Management of Agricultural Non-point Source Pollution – A Case Study on Yarra River

By

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ABSTRACT

The development and use of any specific model depend on the availability of data and the hydrological settings of a country. Because of data limitations (especially water quality and land management data), the water quality models developed for Australian catchments are lumped/semi-distributed conceptual models. Even within these modelling frameworks, water quality component is empirical or generation rates-based. In this context, developing an effective water quality management plan in the data-poor conditions of Australia still remains as a major challenge for water catchment managers, despite huge investment on river health improvement programs.

Physics-based distributed water quality models such as SWAT are most suitable for agricultural non-point source pollution studies. However, because of high data requirement and processing, the applications of these models are limited in many data-poor catchments. In this study, relevant input data sources and analysis techniques were addressed especially for sparsely available water quality data to assemble, and to rigorously calibrate and validate the SWAT based Middle Yarra Water Quality Model (MYWQM) for the case study area - Middle Yarra Catchment (MYC) of Victoria, Australia. The regression based model LOADEST was used for estimating sediment, and nutrient observed loads from monthly water quality grab sample data. The MYWQM was then used to develop a water quality management plan for agricultural non-point source pollution in the MYC.

In general, the MYWQM was found capable of predicting streamflow, sediment and nutrient loads in the MYC. The model was also found effective for simulating individual and integrated effects of several Best Management Practices (BMPs) in the MYC. Moreover, the model showed that the in-stream processes if not considered can result in incorrect estimates when simulating BMPs in the model. Overall, the performance of the MYWQM on evaluating the BMPs in the MYC demonstrated that data-intensive physics-based models can be applied in the data-poor conditions of Australia.

DECLARATION

"I, Sushil Kumar Das, declare that the PhD thesis entitled 'Management of Agricultural Non-point Source Pollution – A Case Study on Yarra River' 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]

Signature Date: 30/08/2016

Dedicated

To

My parents with love and appreciation

"All that I am or ever hope to be, I owe to my angel mother"

-Abraham Lincoln

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LIST OF ABBREVIATIONS

The following list of abbreviations is used throughout this thesis. The other abbreviations, which were used only in particular sections or chapters are defined in the relevant sections or chapters.

ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ABS	Australian Bureau of Statistics
ACLEP	Australian Collaborative Land Evaluation Program
AIC	Akaike Information Criterion
ArcSWAT	ArcGIS-ArcView extension and graphical user input interface for SWAT
ASRIS	Australian Soil Resource Information System
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BFI	Base Flow Index
BMPs	Best Management Practices
CN	Curve Number
CSIRO	Commonwealth Scientific and Industrial Research Organization
DEM	Digital Elevation Model
E_{NS}^2	Nash-Sutcliffe Efficiency
GDEM	Global Digital Elevation Model
GIS	Geographic Information System
GLUE	Generalized Likelihood Uncertainty Estimation
HRUs	Hydrologic Response Units
ISC	Index of Stream Conditions
LH	Latin-Hypercube
LH-OAT	The Latin-Hypercube and One-factor-At-a-Time
LOADEST	LOAD ESTimator
MYC	Middle Yarra catchment
MYWQM	Middle Yarra Water Quality Model
NPS	Non-point Source
OAT	One-factor-At-a-Time
ParaSol	Parameter Solution
PBIAS	Percent Bias
PET	Potential Evapotranspiration
Q	Streamflow
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
RSR	Ratio of the RMSE to the standard deviation of measured data
SCE-UA	Shuffled Complex Evolution – The University of Arizona

SILO	Scientific Information for Land Owners
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
TN	Total Nitrogen
TP	Total Phosphorus
TSS	Total Suspended Solid
VFSs	Vegetative filter strips

LIST OF PUBLICATIONS AND AWARDS

Publications:

1. Das, S. K. and Ng, A. W. M. and Perera, B. J. C. (2013). Development of a SWAT model in the Yarra River catchment. In: MODSIM2013, 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1-6 December 2013. Piantadosi, J. and Anderssen, R. S. and Boland, J., eds. Modelling and Simulation Society of Australia and New Zealand, Canberra, ACT, pp. 2457-2463. ISBN 9780987214331

2. Das, S. K. and Ng, A. W. M. and Perera, B. J. C. (2013). Sensitivity analysis of SWAT model in the Yarra River catchment. In: MODSIM2013, 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1-6 December 2013. Piantadosi, J. and Anderssen, R. S. and Boland, J., eds. Modelling and Simulation Society of Australia and New Zealand, Canberra, ACT, pp. 1666-1672. ISBN 9780987214331

3. Das, S. K. and Ng, A. W. M. and Perera, B. J. C. and Adhikary, S. K. (2013). Effects of climate and land use activities on water quality in the Yarra River catchment. In: MODSIM2013, 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1-6 December 2013. Piantadosi, J. and Anderssen, R. S. and Boland, J., eds. Modelling and Simulation Society of Australia and New Zealand, Canberra, ACT, pp. 2618-2624. ISBN 9780987214331

