).

Hydrological services

Powered by solar energy and gravity, water is continually cycled between the atmosphere, the oceans and land. Globally, an imbalance occurs where evaporation from oceans fuels greater precipitation rates on land, allowing the existence of rivers and ground runoffs. In Australia, evaporation rates are high; on average 11 % of precipitation makes river runoff and 1% (4mm average) becomes groundwater recharge (Boulton & Brock, 1999, p.14).

The main freshwater supply for human use comes from inland wetlands and groundwater recharged from wetlands (Millennium Ecosystem Assessment, 2005). Aquifers, which supply towns and farms, are recharged from water entering from wetlands at the heads of rivers and along the floodplains and swamps. Flood mitigation is provided by the storage of runoff and its subsequent slow release to ecosystems. Water clarity and purity are improved by the ‘filtering’ services provided by marshes and it known that coastal and estuarine plants slow water velocities and permit fallout of fine sediment (National Parks Association of NSW, 1988).

Social services

Aesthetically, humans are attracted to wetland areas for a variety of social and recreational activities. These include swimming, boating, canoeing, walking, picnicking, photographing, diving, fishing, hunting and bird-watching (Bennett, 1997). For instance, waterfowl, ducks and geese have been hunted for recreation in several Australian states (Kingsford, 1997).

Many sites provide good educational opportunities for students to learn about terrestrial, freshwater and marine ecosystems and their associated biodiversity.

Wetland archaeology shows that people have often resided near and in wetlands to tap easily obtainable food resources (Bayliss-Smith, 1996; Coles, 1994; van Andel & Runnels, 1995). For example, in the Northern Territory of Australia, aboriginal peoples have traditionally harvested magpie geese (*Anseranas semipalmata*) and their eggs, and, in Cambodia 60-80% of total protein consumed by humans comes from the fishery in Tonle Sap and its associated floodplains (Dexter & Bayliss, 1991; Millennium Ecosystem Assessment, 2005). As many populations rely on wildlife resources harvested from wetlands, it seems natural that over time, important sites can come to have social and ceremonial importance in local cultures.

Economic services

In their extensive analyses of 167 wetland studies worldwide, Ghermandi et al. (2008) listed the economic services of several wetland types to include commercial fishing and hunting, harvesting of natural materials, recreational values, biodiversity, and hydrological services. As Gedan et al. (2009) note, wetlands provide many economic services, including those that are marketable and others that are more difficult to quantify. Fishing is one example of a marketable service with two thirds of the fish eaten in the world being dependent upon wetlands for some stage in their life cycle (Dugan, 1990). Further, indirect food benefits can come about through the provision of regular water supplies or through wetland birds, such as ibis, controlling locusts and other agricultural pests (Cook, Stearne & Williamson, 2003; National Parks Association of NSW, 1988).

Importantly, “many services delivered by wetlands are not marketed (such as flood mitigation, climate regulation, groundwater recharge, and prevention of erosion) and accrue to society at large at local and global scales” (Millennium Ecosystem Assessment, 2005, p.46). As noted by Gardiner (1994), wetlands collectively make a significant contribution to global homeostasis. Growing concern about rising sea levels worldwide, spotlights the roles of the Arctic tundra and floodplain forest of the Amazon, amongst others, as a carbon sinks to buffer against the effects of global warming (Gardiner, 1994; Williams, 1994). In 1989, Heron scoped the probable effect of greenhouse gases on sea levels and weather changes in the state of Victoria, in Australia. There, she concluded, coastal wetlands would be impacted due to altered water tables which would cause the creation of larger, more saline wetlands than currently existed at the time of her study (Heron, 1989).

Much development and modification of wetlands occurs in the name of short-term economic gain. Non-marketable wetland goods and services are so often taken for granted that “much wetland loss is the result of ignorance of the true value of the resources concerned, or of how certain actions lead directly or indirectly to wetland loss” (Dugan, 1990, p.6). There are often conflicting interests between landowners and the general public and between developers and conservationists in deciding the ‘wise use’ and sustainable development of any wetland (Votteler & Muir, 2002).

Appendix B

Ramsar classification system for wetland types

The material in this Appendix has been sourced directly from "The Ramsar Convention on Wetlands" website, and from the "Ramsar Classification system for Wetland Type" web page, found at http://www.ramsar.org/cda/en/ramsar-documents-info-information-sheet-on/main/ramsar/1-31-59%5E21253_4000_0__#type.

Here, it is reproduced verbatim.

Annex I

Ramsar Classification System for Wetland Type

The codes are based upon the Ramsar Classification System for Wetland Type as approved by Recommendation 4.7 and amended by Resolutions VI.5 and VII.11 of the Conference of the Contracting Parties. The categories listed herein are intended to provide only a very broad framework to aid rapid identification of the main wetland habitats represented at each site.

To assist in identification of the correct Wetland Types to list in section 19 of the RIS, the Secretariat has provided below are tabulations for Marine/Coastal Wetlands and Inland Wetlands of some of the characteristics of each Wetland Type.

Marine/Coastal Wetlands

A-- **Permanent shallow marine waters** in most cases less than six metres deep at low tide; includes sea bays and straits.
B -- **Marine subtidal aquatic beds**; includes kelp beds, sea-grass beds, tropical marine meadows.
C -- **Coral reefs**.
D -- **Rocky marine shores**; includes rocky offshore islands, sea cliffs.
E-- **Sand, shingle or pebble shores**; includes sand bars, spits and sandy islets; includes dune systems and humid dune slacks.
F -- **Estuarine waters**; permanent water of estuaries and estuarine systems of deltas.
G -- **Intertidal mud, sand or salt flats**.
H -- **Intertidal marshes**; includes salt marshes, salt meadows, saltings, raised salt marshes; includes tidal brackish and freshwater marshes.
I -- **Intertidal forested wetlands**; includes mangrove swamps, nipah swamps and tidal freshwater swamp forests.
J -- **Coastal brackish/saline lagoons**; brackish to saline lagoons with at least one relatively narrow connection to the sea.
K -- **Coastal freshwater lagoons**; includes freshwater delta lagoons.
Zk(a) - Karst and other subterranean hydrological systems, marine/coastal

Inland Wetlands

L -- Permanent inland deltas.
M-- Permanent rivers/streams/creeks; includes waterfalls.
N -- Seasonal/intermittent/irregular rivers/streams/creeks.
O -- Permanent freshwater lakes (over 8 ha); includes large oxbow lakes.
P -- Seasonal/intermittent freshwater lakes (over 8 ha); includes floodplain lakes.
Q -- Permanent saline/brackish/alkaline lakes.
R -- Seasonal/intermittent saline/brackish/alkaline lakes and flats.
Sp -- Permanent saline/brackish/alkaline marshes/pools.
Ss -- Seasonal/intermittent saline/brackish/alkaline marshes/pools.
Tp -- Permanent freshwater marshes/pools; ponds (below 8 ha), marshes and swamps on inorganic soils; with emergent vegetation water-logged for at least most of the growing season.
Ts -- Seasonal/intermittent freshwater marshes/pools on inorganic soils; includes sloughs, potholes, seasonally flooded meadows, sedge marshes.
U -- Non-forested peatlands; includes shrub or open bogs, swamps, fens.
Va -- Alpine wetlands; includes alpine meadows, temporary waters from snowmelt.
Vt -- Tundra wetlands; includes tundra pools, temporary waters from snowmelt.
W -- Shrub-dominated wetlands; shrub swamps, shrub-dominated freshwater marshes, shrub carr, alder thicket on inorganic soils.
Xf -- Freshwater, tree-dominated wetlands; includes freshwater swamp forests, seasonally flooded forests, wooded swamps on inorganic soils.
Xp -- Forested peatlands; peatswamp forests.
Y -- Freshwater springs; oases.
Zg -- Geothermal wetlands
Zk(b) - Karst and other subterranean hydrological systems, inland

Note: "**floodplain**" is a broad term used to refer to one or more wetland types, which may include examples from the R, Ss, Ts, W, Xf, Xp, or other wetland types. Some examples of floodplain wetlands are seasonally inundated grassland (including natural wet meadows), shrublands, woodlands and forests. Floodplain wetlands are not listed as a specific wetland type herein.

Human-made wetlands

1 -- A**quaculture** (e.g., fish/shrimp) **ponds**
2 -- **Ponds**; includes farm ponds, stock ponds, small tanks; (generally below 8 ha).
3 -- **Irrigated land**; includes irrigation channels and rice fields.
4 -- **Seasonally flooded agricultural land** (including intensively managed or grazed wet meadow or pasture).
5 -- **Salt exploitation sites**; salt pans, salines, etc.
6 -- **Water storage areas**; reservoirs/barrages/dams/impoundments (generally over 8 ha).
7 -- **Excavations**; gravel/brick/clay pits; borrow pits, mining pools.
8 -- **Wastewater treatment areas**; sewage farms, settling ponds, oxidation basins, etc.
9 -- **Canals and drainage channels, ditches**.
Zk(c) - Karst and other subterranean hydrological systems, human-made

Tabulations of Wetland Type characteristics

Marine / Coastal Wetlands:

<table>
<tr><td rowspan="5">Saline water</td><td rowspan="3">Permanent</td><td>< 6 m deep</td><td>A</td></tr>
<tr><td>Underwater vegetation</td><td>B</td></tr>
<tr><td>Coral reefs</td><td>C</td></tr>
<tr><td rowspan="2">Shores</td><td>Rocky</td><td>D</td></tr>
<tr><td>Sand, shingle or pebble</td><td>E</td></tr>
<tr><td rowspan="5">Saline or brackish water</td><td rowspan="3">Intertidal</td><td>Flats (mud, sand or salt)</td><td>G</td></tr>
<tr><td>Marshes</td><td>H</td></tr>
<tr><td>Forested</td><td>I</td></tr>
<tr><td colspan="2">Lagoons</td><td>J</td></tr>
<tr><td colspan="2">Estuarine waters</td><td>F</td></tr>
<tr><td>Saline, brackish or fresh water</td><td colspan="2">Subterranean</td><td>Zk(a)</td></tr>
<tr><td>Fresh water</td><td colspan="2">Lagoons</td><td>K</td></tr>
</table>

Inland Wetlands:

Fresh water	Flowing water	Permanent	Rivers, streams, creeks	M
			Deltas	L
			Springs, oases	Y
		Seasonal/intermittent	Rivers, streams, creeks	N
	Lakes and pools	Permanent	> 8 ha	O
			< 8 ha	Tp
		Seasonal/intermittent	> 8 ha	P
			< 8 ha	Ts
	Marshes on inorganic soils	Permanent	Herb-dominated	Tp
		Permanent/ Seasonal/intermittent	Shrub-dominated	W
			Tree-dominated	Xf
		Seasonal/intermittent	Herb-dominated	Ts
	Marshes on peat soils	Permanent	Non-forested	U
			Forested	Xp
	Marshes on inorganic or peat soils	High altitude (alpine)		Va
		Tundra		Vt
Saline, brackish or alkaline water	Lakes	Permanent		Q
		Seasonal/intermittent		R
	Marshes & pools	Permanent		Sp
		Seasonal/intermittent		Ss
Fresh, saline, brackish or alkaline water	Geothermal			Zg
	Subterranean			Zk(b)

Appendix C

Significant wetlands of West Gippsland

This listing of significant wetlands has been sourced from the West Gippsland Catchment Management Authority: Wetlands Plan, Part A- Background and Method, 2007, Table 1, page 13.

<table>
<tr><th>Wetland name</th><th>Basin</th><th>Wetland of National Importance (Directory of Important Wetlands Australia – DIWA)</th><th>Wetland of International Importance (Ramsar)</th></tr>
<tr><td>Caledonia Fen</td><td>Thomson</td><td>Caledonia Fen</td><td rowspan="6"></td></tr>
<tr><td>Lake Tarli Karng</td><td>Thomson</td><td>Lake Tarli Karng</td></tr>
<tr><td>Billabong (Flora and Fauna Reserve)</td><td>Thomson</td><td>Billabong (Flora and Fauna Reserve)</td></tr>
<tr><td>Snipe Wetland</td><td>Latrobe</td><td>Lake Victoria Wetlands</td></tr>
<tr><td>Heart Morass</td><td>Latrobe</td><td rowspan="12">Lake Wellington Wetlands</td></tr>
<tr><td>Lake Kakydra</td><td>Thomson</td></tr>
<tr><td>Dowd Morass</td><td>Latrobe</td><td rowspan="11">Gippsland Lakes Ramsar Site</td></tr>
<tr><td>Sale Common</td><td>Thomson</td></tr>
<tr><td>Heart Morass (Wildlife Reserve)</td><td>Latrobe</td></tr>
<tr><td>Clydebank Morass</td><td>Thomson</td></tr>
<tr><td>Red Morass</td><td>Latrobe</td></tr>
<tr><td>Lake Victoria</td><td>Latrobe</td></tr>
<tr><td>Lake Betsy</td><td>Latrobe</td></tr>
<tr><td>Morley Swamp</td><td>Latrobe</td></tr>
<tr><td>Lake Coleman & Tucker Swamp</td><td>Latrobe</td></tr>
<tr><td>Lake Wellington</td><td>Thomson
Latrobe</td></tr>
<tr><td>Lake Reeve</td><td>Latrobe
South Gippsland</td><td></td></tr>
<tr><td>Jack Smith Lake</td><td>South Gippsland</td><td>Jack Smith Lake State Game Reserve</td><td></td></tr>
<tr><td>Corner Inlet</td><td>South Gippsland</td><td>Corner Inlet</td><td>Corner Inlet Ramsar Site</td></tr>
<tr><td>Shallow Inlet</td><td>South Gippsland</td><td>Shallow Inlet Marine and Coastal Park</td><td rowspan="4"></td></tr>
<tr><td>Anderson Inlet</td><td>South Gippsland</td><td>Anderson Inlet</td></tr>
<tr><td>Bald Hills Wetland</td><td>South Gippsland</td><td>Bald Hills State Wildlife Reserve</td></tr>
<tr><td>Powlett River Mouth</td><td>South Gippsland</td><td>Powlett River Mouth</td></tr>
</table>

Appendix D

WGCMA Wetland value scoring system

Original source of the following scales is found in Appendix 1 of the West Gippsland Wetlands Plan Part A- Background and Methods (WGCMA, 2007) reference.