4. Das, S. K. and Ng, A. W. M. and Perera, B. J. C. (2013). Use of specific flow regimes in water quality analysis - a case study in the Yarra River catchment, Australia. In: Proceedings of the 35th IAHR World Congress held in Chengdu, China, 8-13 September 2013. Zhaoyin, Wang and Lee, Joseph Hun-wi and Jizhang, Gao and Shuyou, Cao, eds. International Association for Hydro-Environment Engineering and Research, Chengdu, China. ISBN 9787894145888

5. Das, S. K. and Ng, A. W. M. and Perera, B. J. C. (2013). Data processing for complex diffuse pollution models. In: Proceedings of the 16th International Conference on Diffuse Pollution and Eutrophication held in Beijing, China, August 18-23, 2013. International Water Association (IWA), Beijing, China

6. Das, S. K. and Ng, A. W. M. and Perera, B. J. C. (2011). Assessment of nutrient and sediment loads in the Yarra River Catchment. In: MODSIM2011, 19th International Congress on Modelling and Simulation, Perth, Australia, 12-16 December 2011. Chan, F. and Marinova, D. and Anderssen, R. S., eds. Modelling and Simulation Society of Australia and New Zealand, Canberra, ACT, pp. 3490-3496. ISBN 9780987214317

Award:

1. Best research poster presentation award at the Postgraduate Research Conference July 2010 held in Victoria University, Australia. The poster was on Assessment of Nutrient and Sediment Loads in the Yarra River Catchment.

1. INTRODUCTION

1.1. PROBLEM STATEMENT

Scarcity of water, deterioration of water quality and excessive sediments in rivers and creeks have become challenging issues for food supply, food security, human health and natural ecosystems. This is particularly the case with rapid changes in land use and agricultural practices. In the last few decades, changes in land use patterns caused by demographic, economic, political and/or cultural mutations have notable effects on water supply, water quality and soil erosion (Ingram et al, 1996). A consequence of the conversion of tropical rainforests to pastures or cultivated land results in a decrease of the porosity of the top-soil where organic matter and nutrients concentrate. This leads to more runoff, nutrient leaching and erosion, causing reductions of on-site fertility and off-site consequences (e.g. water pollution by nutrients which in turn increases the eutrophication hazards). All these on-site and off-site effects may dramatically jeopardize the future of natural ecosystems and the economic development of society.

Catchment-scale management programs have been proven to be efficient in reducing water pollution from land use activities and agricultural practices (Guo et al, 2002). Unlike point source pollution from industrial and sewage treatment plants, non-point source (NPS) pollution comes from many diffuse sources (such as agriculture land runoff) and caused by rainfall or snowmelt moving over and through the ground. Management of NPS pollution especially from agricultural practices is much more difficult than point source pollution, because agricultural production systems are complex, and influenced by many factors such as climatic, economic and social factors. The type of agricultural system practised depends on local conditions, availability of resources and environmental limitations. Because of adverse climatic and geographic conditions and space limitations, it is still a challenge in many locations to maintain reasonable agricultural production levels without overusing natural resources. As a result, NPS pollution is still a major concern to the water catchment managers in many parts of the world.

Successful management of NPS pollution requires an understanding of the processes through which the pollutants are transported from runoff to surface water. These processes are very complex, and several factors such as hydrological, topographical, chemical transport, soil-type and land use conditions determine the NPS pollution processes. Mathematical computer models simulating and simplifying these complex processes are cost effective analysis tools to understand the problems and find solutions through land use changes and best management practices (BMPs) for particular catchments and agronomic settings (Wurbs, 1998; Muttiah and Wurbs, 2002; Borah and Bera, 2004).

In the last two decades, NPS pollution has become a topic for research that has resulted in the development of numerous software tools and modelling techniques (mainly three types: Empirical, Conceptual and Physics-based models) that help to analyze the effects of land use and agricultural practices on in-stream water quality through simulation of BMPs. These models differ in terms of complexity, processes considered, weaknesses and strengths, and the data requirements. The development and use of any specific model depend on the hydrological settings of a country.

Australia has a unique hydrological setting that has strongly influenced the development of water quality models built for Australian catchments (Croke and Jakeman, 2001). In Australia, Grayson et al (1999b) found that there is only limited continuous water quality data available and much of the spot sample data held is largely inaccessible. Information on erosion, soil properties or spatially referenced land use and ecosystem data is also relatively sparse, complicating the development of water quality models in Australia (Kragt and Newham, 2009). Therefore, traditionally and commonly used water quality models in Australia are either empirical or lumped/semi-distributed conceptual models. Even within these modelling framework, water quality component is empirical or generation rates-based because of data limitations. Many researchers (Thorsen et al, 2001; Borah and Bera, 2003) pointed out that physics-based models are better suited for agricultural NPS pollution modelling for their diffuse and chronic nature.

In this context, developing an effective water quality management plan in the data-poor conditions of Australia still remains as a major challenge for water catchment managers. As a result, despite huge investment on river health improvement programs, water quality was not improved substantially in Australian catchments. A national comparison of water quality (Sinclair Knight Merz, 2011) against Australian water quality guidelines for fresh and marine waters (ANECC and ARMCAN, 2000) and the Queensland water quality guidelines (QDERM, 2009) showed exceedances in sediment, total nitrogen and total phosphorus in parts of all drainage divisions of Australia (SoE, 2011). Despite huge investment on the Yarra River by Victorian government, over half (57%) of the river length is in poor or worse condition as per the third Index of Stream conditions (ISC) (DEPI, 2013).

This thesis concentrates on developing a water quality management plan using a data-intensive physics-based model in the data-poor conditions of Australia. The results of this research would contribute to the development of methods that combine scarce data with creative processing techniques and expert knowledge to improve/complete available information to apply data-intensive complex models in data-poor environments.

1.2. OBJECTIVES OF THE STUDY

The main objective of this research was to investigate the applicability of data-intensive physics-based, distributed and continuous water quality models in data-poor catchments.

The specific objectives necessary to realize this research objective are as follows:

1) To address relevant data sources and their processing techniques especially for sparsely available water quality data.
2) To develop a physics-based model for the mid-agricultural part of the Yarra River catchment of Victoria, Australia as a case study.
3) To analyze the effects of in-stream processes on the model performance.
4) To demonstrate the applicability of the physics-based model in the data-poor conditions of Australian through developing a water quality management plan of the study area.

1.3. SIGNIFICANCE OF THE RESEARCH

This research study has produced several significant contributions in the field of agricultural NPS pollution management, especially for Australian conditions. These contributions are outlined below:

- As stated in Section 1.1, complex physics-based distributed and continuous models are most suitable for agricultural NPS studies. This research was the first study to rigorously test the applicability of these complex water quality models in the data-poor conditions of Australia.
- Relevant data sources and their processing techniques were addressed for developing and calibrating a complex model specifically for Australian conditions as a case study. These analysis techniques and most data sources are also applicable for other data-poor catchment. Based on the literature review, the author finds no single research study available in the literature discussing data sources and their appropriate processing which would enhance the applications and development of data-intensive physics-based models in data-poor conditions.
- Physics-based models need observed data (such as nutrient loads, surface runoff and baseflow) for calibration and validation. Identification and application of appropriate nutrient load calculation methods were addressed for use with sparsely available water quality grab sample data. Appropriate streamflow separation methods were also discussed and identified.
- Catchment water quality models do not consider in-stream biotic and abiotic processes. This affects the capability of catchment models especially when these are calibrated only at the catchment outlet which is the general case. This study has considered QUAL2E-based in-stream kinetic functions with the SWAT catchment model where relative effects of considering or not considering in-stream processes on sediment and nutrients were analyzed. Based on the literature review, the author found no such studies in the literature except Tuppad et al (2010a; 2010b) and Cho et al (2010b) who considered only the default SWAT in-stream processes option in their agricultural management simulations.
- Recommended Water Quality Management Plan developed for the mid-agricultural part of the Yarra River catchment will help to identify the critical areas within the catchment that are responsible for a disproportionate amount of the pollutant yield from the catchment. NPS pollution control resources and investments can then be targeted only on these critical areas to maximize improvements in downstream water quality.

1.4. OUTLINE OF THE THESIS

The thesis consists of six chapters. *Chapter 1* describes the background of the research project, the aims and research significance of this project.

Chapter 2 presents a critical review of literature related to the research project. It provides the reader with a general overview of the application of data-intensive models in management of agricultural NPS pollution with an emphasis on SWAT model. Strengths and weaknesses of different types of water quality catchment models are discussed to point out the capability of data-intensive complex models in understanding contaminant fate and transport, and simulating agricultural BMPs. Then the water quality modelling tools developed and used in Australian conditions are discussed with a view to test the applicability of complex water quality models in the data-poor conditions of Australia. Model sensitivity analysis, calibration and validation, and uncertainty analysis along with the evaluation statistics are discussed as essential criteria for acceptance reliability of model outputs. Streamflow and water quality sparse data processing techniques are discussed in detail to facilitate the calibration processes like generating continuous data from water quality grab samples. At the end of the chapter, some data sources for water quality models are discussed which would enhance the applications and development of physics-based models in data limited conditions.