Economic value ranking scale

Table D.1: Economic value ranking scale used in WGCMA wetland assessment process.

Economic value	0	1	2	3	4	5
Commercial fishing	No data	Not present		Eel or Carp access license/permit operating in wetland		Bay and Inlet Fisheries access licence operating in wetland
Tourism	No data	Not thought to be used by tourists		Informal use by tourists/seasonal activity	Formal use by tourists	Focus on tourism or event focused
Production value	No data	Non-agricultural	Lifestyle/hobby farming	Dryland/mixed grazing	Irrigation, high rainfall, broad acre cropping, mixed grazing or forestry	High productivity area-intensive irrigation or high rainfall dairy or intensive agriculture or urban residential.
Drainage disposal	No data	Does not receive drainage water from urban or agricultural sources		Yes receives stormwater, irrigation drainage or other agricultural discharge as well as water from other sources		Yes receives the majority of its water from stormwater, irrigation drainage or other agricultural discharge
Water supply	No data	Not part of a stock and domestic water supply system		Part of a stock and domestic water supply system OR not currently used for irrigation extraction (historic use)		Currently used to supply irrigation water

Social value ranking scale

Table D.2: Social value ranking scale used in WGCMA wetland assessment process.

Social value	0	1	2	3	4	5
Recreational fishing	No data	No recreational fishing	Occasional recreational fishing	Seasonal recreational fishing		Frequent recreational fishing
Swimming	No data	No swimming	Occasional swimming	Seasonal swimming location		Frequently used swimming location
Camping	No data	No camping	Occasional camping	Seasonal use for camping		Frequently used camping site
Hunting	No data	No hunting	Occasional hunting activity	Seasonal hunting activity		Frequently used for hunting
Boating	No data	No boating	Occasional boating activity	Seasonal boating activity		Frequent boating activity
Passive recreation	No data	No passive recreation	Occasional use for passive recreation	Seasonal use for passive recreation		Frequent use for passive recreation
Bird watching	No data	No bird watching	Occasional bird watching	Seasonal bird watching		Frequent bird watching
Education	No data	Not used for education purposes	Occasional use for educational purposes	Seasonal use for educational purposes		Frequent use for educational purposes
Park value	No data	Wetland not located in a park or on reserved crown land	Wetland located in a State forest or other reserved crown land	Wetland located in a nature conservation reserve, natural features reserve or historic and cultural features reserve (including those gazetted as a State Game Reserve)	Wetland located in a Regional or State Park, Coastal Park or a Marine and Coastal Park	Wetland located in a National Park, Reference Area or Wilderness are, Marine National Park, Marine Sanctuary or Marine Park

Environmental value ranking scale

Table D.3: Environmental value ranking scale used in WGCMA wetland assessment process.

Environmental value	**0**	**1**	**2**	**3**	**4**	**5**
Wetland rarity	No data	* Permanent open freshwater, Semi-permanent saline, Permanent saline		** Freshwater meadow, Shallow freshwater meadow	*** Deep freshwater marsh	**** Endangered or presumed Extinct wetland type
Significant flora	No data	No threatened species listed	Victorian conservation status poorly known	Victorian conservation status 'rare'	Victorian conservation status 'vulnerable'	Listed under EPBC Act or Victorian conservation status 'presumed extinct, critically endangered or endangered' OR listed as threatened in Victoria (FFG listed)
Significant fauna	No data	No threatened species listed		Victorian conservation status 'near threatened'	Victorian conservation status 'vulnerable'	As above
Habitat value		<50% applicable habitat components identified in wetland		>50%-90% applicable habitat components identified in wetland	>90% applicable habitat components identified as present in wetland	>90% applicable habitat components identified in wetland. At least 50% of those identified as abundant
Hydrology	No data	Significant shift in the seasonality of flooding. Change in flooding duration that leads to a change in permanency of the wetland		A change in the time of flooding but within the same season. Change in flooding frequency and/or duration but not great enough to lead to a significant change in permanency of the wetland		Little or no change in the wetland's flooding frequency, duration and seasonality

Table D.3: Environmental value ranking scale used in WGCMA wetland assessment process.

Vegetation intactness– Critical life form groupings	No data	All critical life-forms effectively absent (0)	>0-<50% of critical life-form groupings present (5) or >50%-90% critical life-form groupings present, of those present – at least 50% substantially modified (10)	>50%-90% critical life-form groupings present, of those present – less than 50% substantially modified (15)	>90% of critical life-form groupings present, of those present – at least 50% substantially modified	>90% of critical life-form groupings present, of those present – less than 50% substantially modified
Width of vegetation fringe	No data	0 m	>0m – 5m	>5m – 20m	>20m – 50m	>50m

* Least concern wetland type with > 50% pre-European area remains in Victoria

** Rare or depleted wetland type with 30-50% pre-European extent remains in Victoria or >50% pre-European extent remains in Victoria and moderately degraded

*** Vulnerable wetland type with 10-30% pre-European extent remains in Victoria

**** wetland type with <10% pre-European extent remains in Victoria or probably no longer present in Victoria

Threat category ranking scale

Table D.4: Threat category ranking scale used in WGCMA wetland assessment process.

Environmental value	0	1	2	3	4	5
Loss of wetland connectivity	No data	Threat absent		Identified as minor threat		Identified as a key threat
Stock access (grazing)	No data	Threat absent		Identified as minor threat		Identified as a key threat
Pest plants	No data	Total cover of weeds <5% and nil or <50% weeds cover make up of high threat weeds	Total cover of weeds 5-25% and nil weeds cover made up of high threat weeds, OR total cover of weeds <5%-25% and <50% or >50% weeds cover made up of high threat weeds	Total cover of weeds 25-50% and nil weeds or <50% of weed cover made up of high threat weeds, OR total cover of weeds <5%-25% and <50% or >50% weeds cover made up of high threat weeds	Total cover of weeds >50% and nil or <50% of weed cover made up of high threat weeds OR total cover of weeds 25-50% and >50% of weed cover made up of high threat weeds	Total cover of weeds in EVC >50% and >50% of weed cover made up of high threat weeds
Pest animals	No data	Threat absent		Identified as minor threat		Identified as a key threat
Urban development	No data	Threat absent		Identified as minor threat		Identified as a key threat
Altered hydrology	No data	Hydrologic modification activity absent	Hydrologic modification activity present- no impact	Wetland area/shape; moderate-low impact	Hydrological modification activity present-moderate impact	Hydrological modification activity-severe impact
Native vegetation decline	No data	Threat absent		Identified as minor threat		Identified as a key threat
Land use	No data	Reserve, covenant	Roadside, rail reserve	Urban, industrial or mixed dryland grazing	Plantations	Cropping, irrigated pasture, centre pivot, laser levelling

Table D.4: Threat category ranking scale used in WGCMA wetland assessment process.

Physical alteration	No data	Wetland area/shape activity absent	Wetland area/shape activity present- no impact	Wetland area/shape activity; moderate-low impact	Wetland area/shape activity; moderate impact	Activity leading to a change in wetland area and/or shape-severe impact
Erosion	No data	Threat absent		Identified as minor threat		Identified as a key threat
Fire regime	No data	Threat absent		Identified as minor threat		Identified as a key threat
Recreation	No data	Threat absent		Identified as minor threat		Identified as a key threat
Water source	No data	Wetland primarily filled by catchment runoff/groundwater/flooding		Wetland filled by combination of rainfall/groundwater/flooding and agricultural/irrigation/runoff and/or stormwater	Wetland filled primarily by diverted farm runoff (i.e. grazing)	Wetland filled primarily by irrigation runoff/urban stormwater
Salinity	No data	Depth to watertable >5m not identified as threat in Wetland Database	Depth to watertable >5m and identified as minor or key threat in Wetland Database	Depth to watertable 2-<5m and identified as minor or key threat in Wetland Database	Depth to watertable 2-<5m and identified as major threat in Wetland Database or depth to watertable <2m and/or identified as minor threat in wetland database	Depth to watertable <2m and/or identified as key threat in Wetland Database

Appendix E

WGCMA Wetland Inventory Documents

Original source of the following documents are Appendices 3 and 4 of Greening Australia (2006) and are given here with permission.

Field survey data sheets

West Gippsland Wetland Inventory July 2006

WEST GIPPSLAND WETLAND INVENTORY, FIELD SURVEY DATA SHEET

Wetland Details			
Assessor:			
Date:		**Time:**	
Sub-catchment:		**Catchment:**	
Wetland ID	**New (2005):**	**Old (1994):**	
Land Manager			
Address/Site Visit Directions			
Phone Number(s)			
Wetland Photo Point	**Easting:**	**Northing:**	
	Accuracy if more than 5 m:		
Physical Features			
Wetland Size (Ha)			

		Indicate %
Inundation Status	Dry soil	
	Damp / waterlogged soil	
	Water	
	Unknown	

Wetland Type				
		Flooded River Flat		Permanent Open Freshwater
		Freshwater Meadow		Semi-permanent Saline Wetland
		Shallow Freshwater Marsh		Permanent Saline Wetland
		Deep Freshwater Marsh		

Wetland EVC			% of wetland			% of wetland
Species observations:		11 Coastal Lagoon Wetland			656 Brackish Wetland	
		12 Wet Swale Herbland			721 Fern Swamp	
		125 Plains Grassy Wetland			723 Forest Bog	
		13 Brackish Sedgeland			728 Forest Creekline Sedge Swamp	
		136 Sedge Wetland			767 Plains Grassy Wetland/Brackish	
		172 Floodplain Wetland Aggregate			8 Wet Heathland	
		185 Perched Boggy Scrubland			809 Floodplain Grassy Wetland	
		210 Sub-alpine Wet Heathland			810 Floodway pond herbland	
		306 Aquatic Grassy Wetland			819 Spike Sedge Wetland	
		308 Aquatic Sedgeland			821 Tall Marsh	
		318 Montane Swamp			875 Blocked Coastal Stream Swamp	
		334 Billabong Wetland			883 Sedge Wetland/Calcereous	
		537 Brackish Aquatic Herbland			917 Sub-alpine Wet Sedgeland	
		538 Brackish Herbland			918 Submerged Aquatic Herbland	
		539 Brackish Lake Bed Herbland			932 Wet Verge Sedgeland	

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		591 Calcereous Wet Herbland			949 Dwarf Floating Aquatic Herbland	
		606 Cane Grass Wetland/ Brackish			963 Sedge Wetland/Aquatic Sedge Wetland	
		647 Plains sedgy Wetland			968 Gahnia Sedgeland	
		648 Saline Lake Verge Aggregate			976 Coastal Ephemeral Wetland	
		653 Aquatic Herbland			990 Unvegetated	

Substrate

	Clay	Silt	Sand	Gravel	Rock	Peat
33-main component of substrate 3- secondary component of substrate.						
Other – list:						

Water Quality

PH	
Electrical Conductivity (uS/cm)	
Turbidity (NTU)	

Hydrology

		Absent	Severe	Moderate	No Impact
Hydrological Modification Activity (Assessment should be verified in interview)	Water storage, regulation and water extraction from the river (floodplain wetlands only)				
	Disposal of water into wetland (eg stormwater, saline water)				
	Drainage and/or extraction of water directly from the wetland				
	Obstruction or regulation of natural water inlets and outlets (not associated with maintaining reference condition)				
	Redirection of natural flow (surface water and/or groundwater)				
Activity leading to a change in wetland area and/or shape (Assessment should be verified in interview)	Dam/levee/regulators that permanently affects the maximum inundation level				
	Channels/drains that permanently affects the maximum inundation level				
	Excavation/deep vehicle tracks				
	Filling/raised bed cropping				
	Other (state):				

Flora Diversity

Assessment of Dominant Wetland EVC	Critical Lifeforms Present:	% Cover of the critical lifeform	Is critical lifeform substantially modified?	Number of species present in critical lifeform:
	1		Y / N	
	2		Y / N	
	3		Y / N	
	4		Y / N	
	5		Y / N	

Weediness		
Assessment of Dominant Wetland EVC	High threat weeds present in EVC identified in the benchmark	Proportion of weed cover that is high threat weeds (%):
	1	
	2	
	3	
	4	
	5	
	Other weeds present in EVC	
	1	4
	2	5
	3	6
	Proportion of weed cover in EVC (%):	

Fauna Diversity			
Fauna present (O=Observed; C=Heard call; T=Saw tracks; P=Photographed; S=Scats; N=Nest/burrow; L=Characteristic scratchings; H=Other(specify))			
1		9	
2		10	
3		11	
4		12	
5		13	
6		14	
7		15	
8		16	