Chapter 3 starts with the general description of the Yarra River catchment with respect to its water quality condition and management practices. Then the study area - Middle Yarra catchment (MYC) is described, followed by sources and processes of data required for developing the SWAT based Middle Yarra Water Quality Model (MYWQM) in this project. Finally the streamflow data analysis and pollutant load estimation processes from water quality grab samples are illustrated.

The assembly of the MYWQM and its performance evaluations are described in *Chapter 4*. *Chapter 5* illustrates the development of water quality management plan through simulations of BMPs for the study area. Finally, a summary of the thesis and the main conclusions, and the recommendations for future work are presented in *Chapter 6*.

2. WATER QUALITY PROCESSES AND MODELLING

2.1. INTRODUCTION

In Chapter 1, the overall background and objectives of this thesis were discussed. As mentioned in Section 1.1, changes in land use patterns during the last few decades have notable effects on water quality. A consequence of the conversion of tropical rainforests to pastures or agricultural land results in more runoff generation, nutrient leaching and soil erosion. Unsuccessful traditional agricultural practices have increased pressures on the soil, nutrient resources and water. This condition creates the need for improved agricultural production systems that embrace sustainable use of resources and pollution control of surrounding water systems. In this instance, regulatory agencies promote Best Management Practices (BMPs) to improve the agricultural production systems. Catchment water quality models are cost effective tools to analyze the impacts of various BMPs (individual or integrated effects of several BMPs) and to develop water quality management plans (Wurbs, 1998; Muttiah and Wurbs, 2002).

The purpose of the literature review in this chapter is to provide the reader with a general overview of the application of data-intensive models in management of agricultural non-point source pollution in relatively data-poor environments of Australia, with an emphasis on the Soil and Water Assessment Tool (SWAT) model.

The chapter starts with a brief discussion of overland and in-stream water quality processes of sediment and nutrients generation and their transport which affect the water quality issues in Section 2.2. Then Section 2.3 discusses the water quality pollution issues and best management practices (BMPs) used in management of agricultural non-point source pollution. The strengths and weaknesses of different types of water quality models, and the water quality models developed and used in Australian catchments are discussed in Section 2.4 with a view to select the most suitable model for the Middle Yarra catchment in Victoria, which was used as the case study area in this thesis. Finally the model evaluation processes and statistics which are essential to make a developed model scientifically robust, reliable and acceptable are discussed in Section 2.5. This section also addresses streamflow and water quality sparse data process techniques especially on how to generate constituent loads from water quality grab samples for calibration purposes. In Section 2.6, some data sources for water quality models are discussed which would enhance the applications and development of physics-based model in data limited conditions. At the end, a summary of the chapter is provided.

2.2. WATER QUALITY PROCESSES

Basic understanding of the processes that affect water quality helps to develop appropriate models for effective management of a catchment. These processes comprise of overland processes (such as soil erosion, transformation and movement of nutrients) and in-stream processes (such as dilution, sedimentation, resuspension and adsorption of pollutants).

Catchment water quality models do not consider in-stream processes. To overcome this limitation, in-stream processes from a river water quality model is either incorporated or integrated with the catchment water quality model. In most catchment-modelling studies, streamflow, sediment and nutrients are calibrated at one monitoring site, usually at the catchment outlet. Therefore, incorporating in-stream kinetics of a river water quality model into a catchment water quality model improves the overall capability of the catchment water quality model (Ramanarayanan et al, 1996). To the best of knowledge of the author, no studies were found in literature where relative effects of considering or not considering in-stream processes on nutrients and sediment were analyzed. Only Tuppad et al (2010a; 2010b) and Cho et al (2010b) considered the default SWAT in-stream processes option in their simulation. Kirsch et al (2002) recommended additional research on BMPs considering in-stream processes in the modelling.

In this thesis, water quality constituent - sediment and nutrients (nitrogen and phosphorus) were considered because of their significant impact on water quality of the Yarra River (Discussed in Section 3.2.3.2) in Australia where the study area is located. The overland and in-stream processes that involve sediment and nutrients are addressed in this review section.

2.2.1. OVERLAND PROCESSES

2.2.1.1. SOIL EROSION

Soil erosion by water involves the detachment, transport and deposition of soil particles by the erosive forces of rainfall and surface runoff. This can be in the form of splash, sheet, rill, or gully erosion (Summer et al, 1998). Soil particles will detach and then splash into the air as raindrops strike the soil. Sheet erosion refers to the uniform detachment and removal of soil, or sediment particles from the soil surface by overland flow or raindrop impact, evenly distributed across a slope (Hairsine and Rose, 1992).

Rill erosion occurs when water moving over the soil surface flows along preferential pathways forming an easily recognizable channel (Rose, 1993). Rill initiation is controlled by the cohesive strength of the soil and the shear forces exerted on the soil. Flow in rills acts as a transporting agent for the removal of sediment down slope from rill and interill sources, although if the shear stress in the rill is high enough the rill flow may also detach significant amounts of soil (Nearing et al, 1994). Gully erosion, in contrast to rill erosion, describes channels of concentrated flow that are too deep to be obliterated by cultivation (Rose, 1993; Loch and Silburn, 1996). Gully flows differ from sheet and rill flows in that raindrop impact is not an important factor in terms of flow resistance or in sediment particle detachment (Bennett, 1974).

The soil surface is the part of the soil profile highest in organic matter and nutrients. Organic matter forms complexes with soil particles so that erosion of the soil particles will also remove nutrients. Excessive erosion can deplete soil reserves of nitrogen and phosphorus needed by plants to grow and extreme erosion can degrade the soil to the point that it is unable to support plant life. If erosion is severe and widespread enough, the ecological balance (water quality) of a catchment can be altered.

2.2.1.2. NITROGEN CYCLE

In the soil, transformation of nitrogen from one form to another is governed by the nitrogen cycle. Movement of nitrogen from overland to main channel is governed by the overland hydrology and soil erosion. The nitrogen cycle is a dynamic system that includes the water, atmosphere and soil. The three major forms of nitrogen in mineral soils are organic nitrogen associated with humus, mineral forms of nitrogen held by soil colloids, and mineral forms of nitrogen in solution. Nitrogen may be added to the soil by fertilizer, manure or residue application, fixation by symbiotic or nonsymbiotic bacteria, and rain. Nitrogen is removed from the soil by plant uptake, leaching, volatilization, denitrification and erosion. Figure 2.1 shows the major components of the nitrogen cycle in soil.

The interactions among different pools of nitrogen occur through mineralization and decomposition, immobilization, nitrification and ammonia volatilization, and denitrification. Decomposition is the breakdown of fresh organic residue into simpler organic components. Mineralization is the microbial conversion of organic (plant unavailable) nitrogen to inorganic (plant-available) nitrogen, whereas immobilization is the reverse process of mineralization. Nitrification is the two-step bacterial oxidation of NH_4^+ to NO_3^-. On the other hand, denitrification is the bacterial reduction of nitrate, NO_3^- to N_2 or N_2O gases under anaerobic conditions. Denitrification is a function of water content, temperature and presence of a carbon source. For a regular cropping system, an estimated 10-20% of nitrogen fertilizer may be lost to denitrification (Neitsch et al, 2005).

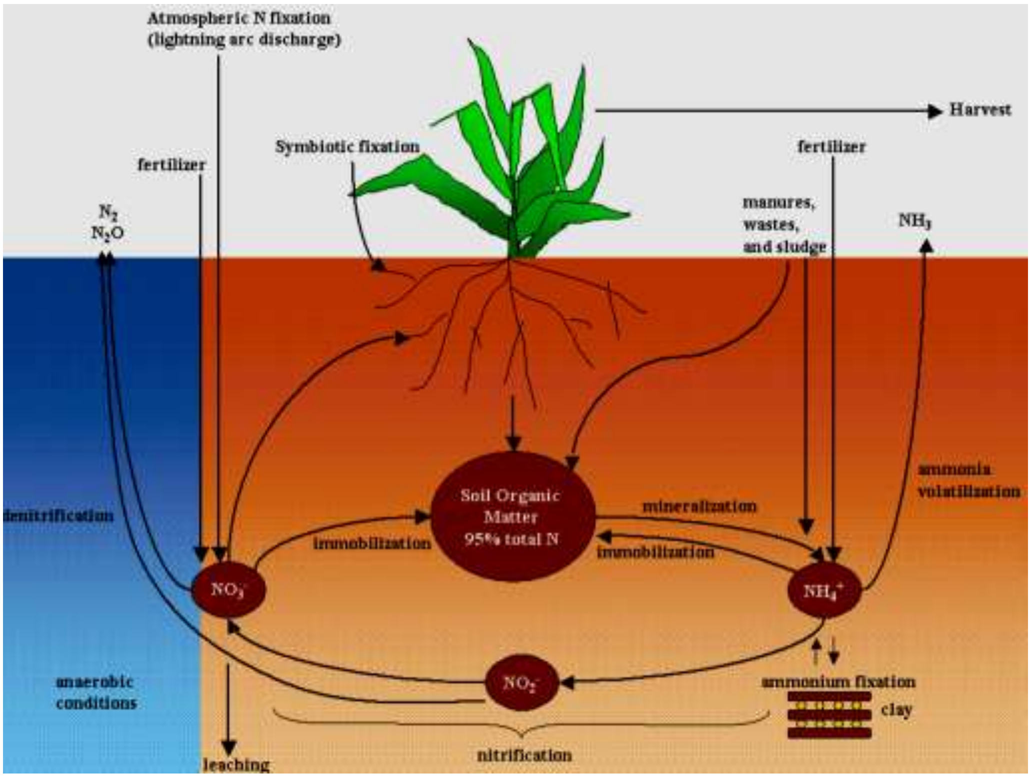


Figure 2.1 Nitrogen cycle in soil (Neitsch et al, 2005)