Terrestrial EVC	
Width of vegetation fringe (average) (m)	

	997 Cleared/Agricultural		132_61 Latrobe Valley Plains Grassland
	1 Coastal dune scrub/Coastal Dune Grassland Mosaic		134 Sand Forest
	2 Coast Banksia Woodland		136 Sedge Wetland
	3 Damps Sands herb rich woodland		140 mangrove Shrubland
	6 Sand heathland		141 Sandy Flood Scrub
	7 Clay heathland		151 Plains Grassy Forest
	8 Wet Heathland		155 Bird Colony Succulent heathland
	9 Coastal saltmarsh		160 Coastal Dune Scrub
	10 Estuarine Wetland		161 Coastal heathland Scrub
	11 Coastal Lagoon Wetland		163 Coastal Tussock Grassland
	12 Wet Swale herbland		164 Creekline Herb-Rich Woodland
	16 Lowland Froest		172 Floodplain Wetland Complex
	17 Riparian Scrub/Swampy Riparian Scrub Complex		175 Grassy Woodland
	18 Riparian Froest		191 Riparian Scrub

	19 Riparian Scrubland		259 Plains Grassy Woodland/Gilgai Wetland Mosaic
	23 herb-Rich Foothills Forest		300 Reed Swamp
	29 Damp forest		309 Calcareous Swale Grassland
	30 wet Forest		334 Billabong Wetland
	32 Warm Temperate Rainforest		641 Riparian Woodland
	45 Shrubby Foothill Forest		651 Plains Swampy Woodland
	47 Valley Grassy Forest		653 Aquatic herbland
	48 Heathy Woodland		656 Brackish Wetland
	53_61 Swamp Scrub		674 Sandy Stream Woodland
	53_62 Estuarine Swamp Scrub		681 Deep Freshwater Marsh
	55 Plains Grassy Woodland		710 Damp heathland
	56 Floodplain Riparian Woodland		793 Damp heathy Woodland
	59 Riparian Thicket		863 Floodplain Reedbed
	61 Box ironbark Forest		875 Blocked Coastal Stream Swamp
	68 Creekline Grassy Woodland		876 Spray-zone Coastal Shrubland
	74 Wetland Fromation		878 Damp Sands Herb-rich Woodland/Swamp Scrub Complex
	82 Riverine Escarpment Scrub		879 Coastal Dune Grassland
	83 Swampy Riparian Woodland		914 Estuarine Flats Grassland
	125 Plains Grassy Wetland		Brackish Grassland
	126 Swampy Riparian Complex		937 Swampy Woodland

Habitat Value

		Abundant	Present	Absent
Within Wetland Extent	Presence of permanent deep water / pools			
	Presence of shallow - medium water			
	Presence of exposed substrate			
	Presence of submerged / free-floating vegetation			
	Presence of emergent vegetation			
	Presence of edge vegetation			
	Logs			
	Rocks			
	Other (specify):			
Terrestrial Zone	Shrubs			
	Trees – alive			
	Trees – dead			
Shoreline profile		Regular	Irregular	Islands
	Shoreline profile			

Heritage Value		YES	NO	Comment
	Indigenous cultural value			
	Post-Settlement Cultural heritage value			

Threats (Note: This should be confirmed during your discussion with the land manager)	No	Present as a key threat	Present as a minor threat	Comment
Loss of wetland connectivity				
Inappropriate grazing practices				
Lack of reservation				
Exotic flora				
Introduced fauna				
Eutrophication				
Salinity				
Erosion				
Change in size since European settlement				
Surrounding land practices				
Native vegetation decline				
Altered hydrology				
Physical alteration				
Fire regime				
Resource utilization (other than grazing)				
Sedimentation				
Inappropriate recreation				
Drainage into wetland				

Urban development				
Other :				

Field procedure notes

Field Procedure - Notes for completing Field Survey Form

General note: Data collected for this inventory is baseline data and is not required to be overly time consuming to collect.

- Aim to spend less than 1.5 hours surveying the wetland and less than 0.5 hours for the landholder interview.
- Use lead pencil or other water resistant ink when filling out field survey sheets and annotating field maps.

Assessor:	Name of person undertaking the wetland survey
Date/Time:	State the day/month/year and time the survey was begun to the nearest half hour.
Wetland ID	List the new and old wetland identifiers– both are available from the wetland list provided. The new identifier was created as part of the WG 2005 mapping project and is a combination of part of the easting and northing for the centre of the wetland in GDA94 datum. The old identifier was created as part of the 1994 statewide mapping and was similarly constructed. It is used in the Statewide Wetland database and refers to an ADG66 datum coordinate. Newly mapped wetlands will not have an old identifier.
Land Manager	State the land manager. Can be private/public landmanager.
Address/Site Visit Directions	Physical/location address of property and/or any directions that are relevant for getting there.
Phone Number(s)	List any relevant phone numbers or other methods for contacting the land manager.
Wetland Photopoint	Following an appraisal of the wetland (walk around/familiarisation) establish one photopoint in a central location. Take one GPS reading from the photopoint location and record the easting and northing for this. If the GPS reading has an accuracy of more than 5 m, record the accuracy for the photopoint. Take two photographs from this location. Ideally the photos will be in opposite directions and will capture the majority of the wetland. Note the location of the photopoint on the map and the directions (by arrows) in which you took your photos.
Wetland Size	Convey the wetland size from the wetland sample list. Confirm the approximate wetland size in the field by observing the general shape of the wetland, compared with the mapped polygon/aerial photograph. The actual wetland extent will be determined via vegetation.
Inundation Status	Record the inundation status of the wetland by estimating the percentage of the whole wetland covered by dry soil, damp or waterlogged soil and water, to the nearest ten per cent.
Wetland Type	Record the Wetland Category from the wetland sample list to the field sheet. Reassess in the field utilising the Corrick and Norman definition if possible.
Wetland EVC	There is no comprehensive mapping of wetland EVCs in Victoria and some of the current EVC mapping that includes wetland EVCs is not in line with the EVC typology. Once potential EVCs have been determined for a wetland with the aid of landscape profile diagrams, the defining characteristics and indicator species for those EVCs can be checked to confirm identification of the EVC or EVCs present at the wetland.

	Use IWC vegetation assessment wetland habitat, sub-habitat lists to assist in identifying likely EVC's. Also use indicator plants, Matt's EVC list and own plant and wetland EVC knowledge to choose the most likely wetland EVC to allocate to the wetland. You may choose more than one wetland EVC type and assign a percentage to each or choose an aggregate EVC for the entire wetland. For assessment of flora diversity and weediness, you will only assess the dominant EVC type.
Substrate	Substrate is the soil plus organic material which make up the base of the wetland.
	Clay – holds together when moistened
	Silt – loosely holds together when moistened, sand grains generally not visible.
	Sand- individual sand grains visible. Gritty, doesn't hold together when moistened.
	Gravel- large grains, stones or pebbles.
	Rock- larger than gravel.
	Peat – organically laden, containing partly decomposed plant remains. Spongy when wet.
	Other
Water Monitoring	If the wetland contains enough water to collect a relatively representative sample do so.
PH	Refer to Waterwatch training notes p 26 of Module 4.
EC	Refer to Waterwatch training notes p 23 of Module 4.
Turbidity	Refer to Waterwatch training notes p 19 of Module 4.
Hydrological Modification Activity	**Determining the severity of hydrological change:** The IWC uses three categories for estimating the collective severity of activities that change the water regime of the wetland. **Severity rating = Expected impact on the wetland's water regime** **Very High - High** • A significant shift in the seasonality of flooding - i.e. the wetland now fills in a different season • Change in flooding duration and/or frequency that leads to a change in the permanency of the wetland , for example from permanent to semi-permanent or vice versa **Medium** • A change in the time of flooding but within same season • Change in the flooding frequency and/or duration but not great enough to lead to a significant change in the permanency of the wetland **Low-Very Low** • Little or no change in the wetland's flooding frequency, duration and seasonality
Activity leading to a change in wetland area and/or shape	Bathymetry is the underwater topography of the wetland defined by patterns in depth. The assessment estimates the percentage of the wetland where the bathymetry of the wetland has been significantly changed by excavation or landforming activities. These are activities which cause significant change in depth (eg. digging of channels or dams) or which change the natural form of the bed (eg. laser levelling, raised-bed cropping or building of mounds). Disturbance to wetland soils is not considered to be a change to the form of the wetland.
Assessment	Use the whole area occupied by the dominant EVC to undertake the assessment. This

of dominant wetland EVC – Flora Diversity	involves inspecting the whole EVC on the ground before evaluating vegetation quality against the benchmarks. If this is not possible because of access difficulty or poor visibility (eg. in EVCs dominated by dense reeds), inspect sites within the EVC that appear to cover the full range of quality within the EVC. A recent high quality air photo may assist in this decision. For some EVCs, there are conditions when the EVC should not be assessed. These are listed on the EVC benchmark and typically include extremes of inundation such as conditions of recent flooding when the vegetation has not sufficiently developed or severe drought. If the EVC was not assessed, record 'NA'. **Critical lifeform groupings** See Section 1 of the EVC benchmark. Benchmark descriptions specify the critical lifeform groupings which are expected to be Present in each EVC. The benchmark also specifies minimum species diversity and cover Levels for each lifeform grouping. The focus is to avoid underscoring apparently naturally species-poor variants of the respective EVCs. In the absence of high-level understanding of wetland vegetation, diversity losses in relatively species-rich vegetation could only be detected by evaluation against high-quality historical data. Assessment is based on the presence of lifeform groupings and whether or not they are substantially modified. A critical lifeform grouping is considered to be substantially modified if it fails to meet the benchmark thresholds for species numbers and/or cover. **Indicators of altered processes** This attribute assesses the extent of major changes occurring in the structure and composition of the vegetation, which are recognisable as simple indicators of ecological change. The assessment focuses on invasions of habitat by key indigenous indicator species or lifeforms. As the method is designed for use by operators of limited botanical experience, the assessment potential is restricted to a range of coarse indicators, in particular invasion by River Red Gum *Eucalyptus camaldulensis* seedlings, Tangled Lignum *M. florulenta*, Cumbungi *Typha spp.* or Samphires, which are indicative of hydrological or hydrogeological changes. **Vegetation structure and health** This attribute assesses the condition of the structurally predominant species or group of species within the relevant lifeform. The assessment utilises a cover value benchmark and visual assessment of proportion of health. Allowance is made for herbaceous species where major fluctuations of cover or seasonal die-back are normal. The approach provides some assessment of indicators of poor health of the predominant cover species for lifeforms other than trees where the latter are absent or incidental.
Weediness	This attribute assesses the extent of impact of invasion by introduced plant species, with consideration of the ecological competitiveness of the relevant species within the respective EVC. • See Section 2 of the EVC benchmark. • The assessment is based on quantifying the proportion/percentage cover of weeds and, of those, the percentage that are classed as high threat. • High threat weed species are specified on the EVC benchmark. The assessor can also record additional species considered as being of high threat on the field assessment sheet. • The benchmark also specifies instances where it is appropriate to overlook low-threat weeds, eg. when these are opportunistic species occurring out of phase with the wetland EVC being assessed, and, consequently, not impacting the indigenous species representing the EVC. This does not imply that these species are not impacting another EVC representing a different phase of the wetland; however such cases are generally rare.

Fauna Diversity	<u>During wetland appraisal walk: (10 + minutes)</u> Note any burrows, tracks, feeding sites, hollows, nests or animals present. <u>During stationary assessment (20 + minutes)</u> Listen for bird and frog calls. Record what you definitely recognise.
Width of vegetation fringe/wetland buffer	The buffer is the native vegetation adjacent to the wetland (from the maximum inundation level outwards). For the purposes of the assessment, native vegetation is defined as vegetation where native species make up more than 25% of the total **understorey cover**. The buffer only includes native vegetation contiguous with the wetland, that is, where there is no break between the native vegetation and the wetland boundary. It may extend any distance away from the wetland but the maximum buffer width class measured in the IWC is greater than 50 metres. In the situation where there is a river or other waterbody located within 50 metres of the wetland, only assess the buffer width between the wetland boundary and the edge of the river or waterbody. Do not include the vegetation on the other side of the river On survey sheet, if width: - is 0-50m, then indicate to the nearest metre. - is greater than 50m then write: > 50 m.
Terrestrial EVC	Identify mapped terrestrial EVC prior to going into the field. Take map if more than one EVC is identified. Confirm or record actual EVC using appropriate benchmark or own knowledge.
Habitat Value	Habitat is based on evidence currently present. No speculation (however obvious). Record parameters as being present,absent or abundant. **Within wetland boundary:** Presence of permanent deep water / pools = water greater than 1 m Presence of shallow - medium water = water 0-1 m Presence of exposed substrate = can be moist/muddy and contain live or dead vegetation. Or may be unvegetated soil, mud, sand or rock. Presence of submerged / free-floating vegetation: identify (don't record)plants that are known to be associated with deepwater habitats. Presence of emergent vegetation: identify plants that are known to be associated with the emergent zone or wetland fringe. Presence of edge vegetation: identify plants that are known to be associated with edges of wetlands. Logs, Rocks = present if more than one, abundant – use own discretion will change from site to site. Other; can include trees (alive/dead) and shrubs within the wetland.
	Wetland buffer: up to 50 m from edge of wetland. Shrubs, Trees-alive/dead = present if more than one, abundant – use own discretion will change from site to site.
	Shoreline profile: the edge of the wetland. Regular: where the shoreline has no peninsulas or relatively smooth edges. Irregular: where the shoreline has a lot of peninsulas. Islands: areas of elevated ground which would exist above the max. inundation level.