The transport of nutrients from land areas into streams and water bodies is a normal result of soil weathering and erosion processes. Nitrate may be transported with surface runoff, lateral flow or percolation. The amount of nitrate moved with the water depends on the concentration of nitrate in the mobile water, and the volume of water moving in each pathway. Organic N attached to soil particles may be transported by surface runoff to the main channel. This form of nitrogen is associated with the sediment loading from the catchment and changes in sediment loading will be reflected in the organic nitrogen loading (Neitsch et al, 2005).

2.2.1.3. PHOSPHORUS CYCLE

The transformation of phosphorus from one form to another in the soil is controlled by the phosphorus cycle. Movement of phosphorus from overland to main channel is governed by the overland hydrology and soil erosion. The three major forms of phosphorus in mineral soils are organic phosphorus with humus, insoluble forms of mineral phosphorus, and plant-available phosphorus in soil solution. Phosphorus is added to the soil by fertilizer, manure or residue application, and is removed by plant uptake and soil erosion. Figure 2.2 shows the major components of the phosphorus cycle in soil.

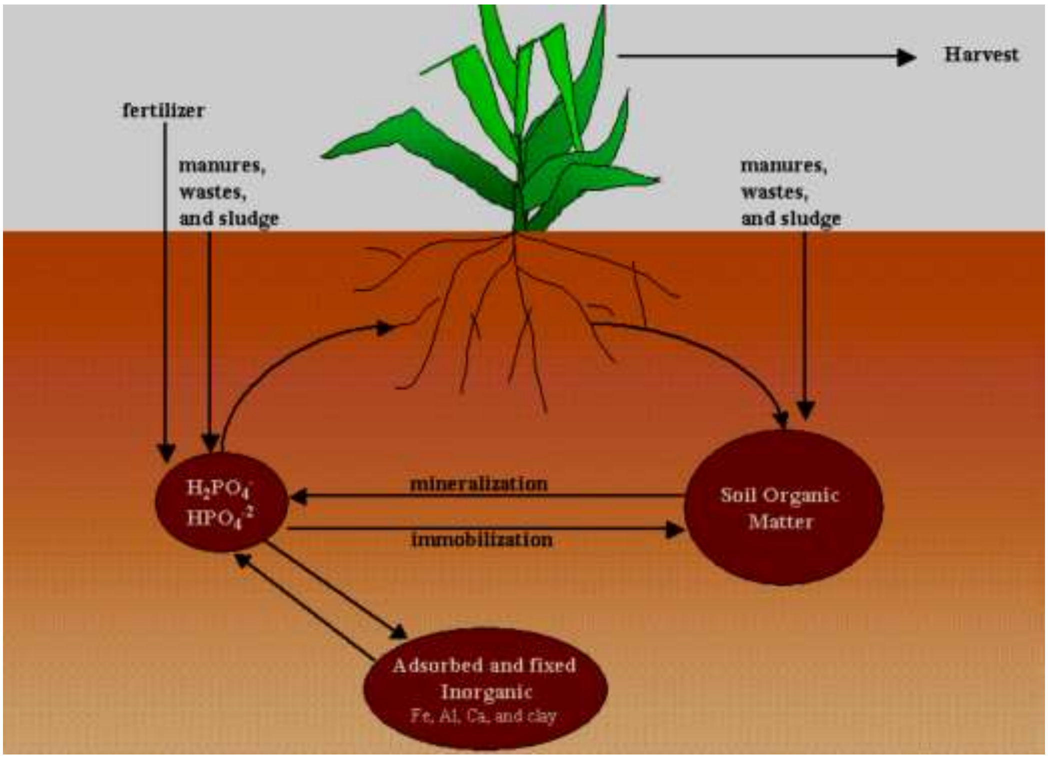


Figure 2.2 Phosphorus cycle in soil (Neitsch et al, 2005)

Unlike nitrogen which is highly mobile, phosphorus solubility is limited in most environments. Phosphorus combines with other ions to form a number of insoluble compounds that precipitate out of solution. These characteristics contribute to a build-up of phosphorus near the soil surface that is readily available for transport in surface runoff. The primary mechanism of soluble phosphorus movement in the soil is by diffusion. Diffusion is the migration of ions over small distances (1-2 mm) in the soil solution in response to a concentration gradient. Due to the low mobility of soluble phosphorus, surface runoff will only partially interact with the soluble P stored in the top 10 mm of soil.