Heritage Value	Indigenous/Post Settlement: Whilst undertaking the initial appraisal of the wetland note any observations of Indigenous and/or Post-Settlement cultural heritage sites that you recognise. Indicate Present: if you observe/can confirm an Indigenous or Post-Settlement cultural heritage site. Indicate Absent: if you do not observe an Indigenous/Post-Settlement cultural heritage site or if a suspected site is confirmed as not being a culturally significant site by an indigenous cultural heritage officer or history expert at a later date.	
Threats	Following your appraisal of the wetland, indicate whether you observed any occurances of the below mentioned threats to the integrity of the wetland. Confirm your observations or add to your records following the interview with the land manager. Identify the level or certainty of threat via determining if it is present as a: Key Threat: one which you can actually see; or as a Minor Threat: one which you may not actually be able to observe or confirm but you strongly suspect that it is occurring.	
	Loss of wetland connectivity	The loss of connection between the wetland and other wetlands or river systems so that it is no longer connected under any flow conditions. Or degradation of native flora connecting two wetlands.
	Inappropriate grazing practices	Grazing practices that cause damage to a wetland.
	Lack of reservation	Land that is freehold.
	Exotic flora	Flora that is not native to the area and has the potential to become invasive and displace endemic flora. May result from planting of inappropriate species, introduction of diseases, spread of invasive species, translocation of live aquatic organisms.
	Introduced fauna	Fauna not native to the area that has the potential to become invasive and displace endemic fauna.
	Eutrophication	The nutrient enrichment of a waterbody, usually leading to growth and proliferation of large masses of plant material (phytoplankton, macrophytes or both).
	Salinity	The concentration of salt in the soil and/or water which may have changed due to disposal of irrigation tailwater, rise of groundwater or a change in the salt content of a wetland from the natural or desired state. As part of this process it is important to determine if the wetland has primary/natural salinity.
	Erosion	The dislodgement of soil particles, their removal and eventual deposition away from the original position.
	Change in size since European settlement	Loss of wetland area since European settlement.
	Surrounding Land-use practices	Poor land-use practices in area surrounding wetland.

	Native vegetation decline	Degradation of riparian native vegetation.
	Altered hydrology	Alteration of a wetland's water regime such that it receives less or more water and/or water at different times to its undisturbed condition (including impacts of irrigation).
	Physical alteration	Large scale movement of soil (excavation, infilling or landforming) within a wetland that changes its shape and possibly the flow of water.
	Fire regime	A fire regime that differs from the undisturbed condition.
	Resource utilisation (other than grazing)	Unsustainable resource utilisation other than grazing
	Sedimentation	The deposition of soil particles
	Inappropriate recreation	Recreational use of a wetland that can cause damage ie. 4-wheel driving, motorbike riding.
	Drainage into wetland	Irrigation drainage and/or groundwater disposal.
	Urban development	Development adjoining wetland or with the potential to affect the wetland in the future.
	Other	

Appendix F

Landholder Questionnaires

APPENDIX 3

WEST GIPPSLAND WETLAND INVENTORY

ALL LANDHOLDERS - QUESTIONNAIRE

Landmanager Name: ______________________________ Date: __________________

Sub-catchment: __________________________________ Wetland No: ____________

The West Gippsland Wetland Inventory project is designed to gather information about the wetlands of the region by having a close look at a random sample of wetlands. This survey will look at their current condition, surrounding land management, and the social and economic value of the wetlands to the landholder and their community.

The landholder survey is designed to gather information that can not readily be seen by looking at the wetland alone and relies on your specialist knowledge of your property and the wetland. The information gathered will be grouped together with the information gathered for this river catchment and for the region to build a more detailed picture so that the West Gippsland Catchment Management Authority can make better decisions about wetlands. A copy of the report for your wetland can be sent to you at your request.

The first set of questions are general and are about you and your relationship to the property

containing the wetland in question and its management:

1. What age group do you fall into?
   - ☐ <35 years
   - ☐ 35-55 years
   - ☐ >55 years
2. Do you own this property?
   - ☐ Yes How long have you owned the property? __________ Years –Go to Q3.
   - ☐ No

   What is your relationship to the property?

   - ☐ Manager of road reserve
   - ☐ Manager of park or reserve
   - ☐ Leasholder of crown land
   - ☐ Leaseholder of private land
   - ☐ Other crown land:____

   OR

   - ☐ Sharefarmer
   - ☐ Partner
   - ☐ Family member
   - ☐ Employed Manager

☐ Other: ____________________

3. Do you make the major decisions about the way the land is used on this property?

☐ Yes
☐ No Who is the main decision maker? ____________________

4. For what period of time have you or the current land manager, managed this property?
__________ Years

5. Does any of this property have a voluntary conservation covenant?

☐No
☐Yes Does the covenant include the wetland? ☐ Yes ☐ No

6. What is the size of the property that contains the wetland? Area: ________ Ha

7. How would you describe the property
☐ A commercial operation
☐ A hobby/lifestyle property
☐ Public property

8. What are the agricultural enterprises on this property?

☐ Dairy	No: _______	☐ Beef	No: _______
☐ Sheep	No: _______	☐ Cropping	Ha: _______
☐ Forestry	Ha: _______	☐ Other: ____________	

9. Do you have plans to change the main agricultural enterprise in the next five years?

☐ No
☐ Yes What enterprise will you change to? ____________________

10. Is your property currently irrigated?
☐ No
☐ Yes, flood irrigated
☐ Yes, with lateral sprays
☐ Yes, with a centre pivot system
☐ Yes, other: ____________

11. Does your property have any of the following?

☐ Laser grading	☐ Irrigation reuse system that uses the wetland
☐ Effluent pond that uses the wetland	☐ Keyline drainage that uses the wetland

12. Do you have plans to change the way your land is used over the next five years?

- ☐ No changes planned
- ☐ Yes, extend current flood irrigation
- ☐ Yes, introduce flood irrigation system
- ☐ Yes, extend current lateral spray irrigation
- ☐ Yes, introduce centre pivot irrigation
- ☐ Yes, extend current centre pivot irrigation
- ☐ Undertake laser grading
- ☐ Yes, introduce lateral spray irrigation system
- ☐ Alter water drainage involving wetlands
- ☐ Introduce a water reuse system involving wetlands

The next series of questions are about the specific wetland(s) included in the survey:

13. Other than you, who controls all or part of the land surrounding the wetland (within 200m)?

- ☐ You control all surrounding land
- ☐ Another landholder
- ☐ Road reserve
- ☐ Crown reserve
- ☐ Other: ________________

14. Has the wetland changed in size over the years?

- ☐ Don't know
- ☐ Increased because dryland returned to wetland
- ☐ No change
- ☐ Increased because water directed into wetland
- ☐ Decreased - land claimed for production
- ☐ Increased because drainage from wetland blocked
- ☐ Decreased - water taken out of wetland
- ☐ Increased but I don't know why
- ☐ Decreased but I don't know why
- ☐ Other ________________

15. Where does the water mainly come from to fill the wetland?

- ☐ Rainfall
- ☐ Groundwater
- ☐ Natural flooding
- ☐ Drainage
- ☐ Irrigation runoff
- ☐ Unknown

16. Has the source of water changed over the years?

- ☐ Don't know
- ☐ Yes, it was originally rainfall
- ☐ No
- ☐ Yes, it was originally groundwater
- ☐ Yes, it was originally irrigation runoff
- ☐ Yes, it was originally natural flooding
- ☐ Yes, it was originally drainage

17. Has the amount of water coming into the wetland changed over the years?

- ☐ Don't know
- ☐ No
- ☐ Yes, but I don't know why
- ☐ Yes, an increase because of natural events
- ☐ Yes, a decrease because of natural events
- ☐ Yes, an increase because of man made changes
- ☐ Yes, a decrease because of man made changes

18. Has the seasonal timing of water flowing into the wetland changed over the years?

- ☐ Don't know
- ☐ No
- ☐ Yes, increased inflow in summer
- ☐ Yes, decreased inflow in wet months
- ☐ Other: ____________________

19. Has the number of times that water flows into the wetland changed over the years?

- ☐ Don't know
- ☐ No
- ☐ Yes, inflows happen more often in summer
- ☐ Yes, inflows occur more often in wet months
- ☐ Yes, inflows occur more often over the year
- ☐ Other: ____________________

20. Has the quality of water coming into the wetland changed over the years?

- ☐ Don't know
- ☐ No
- ☐ Yes, it is more salty
- ☐ Yes, it has more nutrient
- ☐ Yes, it is dirtier
- ☐ Yes, other ______________

21. Has the type of plants in or around the wetland changed over the years?

- ☐ Don't know
- ☐ No
- ☐ Yes, there are new plants
  Which? ____________________________
- ☐ Yes, an increase in one or more types or groups of plants
  Which? ____________________________
- ☐ Yes, a decrease in one or more types or groups of plants
  Which? ____________________________

22. How have you or others used the wetland for recreation over the years? (Tick only one box in each row)

Use	Frequently	Seasonal	Occasional	Never	Comment
a. hunting pests					
b. other hunting What? ________					
c. recreational fishing					
d. pleasure and recreation					
e. swimming					
f. canoeing					
g. bird watching					
h. boating					
i. camping					
j. motorbike riding or 4WD driving					
k. educational purposes					
l. other Specify________					

23. How have you or others made use of the wetland for commercial benefit over the past five years? (Tick only one box in each row)

Use	Unrestricted	Seasonal	Drought only	Never	Comment
a. grazing sheep					
b. grazing cattle					
c. cropping/hay production					
d. commercial fishing					
e. timber for use on the property					

f. timber for commercial use					
g. stock water supply					
h. irrigation water supply					
i. disposal of irrigation drainage					
j. disposal of effluent					
k. tourism					
l. other Specify ____________					

24. Has the wetland been burnt?

☐ No

☐ Yes   How often?   Every ____________Years
Last burn?   State Year ____________

The following questions are general questions.

Consider the tradeoffs between the environment and production and the economy. Using the scale below respond to the following statements:

	Disagree -------		No opinion		-------- Agree
25. It is possible to have a prosperous economy and a healthy environment	1	2	3	4	5
26. As an individual it is too hard for me to do much for the environment	1	2	3	4	5
27. Economic growth always harms the environment	1	2	3	4	5
28. I do what is right for the environment, even when it costs more money or takes more time	1	2	3	4	5

29. Have you participated in any information or training sessions about wetlands?

☐ No

☐ Yes   What? ________________________   When? _________

30. Would you like more information on wetlands?

☐ No

☐ Yes   How would you like to receive this?

- ☐ Information pack in the mail
- ☐ Newspaper/magazine articles
- ☐ Radio/TV
- ☐ Field days

- ☐ Land manager interest groups
- ☐ Visit from expert
- ☐ Other ________________

These questions are about all of the wetlands on your property:

31. What do you like most about the wetlands? (tick only one)

- ☐ Refuge for birds and wildlife
- ☐ Variety of plants it contains
- ☐ Adds to the look of the property
- ☐ Recreational use
- ☐ Contribution to preserving nature
- ☐ Acts as a reserve for drought
- ☐ Productive value to farm income
- ☐ Shelter value to stock
- ☐ Source of alternative income to farm
- ☐ Other ________________

32. What do you like least about the wetland?

- ☐ Source of weeds
- ☐ Harbors animal pests
- ☐ Contributes to soil salinity
- ☐ Creates waterlogging
- ☐ Loss of bogged stock
- ☐ Smell
- ☐ Limits access around the farm
- ☐ Productivity–doesn't make money
- ☐ Cost of maintenance
- ☐ Attracts trespassers to the property
- ☐ Other ________________

33. How could the protection of wetlands on your farm become a higher priority?

- ☐ If I knew more about them
- ☐ If I knew how important they were
- ☐ If I could talk to others who are interested
- ☐ If I could get experts to help me
- ☐ If I could get money to help preserve them
- ☐ If I could see benefits to production
- ☐ If I could make money from them

Thank you for your time

APPENDIX 4

WEST GIPPSLAND WETLAND INVENTORY

MID LANDHOLDER QUESTIONNAIRE

Landmanager Name: ______________________________ Date: ____________

Sub-catchment: _________________________________Wetland No: ____________

These questions are for MID sample landholders ONLY and must be asked by the interviewer. Allow the land holder to speak freely and match their response to one of those listed.