Sharpley and Syers (1979) observed surface runoff is the primary mechanism by which phosphorus is exported from most catchments. Organic and mineral P attached to soil particles may be transported by surface runoff to the main channel. This form of phosphorus is associated with the sediment loading from the catchment and changes in sediment loading will be reflected in the loading of these forms of phosphorus (Neitsch et al, 2005).

2.2.2. IN-STREAM PROCESSES

Once the loadings of sediment and nutrients enter into the main channel from overland processes, the loadings are routed through the stream network of the catchment. In-stream water quality depends on the assimilative capacity of the river, which is an ability to digest pollutants entering the river. This assimilative capacity is controlled by three processes namely physical, biological and chemical process (Schnoor, 1996).

The physical processes reduce organic and inorganic pollutants through dilution, sedimentation, resuspension and adsorption (Chapman and Kimstach, 1996). However, these processes do not consume oxygen in reducing organic and inorganic pollutants in the river. The factors that control the amount of degradation of pollution through dilution, sedimentation, resuspension and adsorption are mainly river flow and velocity (Dojlido and Best, 1993). The water quality pollutants are reduced through dilution process. Through sedimentation, pollutant particles such as suspended solids in the water column settle to the river bottom during low velocity periods. These settled organic matters are subject to resuspension when velocity increases. The organic matters are attached to the soil particles through adsorption, and eventually settled in the river bottom from the water column.

The biological and chemical processes are often combined as biochemical processes (Courchaine, 1968). The biochemical processes reduce or transform pollutant matter by plants and microorganisms through consumption of oxygen (Dojlido and Best, 1993). The degradation of organic matter through biochemical processes involves mineralization and microbially decaying to reduce one form of water quality constituent to another. Not all biochemical processes require the presence of oxygen, for example denitrification. There are many factors which effect the rate of biochemical process, including microorganism population, dissolved oxygen (DO) content, water temperature and pH level (Bowie et al, 1985; Dojlido and Best, 1993). As algae grow and die, they form part of the in-stream nutrient cycle. The biochemical process normally occurs in the nutrient cycle.

2.2.2.1. CHANNEL EROSION

In-stream erosion involves the direct removal of sediment from stream banks (lateral erosion) or the stream bed. During high flow periods, a large proportion of the sediment that is transported through the stream network can originate from the stream channel. The transport of sediment in the channel is controlled by the simultaneous operation of two processes, deposition and degradation (Neitsch et al, 2005). The deposition and degradation depend on the stream power of the channel i.e., the product of water density, flow rate and water surface slope. Changes in stream channel factors, such as stream geometry (width, depth, slope etc), can reduce flow velocity causing some of the soil particles to be deposited as flows lose their capacity to carry the sediment. Excess stream power causes bed degradation resulting in reentrainment of loose and deposited material until all of the material is removed.

2.2.2.2. NITROGEN CYCLE

The nitrogen cycle in water consists of microbial transformations from one form of nitrogen to another and interactions of different forms of nitrogen within the cycle. Figure 2.3 shows the nitrogen cycle in water. In aerobic water, there is a stepwise transformation from organic nitrogen (Org-N) to ammonia (NH_3), to nitrite (NO_2), and finally to nitrate (NO_3). The sum of Org-N and NH_3 is called total kjeldahl nitrogen (TKN), while the sum of all four forms of N is called total nitrogen (TN).

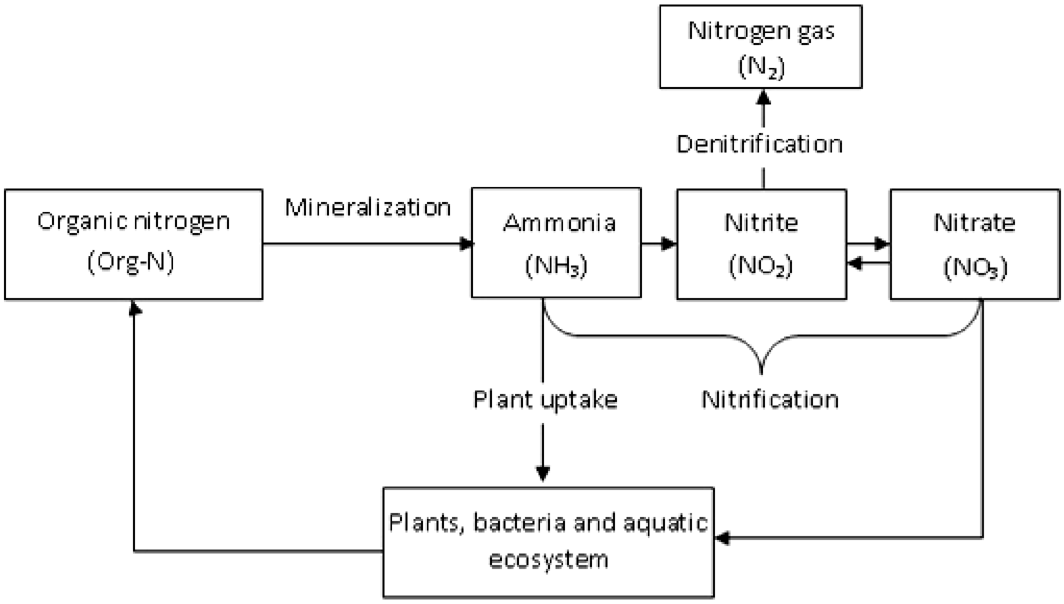


Figure 2.3 Nitrogen cycle in water (Ng, 2001)