Let's move away from just the specific wetland and include all of the wetlands on your property. How important they are the following management activities to you:

31. Excluding stock from wetlands altogether 1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this? ☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other ____________

32. Managing grazing and stock water access to wetlands
1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this? ☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other ____________

33. Maintaining native vegetation in and around the wetland
1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this? ☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other____________

34. Works to restore natural water level fluctuations of the wetland

1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this?
☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other_____________

35. Control of feral animals in wetland

1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this?
☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other_____________

36. Control of weeds in wetland

1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this?
☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other _____________

37. Fire prevention around the wetland

1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this?
☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other _____________

38. Development of a farm management plan that includes things to preserve the wetland in its natural state

1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this?
☐ Yes
☐ No Why not?
☐ Cost ☐ Time

☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other ____________

39. Restoring wetlands and wetland habitats to encourage native wildlife to the wetland

1 2 3 4 5
Unimportant ----- No opinion ----- Important

Have you done this? ☐ Yes
☐ No Why not?
☐ Cost ☐ Time
☐ Lack of knowledge ☐ Not applicable to my wetland
☐ Of no interest ☐ Other____________

On a scale of 1 (strongly disagree) to 5 (strongly agree) tell me what you feel about the following statements:

	Disagree	-------	No opinion	--------	Agree
40. Wetlands make the farm landscape more attractive	1	2	3	4	5
41. Wetlands conserve native plants and animals	1	2	3	4	5
42. Wetlands help with native animal movement	1	2	3	4	5
43. Wetlands provide a place for native fish to live	1	2	3	4	5
44. Wetlands increase bird life which in turn decreases pests (eg ibis)	1	2	3	4	5
45. Wetlands help to trap and recycle nutrients	1	2	3	4	5
46. Wetlands help recharge groundwater	1	2	3	4	5
47. Wetlands help control floods	1	2	3	4	5
48. Wetlands help control soil erosion	1	2	3	4	5
49. Wetlands are valued by the local community	1	2	3	4	5

These questions are about all of the wetlands on your property:

50. What do you like most about the wetlands? (tick only one)

☐ Refuge for birds and wildlife ☐ Variety of plants it contains
☐ Adds to the look of the property ☐ Recreational use
☐ Contribution to preserving nature ☐ Acts as a reserve for drought
☐ Productive value to farm income ☐ Shelter value to stock
☐ Source of alternative income to farm ☐ Other ______________

51. What do you like least about the wetland?

☐ Source of weeds ☐ Harbors animal pests

- ☐ Contributes to soil salinity
- ☐ Creates waterlogging
- ☐ Loss of bogged stock
- ☐ Smell
- ☐ Limits access around the farm
- ☐ Productivity–doesn't make money
- ☐ Cost of maintenance
- ☐ Attracts trespassers to the property
- ☐ Other ____________________

52. How could the protection of wetlands on your farm become a higher priority?

- ☐ If I knew more about them
- ☐ If I knew how important they were
- ☐ If I could talk to others who are interested
- ☐ If I could get experts to help me
- ☐ If I could get money to help preserve them
- ☐ If I could see benefits to production
- ☐ If I could make money from them

Appendix G
Details of WGCMA Database tables

Table G.1: Details the WGCMA Wetland Database tables and attributes used in the 2006 WGCMA wetland evaluations for finding wetlands of high economic value. These Database tables and attributes with their range of values decided the number of columns (independent input variables) used to assemble the Economic data input file for this research. Explanations and qualifications on the decisions made and values assigned are also included for all 12 independent variables were used to represent the economic value inputs under consideration.

Economic value	**Wetland Database Table**	**No. of Columns**	**Range of values**	**Explanation**	**Qualification**
Tourism	tblOCommercialUse	1	tourism 0 to 2	Values assigned to all commercial uses: 0 absent, 1 seasonal, 2 unrestricted	
Production value	tblOCommercialUse	3	food production 0 to 2 conservation forestry 0 or 1 other land use 0 or 1	Values assigned for food production: 0 absent, 1 seasonal, 2 unrestricted Values assigned to both conservation forestry & other land uses: 0 or 1 for absent or present.	If food production was recorded in one of these tables and not the other , then a value of 2 was chosen as the default food production value.
	tblOLandUsePropertyEnterprises				
Drainage disposal	tblBHydrologyModAct	5	drainage 0 to 3 disposal of water 0 to 3 water storage 0 to 3 obstruction 0 to 3 redirection 0 to 3	Values assigned to all hydrological uses: 0 absent, 1 present no impact, 2 moderate to low impact, 3 severe impact	Values assigned to each hydrology modified activity value: 0 absent, 1 no impact present, 2 moderate to low present, 3 severe. Some entries were found recorded in both tables so where conflicting values were given, a maximum of values recorded was taken.
	tblOHydrology	1	diverted or farm runoff 0 to 1	Values assigned to diverted or farm runoff: 0 absent, 1 present	
Water supply	tblOCommercialUse	1	stock water supply 0 to 2	Values assigned to all commercial uses: 0 absent, 1 seasonal, 2 unrestricted	
Commercial fishing	tblOCommercialUse	1	commercial fishing 0 to 2	Values assigned to all commercial uses: 0 absent, 1 seasonal, 2 unrestricted	

Table G.2: Details the WGCMA Wetland Database tables and attributes used in the 2006 WGCMA wetland evaluations for finding wetlands of high social value. These Database tables and attributes with their range of values decided the number of columns (independent input variables) used to assemble the Social data input file for this research. Explanations and qualifications on the decisions made and values assigned are also included for all 12 independent variables were used to represent the social value inputs under consideration.

Social value	Wetland Database Table	No. of Columns	Range of values	Explanation	Qualification
Recreational fishing	tblOSocialValue	1	recreational fishing 0 to 3	Values assigned to each social value: 0 no social value, 1 occasional use, 2 seasonal use and 3 frequently used	
Swimming		1	swimming 0 to 3		
Camping		1	camping 0 to 3		
Hunting		1	hunting 0 to 3		
Boating		2	boating 0 to 3 watershiing 0 to 3		
Passive recreation		2	passive recreation 0 to 3 motor 4WD 0 to 3		
Bird watching		1	Bird watching 0 to 3		
Education		2	education 0 to 3 research 0 to 3		
Park value	These values were supplied for each wetland by the WGCMA Wetlands Project Officer, Michelle Dickson in December 2007.	1	Values assigned 0 to 5: represents no data available; 1 represents wetlands not located in a park or reserved crown land; 2 represents wetlands located in a State forest or other reserved crown land; 3 is used for wetlands located in nature conservation reserves or which have historic and cultural features documented; 4 for wetlands located in Regional or State Parks, Coastal or a Marine and Coastal Park; and, 5 represents wetlands located in National Parks, Reference area or Wilderness area, Marine National Park or Marine Sanctuary or Marine Park.		These values were not stored in the database. The source was from Geographic Information System available to WGCMA using data layer (crown land tenure).

Table G.3: Details the WGCMA Wetland Database tables and attributes used in the 2006 WGCMA wetland evaluations for finding wetlands of high environmental value. These Database tables and attributes with their range of values decided the number of columns (independent input variables) used to assemble the Social data input file for this research. Explanations and qualifications on the decisions made and values assigned are also included for all 31 independent variables were used to represent the environmental value inputs under consideration.

Environmental value	Wetland Database Table	No. of Columns	Range of values	Explanation	Qualification
Wetland rarity	tblBPhysical Features	1	wetlands 1 to 7	1 Permanent saline wetland , 2 Semipermanent saline, 3 Shallow freshwater marsh, 4 Freshwater meadow, 5 Deep freshwater marsh, 6 Permanent open water, 7 Flooded river flat.	
Significant flora	tblYFlora	1	floraVROT 0 to 63	Values assigned to each threatened flora value: 0 no value, 1 poorly known, 2 rare, 3 vulnerable, 4 endangered then total is summed for each site.	
Significant fauna	tblYFauna	2	faunaVROT 0 to 12 faunaFFG 0 to 4	Each FaunaVROT value: 1 rare, 2 vulnerable, 3 endangered and then summed for each site. Fauna FFG value: 0 or 1 for listed as threatened then summed for each site	
Habitat value	tblBHabitatBalueWIthinWetland	0	Wetlands 1 to 7		Assumed already and included above.
	tblBHabitatValueTerrestrialZone	9	rocks 0 to 1 water edge 0 to 2 logs 0 to 2 emergent vegetation 0 to 2 shallow-medium water 0 to 2 exposed substrate 0 to 2 submerged/free floating 0 to 2 permanent deep water 0 to 2 other 0 to 2	Values assigned to each terrestrial habitat type: 0 absent, 1 present, 2 abundant	

Table G.3: continued

Environmental value	Wetland Database Table	No. of Columns	Range of values	Explanation	Qualification
Habitat value	tblBHabitatValueShorelineProfile	4	Shoreline status variables shrubs 0 to 2 alive trees 0 to 2 dead trees 0 to 2 shoreline description 1 to 4	Values assigned to each terrestrial type: 0 absent, 1 present, 2 abundant Value assigned to each shoreline description type: 1 regular, 2 regular with islands, 3 irregular, 4 irregular with islands	
Wetland hydrology	tblBHydrologyModAct	5	drainage 0 to 3 disposal of water 0 to 3 water store 0 to 3 obstruct ion 0 to 3 redirection 0 to 3	Values assigned to each hydrology modified activity value: 0 absent, 1 no impact present, 2 moderate to low present, 3 severe	
Vegetation intactness–critical lifeforms	TblBPhysicalFeaturesWetlandEVC TblBBFFFloraPercentofWetland	0		For the WGCMA evaluation, only the EVC with the greatest % cover was used for TblBBFFFloraPercentofWetland record.	All percentages summed to 100% so could not create different values to represent EVC types.
	TblBFFFlora	8	Values for FloraType were: graminoids 0 to 60 shrubs 0 to 50 herbs 0 to 85 sedges 0 to 50 ferns 0 to 30 grasses 0 to 20 noSpecies 0 to 79 substantially modified 0 or 1	FloraTypes: trees, graminoids, shrubs, herbs, sedges (included rushes&reeds), ferns(included bryophytes), grasses. For each type, summed the % value. NoOfSpecies is total count SubstantiallyModified 0 or 1 for substantially modified. If missing default = 1.	Trees were assigned a column originally but all had values of 0 in input data.
Vegetation intactness– width of vegetation fringe	tblBFFVegFringe	1	VegWid 0 to 1000	Width of vegetation fringe value supplied in table.	

Table G.4: Details the WGCMA Wetland Database tables and attributes used in the 2006 WGCMA wetland evaluations for finding wetlands of threat categories values.

Threats	Wetland Database Table	No. of Columns	Range of values	Explanation	Qualification
Loss of wetland connectivity	tblBThreats	1	loss of wetland connectivity 0 to 2 atock access 0 to 2 pest plants 0 to 2 pest animals 0 to 2 urban development 0 to 2 altered hydrology0 to 2 native vegetation decline 0 to 2 land use 0 to 2 physical alteration 0 to 2 erosion 0 to 2 fire regime 0 to 2 recreation 0 to 2 salinity 0 to 2	Values assigned to each hydrology modified activity value: 0 absent, 1 minor threat present, 2 key threat present	
Stock access		1			
Pest plants		1			
Pest animals		1			
Urban development		1			
Altered hydrology		1			
Native vegetation decline		1			
Land use		1			
Physical alteration		1			
Erosion		1			
Fire regime		1			
Recreation		1			
Salinity		1			
Water source	vtbklookupHydroSource	1	water source 0 to 7	Values assigned: 1 rainfall, 2 groundwater, 3natural flooding, 4 diverted farm drainage, 5 irrigation runoff, 6 unknown, 7 other.	

Table G.6: Details the WGCMA Wetland Database tables and attributes used in the 2006 WGCMA wetland evaluations for finding wetlands of threat categories values that were used only in significant wetland assessments.

Threats	Wetland Database Table	No. of Columns	Range of values	Explanation	Qualification
Change in size since European settlement	tblBThreats	1	change in size 0 to 2 drainage into wetland 0 to 2 eutrophication 0 to 2 inappropriate grazing practices 0 to 2 lack of reservation 0 to 2 resource utilization 0 to 2 sedimentation 0 to 2	WGCMA reports state that these additional threat categories were used only to access significant wetlands and not the catchment wetlands inventoried. However the Wetlands Inventory Database contains records of catchment wetlands with values assessed for these threat s.	
Drainage into wetland		1			
Eutrophication		1			
Inappropriate grazing practices		1			
Lack of reservation		1			
Resource utilization other than grazing		1			
Sedimentation		1			

Appendix H
Contingency tables for Economic value attributes

Table H.1: Contingency table for the Economic value input attributes of tourism and food production. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Economic values. The abbreviation Season is used for Seasonal, and Unres'd is used for unrestricted. Non-empty cells have been shaded.

Economic value		Food production			Commercial fishing			Total
		Absent	Present		Absent	Present		
			Season	Unres'd		Season	Unres'd	
Very low	Count	21	1	2	24	0	0	24
	%	88%	4%	8%	100%	0%	0%	
Low	Count	43	14	52	108	1	0	109
	%	39%	13%	48%	99%	1%	0%	
Moderate	Count	8	0	19	27	0	0	27
	%	30%	0%	70%	100%	0%	0%	
High	Count	0	0	1	0	1	0	1
	%	0%	0%	100%	0%	100%	0%	
Total		72	15	74	159	2	0	161
% within Economic value		45%	9%	46%	99%	1%	0%	

Table H.2: Contingency table for the Economic value input attributes of disposal of water and obstruction. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Economic values. The abbreviation Mod has been used for moderate. Non-empty cells have been shaded.

Economic value		Disposal of water				Obstruction				Total
		Absent	Present			Absent	Present			
			No impact	Mod to low impact	Severe impact		No impact	Mod to low impact	Severe impact	
Very low	Count	22	0	1	1	20	0	2	2	24
	%	92%	0%	4%	4%	84%	0%	8%	8%	
Low	Count	96	2	8	3	72	2	22	13	109
	%	88%	2%	7%	3%	66%	2%	20%	12%	
Moderate	Count	17	0	5	5	12	0	11	4	27
	%	63%	0%	19%	19%	64%	0%	18%	18%	
High	Count	0	0	1	0	0	0	1	0	1
	%	0%	0%	100%	0%	0%	0%	100%	0%	
Total		135	2	15	9	104	2	36	19	161
% within Economic value		84%	1%	9%	6%	65%	1%	22%	12%	

Table H.3: Contingency table for the Economic value input attributes of redirection and water storage. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Economic values. The abbreviation Mod has been used for moderate. Non-empty cells have been shaded.

Economic value		Redirection				Water storage				Total
		Absent	Present			Absent	Present			
			No impact	Mod to low impact	Severe impact		No impact	Mod to low impact	Severe impact	
Very low	Count	13	0	9	2	24	0	0	0	24
	%	84%	0%	8%	8%	100%	0%	0%	0%	
Low	Count	58	0	33	18	104	2	3	0	109
	%	53%	0%	30%	17%	95%	2%	3%	0%	
Moderate	Count	9	0	14	4	18	0	4	5	27
	%	33%	0%	52%	15%	67%	0%	15%	18	
High	Count	0	0	1	0	0	0	1	0	1
	%	0%	0%	100%	0%	0%	0%	100%	0%	
Total		80	0	57	24	146	2	8	5	161
% within Economic value		50%	0%	35%	15%	91%	1%	5%	3%	

Appendix I
Contingency tables for Social value attributes

Table I.1a: Contingency table for the Social value input attribute of boating. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		Boating				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	4	0	0	0	4
	%	100%	0%	0%	0%	
Very low	Count	37	0	0	0	37
	%	100%	0%	0%	0%	
Low	Count	61	9	4	0	74
	%	82%	12%	6%	0%	
Moderate	Count	21	6	13	0	40
	%	53%	15%	32%	0%	
High	Count	1	0	1	3	5
	%	20%	0%	20%	60%	
Total		124	15	18	3	160
% within Social value		78%	9%	11%	2%	

Table I.1b: Contingency table for the Social value input attribute boating with very low and low assessment counts added and moderate and high counts summed. All columns denoting any boating activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between boating and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 4.357 and one-tailed p-value = 0.0184, which is statistically significant.

Social value	**Boating**		**Total**
	Absent	**Present**	
Very low & low	93 (85)	18 (26)	111
Moderate & high	31 (35)	14 (10)	45
Total	124	32	156

Table I.2a: Contingency table for the Social value input attribute of camping. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		Camping				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	4	0	0	0	4
	%	100%	0%	0%	0%	
Very low	Count	37	0	0	0	37
	%	100%	0%	0%	0%	
Low	Count	63	10	1	0	74
	%	85%	14%	1%	0%	
Moderate	Count	30	6	4	0	40
	%	75%	15%	10%	0%	
High	Count	0	3	2	0	5
	%	0%	60%	40%	0%	
Total		134	19	7	0	160
% within Social value		84%	12%	4%	0%	

Table I.2b: Contingency table for the Social value input attribute camping with very low and low assessment counts added and moderate and high counts summed. All columns denoting any camping activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between camping and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 12.649 and one-tailed p-value = 0.0002, which is extremely statistically significant.

Social value	**Camping**		**Total**
	Absent	**Present**	
Very low & low	93 (85)	18 (26)	111
Moderate & high	31 (35)	14 (10)	45
Total	124	32	156

Table I.3a: Contingency table for the Social value input attribute of education. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		Education				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	2	0	1	1	4
	%	50%	0%	25%	25%	
Very low	Count	37	0	0	0	37
	%	100%	0%	0%	0%	
Low	Count	52	14	6	2	74
	%	70%	19%	8%	3%	
Moderate	Count	14	12	9	5	40
	%	35%	30%	22%	13%	
High	Count	0	2	0	3	5
	%	0%	40%	0%	60%	
Total		105	28	16	11	160
% within Social value		66%	17%	10%	7%	

Table I.3b: Contingency table for the Social value input attribute education with very low and low assessment counts added and moderate and high counts summed. All columns denoting any educational activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between education and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 34.369 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Social value	**Camping**		**Total**
	Absent	**Present**	
Very low & low	89 (73)	22 (38)	111
Moderate & high	14 (30)	31 (15)	45
Total	103	53	156

Table I.4a: Contingency table for the Social value input attribute of motorized four-wheel drive. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		Motorized four-wheel drive				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	4	0	0	0	4
	%	100%	0%	0%	0%	
Very low	Count	36	0	0	1	37
	%	97%	0%	0%	3%	
Low	Count	57	15	2	0	74
	%	77%	20%	3%	0%	
Moderate	Count	26	6	2	6	40
	%	65%	15%	5%	15%	
High	Count	5	0	0	0	5
	%	100%	0%	0%	0%	
Total		128	21	4	7	160
% within Social value		80%	13%	3%	4%	

Table I.4b: Contingency table for the Social value input attribute motorized four-wheel drive with very low and low assessment counts added and moderate and high counts summed. All columns denoting any motorized four-wheel drive activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between motorized four-wheel drive and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 4.357 and one-tailed p-value =0.0184, which is statistically significant.

Social value	**Motorized four-wheel drive**		**Total**
	Absent	**Present**	
Very low & low	93 (88)	18 (23)	111
Moderate & high	31 (36)	14 (9)	45
Total	124	32	156

Table I.5a: Contingency table for the Social value input attribute of passive recreation. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		Passive recreation				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	2	0	1	1	4
	%	50%	0%	25%	25%	
Very low	Count	36	0	0	1	37
	%	97%	0%	0%	3%	
Low	Count	46	17	3	8	74
	%	62%	23%	4%	11%	
Moderate	Count	5	7	13	15	40
	%	12%	18%	33%	37%	
High	Count	0	0	0	5	5
	%	0%	0%	0%	100%	
Total		89	24	17	30	160
% within Social value		56%	15%	10%	19%	

Table I.5b: Contingency table for the Social value input attribute passive recreation with very low and low assessment counts added and moderate and high counts summed. All columns denoting any passive recreation activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between passive recreation and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 51.132 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Social value	**Passive recreation**		**Total**
	Absent	**Present**	
Very low & low	82 (62)	29 (49)	111
Moderate & high	5 (25)	40 (20)	45
Total	87	69	156

Table I.6a: Contingency table for the Social value input attribute of recreational fishing. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		**Recreational fishing**				**Total**
		Absent	**Present**			
			Occasional	Seasonal	Frequent	
Unknown	Count	3	0	1	1	4
	%	75%	0%	25%	25%	
Very low	Count	37	0	0	0	37
	%	100%	0%	0%	0%	
Low	Count	58	15	1	0	74
	%	79%	20%	1%	0%	
Moderate	Count	14	18	1	7	40
	%	35%	45%	2%	18%	
High	Count	0	2	0	3	5
	%	0%	40%	0%	60%	
Total		112	35	2	11	160
% within Social value		70%	22%	1%	7%	

Table I.6b: Contingency table for the Social value input attribute recreational fishing with very low and low assessment counts added and moderate and high counts summed. All columns denoting any recreational fishing activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between recreational fishing and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 45.136 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Social value	**Recreational fishing**		**Total**
	Absent	**Present**	
Very low & low	95 (77)	16 (33)	111
Moderate & high	14 (31)	31 (14)	45
Total	109	47	156

Table I.7: Contingency table for the Social value input attribute of research. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		**Research**				**Total**
		Absent	**Present**			
			Occasional	Seasonal	Frequent	
Unknown	Count	4	0	0	0	4
	%	100%	0%	0%	0%	
Very low	Count	37	0	0	0	37
	%	100%	0%	0%	0%	
Low	Count	74	0	0	0	74
	%	100%	0%	0%	0%	
Moderate	Count	40	0	0	0	40
	%	100%	0%	0%	0%	
High	Count	3	0	0	2	5
	%	60%	0%	0%	40%	
Total		158	0	0	2	160
% within Social value		99%	0%	0%	1%	

Table I.8a: Contingency table for the Social value input attribute of swimming. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate and high Social values. Non-empty cells other than for unknown have been shaded.

Social value		Swimming				Total
		Absent	Present			
			Occasional	Seasonal	Frequent	
Unknown	Count	4	0	0	0	4
	%	100%	0%	0%	0%	
Very low	Count	37	0	0	0	37
	%	100%	0%	0%	0%	
Low	Count	69	5	0	0	74
	%	93%	7%	0%	0%	
Moderate	Count	33	0	7	0	40
	%	83%	0%	17%	0%	
High	Count	2	2	0	1	5
	%	40%	40%	0%	20%	
Total		145	7	7	1	160
% within Social value		91%	4%	4%	1%	

Table I.8b: Contingency table for the Social value input attribute swimming with very low and low assessment counts added and moderate and high counts summed. All columns denoting any swimming activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between swimming and the WGCMA Social value assessment. $\chi^2_{(df=1)}$ value = 11.566 and one-tailed p-value = 0.0003, which is extremely statistically significant.

Social value	Swimming		Total
	Absent	Present	
Very low & low	106 (100)	5 (11)	111
Moderate & high	35 (41)	10 (4)	45
Total	141	15	156

Appendix J
Contingency tables for Environmental value attributes

Table J.1: Contingency table for the Environmental value significant flora which is indicated by sum at each site of all faunal Victorian Rare or Threatened (VROTs) species values. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Significant fauna**						**Total**
		Sum of VROT species scores						
		0	1 to 2	3 to 4	6 to 7	8	12	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Low	Count	27	0	0	0	0	0	27
	%	100%	0%	0%	0%	0%	0%	
Moderate	Count	71	3	2	1	0	0	77
	%	92%	4%	3%	1%	0%	0%	
High	Count	40	3	5	1	0	0	49
	%	82%	6%	10%	2%	0%	0%	
Very high	Count	0	1	3	2	1	1	8
	%	0%	12%	38%	25%	25%		
Total		140	7	10	4	1	1	163
% within Environmental value		86%	4%	6%	2%	1%	1%	

Table J.2: Contingency table for the Environmental value significant fauna which is indicated by sum at each site of all faunal species listed in the Flora and Fauna Guarantee (FFG) Act. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells, other than for unknown, have been shaded.

Environmental value		**Significant fauna**					**Total**
		Sum of FFG species scores					
		0	1	2	3	4	
Unknown	Count	1	0	0	0	0	1
	%	100%	0%	0%	0%	0%	
Very low	Count	1	0	0	0	0	1
	%	100%	0%	0%	0%	0%	
Low	Count	27	0	0	0	0	27
	%	100%	0%	0%	0%	0%	
Moderate	Count	74	2	1	0	0	77
	%	97%	3%	1%	0%	0%	
High	Count	42	7	0	0	0	49
	%	86%	14%	0%	0%	0%	
Very high	Count	1	4	1	1	1	8
	%	13%	50%	12%	25%		
Total		146	13	2	1	1	163
% within Environmental value		90%	8%	1%	1%		

Table J.3a: Contingency table for the terrestrial zone habitat type subattribute of emergent vegetation against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Habitat value**			
		Terrestrial zone habitat type			
		Emergent vegetation			
		Absent	**Present**		**Total**
			Usually	Abundant	
Unknown	Count	0	0	1	1
	%	0%	0%	100%	
Very low	Count	0	0	1	1
	%	0%	0%	100%	
Low	Count	6	18	3	27
	%	22%	67%	11%	
Moderate	Count	3	33	41	77
	%	4%	43%	53%	
High	Count	3	7	39	49
	%	6%	14%	80%	
Very high	Count	0	0	8	8
	%	0%	0%	100%	
Total		12	58	93	163
% within Environmental value		7%	36%	57%	

Table J.3b: Contingency table for the attribute emergent vegetation with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any emergent vegetation presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between emergent vegetation and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 9.703 and one-tailed p-value = 0.0009, which is extremely statistically significant.

Environmental value	**Emergent vegetation**		**Total**
	Absent	**Present**	
Very low & low	6 (2)	22 (26)	28
Moderate, high & very high	6 (10)	128 (124)	134
Total	12	150	162

Table J.4a: Contingency table for the terrestrial zone habitat type subattribute of exposed substrate against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Habitat value – Terrestrial zone habitat type – Exposed substrate**			
		Absent	**Present**		**Total**
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	0	1	0	1
	%	0%	100%	0%	
Low	Count	10	13	4	27
	%	37%	48%	15%	
Moderate	Count	20	39	18	77
	%	26%	51%	23%	
High	Count	14	24	11	49
	%	29%	49%	22%	
Very high	Count	4	3	1	8
	%	50%	38%	12%	
Total		49	80	34	163
% within Environmental value		30%	49%	21%	

Table J.4b: Contingency table for the attribute exposed substrate with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any exposed substrate presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between exposed substrate and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.160 and one-tailed p-value = 0.3445, which is not statistically significant.

Environmental value	Exposed substrate		Total
	Absent	Present	
Very low, low & moderate	30 (31)	75 (74)	105
High & very high	18 (17)	39 (40)	57
Total	48	114	162

Table J.5a: Contingency table for the terrestrial zone habitat type subattribute of logs against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Habitat value – Terrestrial zone habitat type – Logs: Absent	Present: Usually	Present: Abundant	Total
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	0	1	0	1
	%	0%	100%	0%	
Low	Count	22	5	0	27
	%	82%	18%	0%	
Moderate	Count	22	42	13	77
	%	29%	54%	17%	
High	Count	14	28	7	49
	%	29%	57%	14%	
Very high	Count	3	4	1	8
	%	37%	50%	13%	
Total		62	80	21	163
% within Environmental value		38%	49%	13%	

Table J.5b: Contingency table for the attribute logs with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any log presences have been summed. Values in brackets are the expected frequencies for each cell if there is no association between logs and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 24.141 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Logs**		**Total**
	Absent	**Present**	
Very low & low	22 (11)	6 (17)	28
Moderate, high & very high	39 (50)	95 (84)	134
Total	61	101	162

Table J.6: Contingency table for the terrestrial zone habitat type subattribute of other against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Habitat value – Terrestrial zone habitat type – Other**			
		Absent	**Present**		**Total**
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	1	0	0	1
	%	100%	0%	0%	
Low	Count	25	1	1	27
	%	92%	4%	4%	
Moderate	Count	74	1	2	77
	%	96%	1%	3%	
High	Count	47	1	1	49
	%	96%	2%	2%	
Very high	Count	6	1	1	8
	%	75%	25%		
Total		154	4	5	163
% within Environmental value		95%	2%	3%	

Table J.7a: Contingency table for the terrestrial zone habitat type subattribute of permanent deep pools against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Habitat value – Terrestrial zone habitat type – Permanent deep pools			
		Absent	Present		Total
			Usually	Abundant	
Unknown	Count	0	0	1	1
	%	0%	0%	100%	
Very low	Count	1	0	0	1
	%	100%	0%	0%	
Low	Count	22	1	4	27
	%	81%	4%	15%	
Moderate	Count	56	7	14	77
	%	73%	9%	18%	
High	Count	41	2	6	49
	%	84%	4%	12%	
Very high	Count	6	2	0	8
	%	75%	25%	0%	
Total		126	12	25	163
% within Environmental value		77%	8%	15%	

Table J.7b: Contingency table for the subattribute permanent deep pools at a site with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting permanent deep pools presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between permanent deep pools and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.373 and one-tailed p-value = 0.2706, which is not statistically significant.

Environmental value	Permanent deep pools		Total
	Absent	Present	
Very low & low	23 (22)	5 (6)	28
Moderate, high & very high	103 (104)	31 (30)	134
Total	126	36	162

Table J.7c: Contingency table for the attribute permanent deep pools at a site with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any permanent deep pools presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between permanent deep pools and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 1.114 and one-tailed p-value = 0.1456, which is not statistically significant.

Environmental value	Permanent deep pools		Total
	Absent	Present	
Very low, low & moderate	79 (82)	26 (23)	105
High & very high	47 (44)	10 (13)	57
Total	126	36	162

Table J.8: Contingency table for the terrestrial zone habitat type subattribute of rocks against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Habitat value**			
		Terrestrial zone habitat type			
		Rocks			
		Absent	**Present**		**Total**
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	1	0	0	1
	%	100%	0%	0%	
Low	Count	26	1	0	27
	%	96%	4%	0%	
Moderate	Count	75	2	0	77
	%	97%	3%	0%	
High	Count	37	12	0	49
	%	76%	24%	0%	
Very high	Count	4	3	1	8
	%	50%	37%	13%	
Total		144	18	1	163
% within Environmental value		88%	11%	1%	

Table J.9a: Contingency table for the terrestrial zone habitat type subattribute of shallow to medium depth water against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Habitat value – Terrestrial zone habitat type – Shallow to medium depth water			
		Absent	Present		Total
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	0	1	0	1
	%	0%	100%	0%	
Low	Count	18	6	3	27
	%	67%	22%	11%	
Moderate	Count	34	21	22	77
	%	44%	27%	29%	
High	Count	27	7	15	49
	%	55%	14%	31%	
Very high	Count	3	2	3	8
	%	38%	24%	38%	
Total		83	37	43	163
% within Environmental value		51%	23%	26%	

Table J.9b: Contingency table for the attribute shallow to medium depth water at a site with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any shallow to medium depth water presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shallow to medium depth water and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 3.744 and one-tailed p-value =0.0265, which is statistically significant.

Environmental value	Shallow to medium depth water		Total
	Absent	Present	
Very low & low	19 (14)	9 (14)	28
Moderate, high & very high	64 (69)	70 (65)	134
Total	83	79	162

Table J.9c: Contingency table for the attribute shallow to medium depth water at a site with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any shallow to medium depth water presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shallow to medium depth water and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.069 and one-tailed p-value =0.3966, which is not statistically significant.

Environmental value	Shallow to medium depth water		Total
	Absent	Present	
Very low, low & moderate	53 (54)	52 (51)	105
High & very high	30 (29)	27 (28)	57
Total	83	79	162

Table J.10a: Contingency table for the terrestrial zone habitat type subattribute of submerged or free-floating vegetation against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Habitat value – Terrestrial zone habitat type – Submerged or free-floating vegetation: Absent	Present: Usually	Present: Abundant	Total
Unknown	Count	0	0	1	1
	%	0%	0%	100%	
Very low	Count	0	0	1	1
	%	0%	0%	100%	
Low	Count	21	6	0	27
	%	78%	22%	0%	
Moderate	Count	35	34	8	77
	%	46%	44%	10%	
High	Count	27	18	4	49
	%	55%	37%	8%	
Very high	Count	4	4	0	8
	%	50%	50%	0%	
Total		87	63	13	163
% within Environmental value		53%	39%	8%	

Table J.10b: Contingency table for the attribute submerged or free-floating vegetation with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any submerged or free-floating vegetation presences have been summed. Values in brackets are the expected frequencies for each cell if there is no association between submerged or free-floating vegetation and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 6.175 and one-tailed p-value = 0.0065, which is statistically significant.

Environmental value	**Submerged or free-floating vegetation**		**Total**
	Absent	**Present**	
Very low & low	21 (15)	7 (13)	28
Moderate, high & very high	66 (72)	68 (62)	134
Total	87	75	162

Table J.10c: Contingency table for the attribute submerged or free-floating vegetation at a site with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any submerged or free-floating vegetation presences have been summed. Values in brackets are the expected frequencies for each cell if there is no association between submerged or free-floating and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.016 and one-tailed p-value = 0.4490, which is not statistically significant.

Environmental value	**Submerged or free-floating vegetation**		**Total**
	Absent	**Present**	
Very low, low & moderate	56 (56)	49 (49)	105
High & very high	31 (31)	26 (26)	57
Total	87	75	162

Table J.11a: Contingency table for the terrestrial zone habitat type subattribute of water edge against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Habitat value**			
		Terrestrial zone habitat type			
		Water edge			
		Absent	**Present**		**Total**
			Usually	Abundant	
Unknown	Count	0	1	0	1
	%	0%	100%	0%	
Very low	Count	0	1	0	1
	%	0%	100%	0%	
Low	Count	13	8	6	27
	%	48%	30%	22%	
Moderate	Count	4	39	34	77
	%	5%	51%	44%	
High	Count	3	10	36	49
	%	6%	20%	74%	
Very high	Count	0	1	7	8
	%	0%	12%	88%	
Total		20	60	83	163
% within Environmental value		12%	37%	51%	

Table J.11b: Contingency table for the attribute water edge with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting water edge presences have been summed. Values in brackets are the expected frequencies for each cell if there is no association between water edge and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 36.337 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	Water edge		Total
	Absent	**Present**	
Very low & low	13 (3)	15 (25)	28
Moderate, high & very high	7 (17)	127 (117)	134
Total	20	142	162

Table J.12a: Contingency table for the shoreline vegetation subattribute of alive trees against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Habitat value – Shoreline profile – Shoreline vegetation – Alive trees			
		Absent	Present		Total
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	0	0	1	1
	%	0%	0%	100%	
Low	Count	17	7	3	27
	%	63%	26%	11%	
Moderate	Count	11	39	27	77
	%	14%	51%	35%	
High	Count	4	7	38	49
	%	8%	14%	78%	
Very high	Count	0	3	8	8
	%	0%	37%	63%	
Total		33	56	74	163
% within Environmental value		20%	35%	45%	

Table J.12b: Contingency table for the attribute shoreline vegetation alive trees with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting shoreline vegetation alive trees presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shoreline vegetation alive trees and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 35.830 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Alive trees**		**Total**
	Absent	**Present**	
Very low & low	17 (6)	11 (22)	28
Moderate, high & very high	15 (26)	119 (108)	134
Total	32	130	162

Table J.13a: Contingency table for the shoreline vegetation subattribute of dead trees against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Habitat value – Shoreline profile – Shoreline vegetation – Dead trees			
		Absent	Present		Total
			Usually	Abundant	
Unknown	Count	1	0	0	1
	%	100%	0%	0%	
Very low	Count	0	1	0	1
	%	0%	100%	0%	
Low	Count	21	6	0	27
	%	78%	22%	0%	
Moderate	Count	33	37	7	77
	%	43%	48%	9%	
High	Count	9	35	5	49
	%	18%	72%	10%	
Very high	Count	1	5	2	8
	%	12%	63%	25%	
Total		65	84	14	163
% within Environmental value		40%	51%	9%	

Table J.13b: Contingency table for the attribute shoreline vegetation dead trees with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting shoreline vegetation dead trees presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shoreline vegetation dead trees and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 17.844 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	Dead trees		Total
	Absent	Present	
Very low & low	21 (11)	7 (17)	28
Moderate, high & very high	43 (53)	91 (81)	134
Total	64	98	162

Table J.13c: Contingency table for the attribute shoreline vegetation dead trees with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any shoreline vegetation dead trees presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shoreline vegetation dead trees and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 17.749 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	Dead trees		Total
	Absent	Present	
Very low, low & moderate	54 (41)	51 (64)	105
High & very high	10 (23)	47 (34)	57
Total	64	98	162

Table J.14a: Contingency table for the shoreline profile, shoreline description of a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded. Unk'n is the abbreviation for unknown physical arrangement.

Environmental value		Habitat value – Shoreline profile – Shoreline description: Unk'n	Regular: No island	Regular: With island	Irregular: No island	Irregular: With island	Total
Unknown	Count	0	1	0	0	0	1
	%	0%	100%	0%	0%	0%	
Very low	Count	0	1	0	0	0	1
	%	0%	100%	0%	0%	0%	
Low	Count	2	12	0	11	2	27
	%	7%	45%	0%	41%	7%	
Moderate	Count	3	18	1	51	4	77
	%	4%	24%	1%	66%	5%	
High	Count	1	21	0	25	2	49
	%	2%	43%	0%	51%	4%	
Very high	Count	0	3	0	4	1	8
	%	0%	38%	0%	50%	12%	
Total		6	56	1	91	9	163
% within Environmental value		4%	34%	1%	56%	5%	

Table J.14b: Contingency table for the attribute shoreline profile, shoreline description with very low and low Environmental value counts added and moderate, high and very high counts summed. Values in brackets are the expected frequencies for each cell if there is no association between shoreline profile physical arrangement and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 2.697 and one-tailed p-value = 0.0503, which is not quite statistically significant.

Environmental value	Shoreline description		Total
	Regular	Irregular	
Very low & low	13 (9)	13 (17)	26
Moderate, high & very high	43 (47)	87 (83)	130
Total	56	100	156

Table J.14c: Contingency table for the attribute shoreline profile, shoreline description with very low, low and moderate Environmental value counts added and high and very high counts summed. Values in brackets are the expected frequencies for each cell if there is no association between shoreline profile physical arrangement and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 1.839 and one-tailed p-value = 0.0875, which is not statistically significant.

Environmental value	Shoreline description		Total
	Regular	Irregular	
Very low, low & moderate	32 (36)	68 (64)	100
High & very high	24 (20)	32 (36)	56
Total	56	100	156

Table J.15a: Contingency table for the attribute disposal of water against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		Hydrology: Disposal of water				
		Absent	Present: No impact	Present: Low to moderate impact	Present: Severe impact	Total
Unknown	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Very low	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Low	Count	22	0	3	2	27
	%	82%	0%	11%	7%	
Moderate	Count	59	2	10	6	77
	%	77%	3%	12%	8%	
High	Count	46	0	3	0	49
	%	94%	0%	6%	0%	
Very high	Count	8	0	0	0	8
	%	100%	0%	0%	0%	
Total		137	2	16	8	163
% within Environmental value		84%	1%	10%	5%	

Table J.15b: Contingency table for the attribute disposal of water with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any disposal of water activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between disposal of water and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.082 and one-tailed p-value = 0.3872, which is not statistically significant.

Environmental value	**Disposal of water**		**Total**
	Absent	**Present**	
Very low & low	23 (24)	5 (4)	28
Moderate, high & very high	113 (112)	21 (22)	134
Total	136	26	162

Table J.16a: Contingency table for the attribute obstruction against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Hydrology**				
		Obstruction				
		Absent	**Present**			**Total**
			No impact	Low to moderate impact	Severe impact	
Unknown	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Very low	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Low	Count	11	0	8	8	27
	%	40%	0%	30%	30%	
Moderate	Count	43	1	25	8	77
	%	56%	1%	33%	10%	
High	Count	42	1	3	3	49
	%	86%	2%	6%	6%	
Very high	Count	8	0	0	0	8
	%	100%	0%	0%	0%	
Total		106	2	36	19	163
% within Environmental value		65%	1%	22%	12%	

Table J.16b: Contingency table for the attribute obstruction with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any obstruction activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between obstruction and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 7.157 and one-tailed p-value = 0.0037, which is statistically significant.

Environmental value	Obstruction		Total
	Absent	Present	
Very low & low	12 (18)	16 (10)	28
Moderate, high & very high	93 (87)	41 (47)	134
Total	105	57	162

Table J.16c: Contingency table for the attribute obstruction with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any obstruction activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between obstruction and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 20.231 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	Obstruction		Total
	Absent	Present	
Very low, low & moderate	55 (68)	50 (37)	105
High & very high	50 (37)	7 (20)	57
Total	105	57	162

Table J.17a: Contingency table for the attribute redirection against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Hydrology – Redirection**				
		Absent	**Present**			**Total**
			No impact	Low to moderate impact	Severe impact	
Unknown	Count	0	0	1	0	1
	%	0%	0%	100%	0%	
Very low	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Low	Count	9	0	10	8	27
	%	33%	0%	37%	30%	
Moderate	Count	24	0	37	16	77
	%	31%	0%	48%	21%	
High	Count	38	0	9	2	49
	%	78%	0%	18%	4%	
Very high	Count	7	0	1	0	8
	%	88%	0%	12%	0%	
Total		79	0	58	26	163
% within Environmental value		48%	0%	36%	16%	

Table J.17b: Contingency table for the attribute redirection with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any redirection activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between redirection and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 2.308 and one-tailed p-value = 0.0644,, which is not statistically significant.

Environmental value	**Redirection**		**Total**
	Absent	**Present**	
Very low & low	10 (14)	18 (14)	28
Moderate, high & very high	69 (65)	65 (69)	134
Total	79	83	162

Table J.17c: Contingency table for the attribute redirection with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any redirection activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between redirection and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 32.064 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Redirection**		**Total**
	Absent	**Present**	
Very low, low & moderate	34 (51)	71 (54)	105
High & very high	45 (28)	12 (29)	57
Total	79	83	162

Table J.18a: Contingency table for the attribute water storage against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded.

Environmental value		**Hydrology**				
		Water storage				
		Absent	**Present**			**Total**
			No impact	Low to moderate impact	Severe impact	
Unknown	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Very low	Count	1	0	0	0	1
	%	100%	0%	0%	0%	
Low	Count	21	0	4	2	27
	%	78%	0%	15%	7%	
Moderate	Count	71	0	4	2	77
	%	92%	0%	5%	3%	
High	Count	46	2	1	0	49
	%	94%	4%	2%	0%	
Very high	Count	8	0	0	0	8
	%	100%	0%	0%	0%	
Total		148	2	9	4	163
% within Environmental value		91%	1%	6%	2%	

Table J.18b: Contingency table for the attribute water storage with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any water storage activity have been summed. Values in brackets are the expected frequencies for each cell if there is no association between water storage and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 5.967 and one-tailed p-value =0.0073, which is very statistically significant.

Environmental value	Water storage		Total
	Absent	Present	
Very low & low	22 (25)	6 (3)	28
Moderate, high & very high	125 (122)	9 (12)	134
Total	147	15	162

Table J.19a: Contingency table for the percentage total ferns coverage at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than unknown and totals have been shaded.

Environmental value		Vegetation intactness– critical lifeforms						Total
		Floral types of most dominant wetland EVC						
		Sum of % ferns coverage per site						
		0%	1 to 19%	20 to 39%	40 to 59%	60 to 79%	≥ 80%	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Low	Count	26	1	0	0	0	0	27
	%	96%	4%	0%	0%	0%	0%	
Moderate	Count	70	7	0	0	0	0	77
	%	91%	9%	0%	0%	0%	0%	
High	Count	40	6	2	1	0	0	49
	%	82%	12%	4%	2%	0%	0%	
Very high	Count	5	1	2	0	0	0	8
	%	63%	12%	25%	0%	0%	0%	
Total		143	15	4	1	0	0	163
% within Environmental value		87%	9%	3%	1%	0%	0%	

Table J.19b: Contingency table for the attribute ferns in dominant EVC with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting ferns in dominant EVC presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between ferns in dominant EVC and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 6.161 and one-tailed p-value = 0.0065, which is statistically significant.

Environmental value	**Ferns**		**Total**
	0	**> 0**	
Very low, low & moderate	97 (92)	8 (13)	105
High & very high	45 (50)	12 (7)	57
Total	142	20	162

Table J.20a: Contingency table for the percentage total graminoids coverage at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells, other than for unknown, have been shaded**.**

Environmental value		Vegetation intactness– critical lifeforms / Floral types of most dominant wetland EVC / Sum of % graminoids coverage per site						Total
		0%	1 to 19%	20 to 39%	40 to 59%	60 to 79%	≥ 80%	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	0	0	0	1	0	0	1
	%	0%	0%	0%	100%	0%	0%	
Low	Count	20	5	1	1	0	0	27
	%	74%	18%	4%	4%	0%	0%	
Moderate	Count	44	24	4	2	2	1	77
	%	57%	31%	5%	3%	3%	1%	
High	Count	30	12	5	1	1	0	49
	%	61%	25%	10%	2%	2%	0%	
Very high	Count	5	2	0	0	1	0	8
	%	63%	25%	0%	0%	12%	0%	
Total		100	43	10	5	4	1	163
% within Environmental value		61%	27%	6%	3%	3%		

Table J.20b: Contingency table for the attribute graminoids in the dominant EVC with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any graminoids presence in the dominant EVC have been summed. Values in brackets are the expected frequencies for each cell if there is no association between graminoids and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 1.516 and one-tailed p-value = 0.1091, which is not statistically significant.

Environmental value	**Graminoids**		**Total**
	0	**> 0**	
Very low & low	20 (17)	8 (11)	28
Moderate, high & very high	79 (82)	55 (52)	134
Total	99	63	162

Table J.20c: Contingency table for the attribute graminoids in the dominant EVC with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting graminoids presence in the dominant EVC have been summed. Values in brackets are the expected frequencies for each cell if there is no association between graminoids in the dominant EVC and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.003 and one-tailed p-value = 0.4776, which is not statistically significant.

Environmental value	**Graminoids**		**Total**
	0	**> 0**	
Very low, low & moderate	64 (64)	41 (41)	105
High & very high	35 (35)	22 (22)	57
Total	99	63	162

Table J.21a: Contingency table for the percentage total grasses coverage at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells, other than for unknown, have been shaded**.**

Environmental value		**Vegetation intactness– critical lifeforms**						**Total**
		Floral types of most dominant wetland EVC						
		Sum of % grasses coverage per site						
		0%	1 to 19%	20 to 39%	40 to 59%	60 to 79%	≥ 80%	
Unknown	Count	0	0	0	1	0	0	1
	%	0%	0%	0%	100%	0%	0%	
Very low	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Low	Count	25	2	0	0	0	0	27
	%	93%	7%	0%	0%	0%	0%	
Moderate	Count	51	20	4	2	0	0	77
	%	66%	26%	5%	3%	0%	0%	
High	Count	37	9	2	1	0	0	49
	%	76%	18%	4%	2%	0%	0%	
Very high	Count	7	1	0	0	0	0	8
	%	88%	12%	0%	0%	0%	0%	
Total		121	32	6	4	0	0	163
% within Environmental value		74%	20%	4%	2%	0%	0%	

Table J.21b: Contingency table for the attribute grasses in dominant EVC with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting grasses in dominant EVC presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between grasses in dominant EVC and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 0.291 and one-tailed p-value = 0.2947, which is not statistically significant.

Environmental value	**Grasses**		**Total**
	0	**> 0**	
Very low, low & moderate	77 (78)	28 (27)	105
High & very high	44 (43)	13 (14)	57
Total	121	41	162

Table J.22a: Contingency table for the percentage total sedges coverage at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells, other than for unknown, have been shaded**.**

Environmental value		**Vegetation intactness– critical lifeforms** – **Floral types of most dominant wetland EVC** – **Sum of % sedges coverage per site**						**Total**
		0%	1 to 19%	20 to 39%	40 to 59%	60 to 79%	≥ 80%	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Low	Count	23	3	1	0	0	0	27
	%	85%	11%	4%	0%	0%	0%	
Moderate	Count	57	15	3	1	1	0	77
	%	74%	20%	4%	1%	1%	0%	
High	Count	19	13	8	6	3	0	49
	%	39%	27%	16%	12%	6%	0%	
Very high	Count	2	4	1	1	0	0	8
	%	25%	50%	25%		0%	0%	
Total		103	35	13	8	4	0	163
% within Environmental value		63%	21%	8%	5%	3%	0%	

Table J.22b: Contingency table for the attribute sedges in dominant EVC with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting sedges in dominant EVC presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between sedges in dominant EVC and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 25.731 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	Sedges		Total
	0	> 0	
Very low, low & moderate	81 (66)	24 (39)	105
High & very high	21 (36)	36 (21)	57
Total	102	60	162

Table J.23a: Contingency table for the percentage total shrubs coverage at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than for unknown have been shaded**.**

Environmental value		**Vegetation intactness– critical lifeforms**						**Total**
		Floral types of most dominant wetland EVC						
		Sum of % shrubs coverage per site						
		0%	1 to 19%	20 to 39%	40 to 59%	60 to 79%	≥ 80%	
Unknown	Count	1	0	0	0	0	0	1
	%	100%	0%	0%	0%	0%	0%	
Very low	Count	0	0	1	0	0	0	1
	%	0%	0%	100%	0%	0%	0%	
Low	Count	27	0	0	0	0	0	27
	%	100%	0%	0%	0%	0%	0%	
Moderate	Count	53	14	5	3	1	1	77
	%	69%	18%	7%	4%	1%	1%	
High	Count	25	8	8	5	3	0	49
	%	52%	16%	16%	10%	6%	0%	
Very high	Count	4	1	3	0	0	0	8
	%	50%	12%	38%	0%	0%	0%	
Total		110	23	17	8	4	1	163
% within Environmental value		67%	14%	10%	5%	3%	1%	

Table J.23b: Contingency table for the attribute shrubs in dominant EVC with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting shrubs in dominant EVC presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between shrubs in dominant EVC and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 10.754 and one-tailed p-value = 0.0005, which is extremely statistically significant.

Environmental value	**Shrubs**		**Total**
	0	**> 0**	
Very low, low & moderate	80 (71)	25 (34)	105
High & very high	29 (38)	28 (19)	57
Total	109	53	162

Table J.24a: Contingency table for the number of floral species present at a site against overall WGCMA Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells, other than for unknown, have been shaded**.**

Environmental value		Vegetation intactness– critical lifeforms						Total
		Number of floral species present						
		0	1 to 5	6 to 10	11 to 15	16 to 20	> 20	
Unknown	Count	0	0	1	0	0	0	1
	%	0%	0%	100%	0%	0%	0%	
Very low	Count	0	0	1	0	0	0	1
	%	0%	0%	100%	0%	0%	0%	
Low	Count	14	7	6	0	0	0	27
	%	52%	26%	22%	0%	0%	0%	
Moderate	Count	5	12	43	14	2	1	77
	%	6%	16%	56%	18%	3%	1%	
High	Count	0	11	21	10	6	1	49
	%	0%	23%	43%	20%	12%	2%	
Very high	Count	1	1	3	1	2	0	8
	%	25%		38%	12%	25%	0%	
Total		20	31	75	25	10	2	163
% within Environmental value		12%	19%	46%	16%	6%	1%	

Table J.24b: Contingency table for the attribute number of floral species present with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any floral species presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between number of floral species and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 44.352 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**No. of floral species present**		**Total**
	0	**> 0**	
Very low & low	14 (3)	14 (25)	28
Moderate, high & very high	6 (17)	128 (117)	134
Total	20	142	162

Table J.25a: Contingency table for substantial modifications at a site against overall Environmental value assessment. The values show the number and percentage of wetlands in the Database categorized as very low, low, moderate, high and very high Environmental values. Non-empty cells other than unknown and totals have been shaded.

Environmental value		Vegetation intactness– critical lifeforms		
		Substantial modifications		
		Absent	Present	Total
Unknown	Count	1	0	1
	%	100%	0%	
Very low	Count	1	0	1
	%	100%	0%	
Low	Count	5	22	27
	%	18%	82%	
Moderate	Count	42	35	77
	%	55%	45%	
High	Count	44	5	49
	%	90%	10%	
Very high	Count	8	0	8
	%	100%	0%	
Total		101	62	163
% within Environmental value		62%	38%	

Table J.25b: Contingency table for the attribute substantial modifications at a site with very low and low Environmental value counts added and moderate, high and very high counts summed. All columns denoting any substantial modification presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between substantial modifications and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 23.271 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Substantial modifications**		**Total**
	Absent	**Present**	
Very low & low	6 (17)	22 (11)	28
Moderate, high & very high	94 (83)	40 (51)	134
Total	100	62	162

Table J.25c: Contingency table for the attribute substantial modifications at a site with very low, low and moderate Environmental value counts added and high and very high counts summed. All columns denoting any substantial modification presence have been summed. Values in brackets are the expected frequencies for each cell if there is no association between substantial modifications and the WGCMA Environmental value assessment. $\chi^2_{(df=1)}$ value = 32.395 and one-tailed p-value < 0.0001, which is extremely statistically significant.

Environmental value	**Substantial modifications**		**Total**
	Absent	**Present**	
Very low, low & moderate	6 (17)	22 (11)	105
High & very high	94 (83)	40 (51)	57
Total	100	62	162