The amount of organic nitrogen in the stream may be increased by the conversion of algal biomass nitrogen to organic nitrogen. Organic nitrogen concentration in the stream may be decreased by the conversion of organic nitrogen to NH_4^+ through mineralization or the settling of organic nitrogen with sediment.

The amount of ammonium (NH_4^+) in the stream may be increased by the mineralization of organic nitrogen and diffusion of ammonium from the streambed sediments. NH_3 may be adsorbed onto suspended particles (not as strongly as phosphorus) and bed sediments during low flows, and these particles would regenerate in the water column during high flows (Goering, 1972). The ammonium concentration in the stream may be decreased by the conversion of NH_4^+ to NO_2^- through nitrification or the uptake of NH_4^+ by algae. The concentration of NH_3 can fluctuate greatly between seasons (Bowie et al, 1985; Dojlido and Best, 1993).

The amount of nitrite (NO_2^-) in the stream will be increased by the conversion of NH_4^+ to NO_2^-, and decreased by the conversion of NO_2^- to NO_3-. The NO_2^- form is unstable under aerobic conditions, and hence it would rapidly be oxidized to NO_3^- (Bowie et al, 1985). The conversion of NO_2^- to NO_3^- occurs more rapidly than the conversion of NH_4^+ to NO_2^- , so the amount of nitrite present in the stream is usually very small. The amount of nitrate (NO_3^-) in the stream may be increased by the oxidation of NO_2^-. The nitrate concentration in the stream may be decreased by the uptake of NO_3^- by algae. If condition becomes anaerobic, NO_3^- can partially undergo a process called denitrification and reduces back to NO_2^-, and then further reduced to N_2, which vaporizes into the atmosphere.

2.2.2.3. PHOSPHORUS CYCLE

The phosphorus cycle is similar to the nitrogen cycle, but less complex. Phosphorus can be found in the river in two main forms: organic phosphorus (Org-P) and dissolved inorganic phosphorus (Diss-P). As Org-P is generally not in a bio-available form, it would require undergoing transformation to Diss-P (Reddy et al, 1999). This form is more readily available for aquatic plant uptake (Thomann and Mueller, 1987).

The amount of Org-P in the stream may be increased by the conversion of algal biomass phosphorus to Org-P. Org-P concentration in the stream may be decreased by the conversion of Org-P to Diss-P or the settling of Org-P with sediment. The rate of breakdown of Org-P to Diss-P is depended upon the water temperature, the composition and the bacteria population (Dojlido and Best, 1993). The phosphorus cycle in water is shown in Figure 2.4. Total phosphorus (TP) is given by the sum of Org-P and Diss-P.

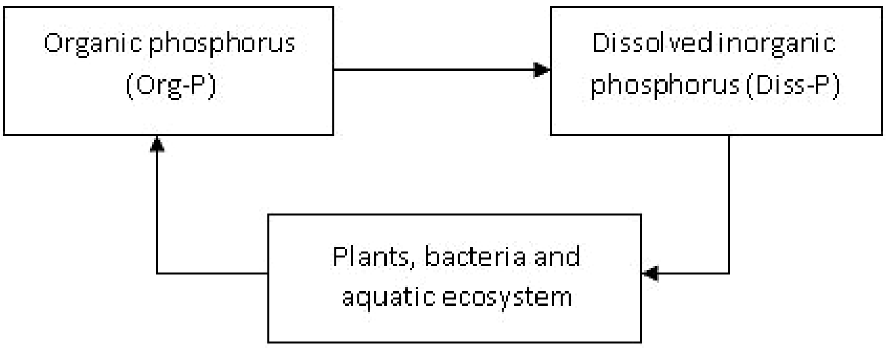


Figure 2.4 Phosphorus cycle in water (Ng, 2001)

The amount of Diss-P in the stream may be increased by the mineralization of organic phosphorus and diffusion of inorganic phosphorus from the streambed sediments. The soluble phosphorus concentration in the stream may be decreased by the uptake of Diss-P by algae.

A major difference in Phosphorus cycle from nitrogen cycle is that phosphorus adsorbs strongly onto soil particles. These particles then settle during low flows and would retain in the river bed which reduce phosphorus in the water column. Once the phosphorus settles in the river bottom, it is subject to resuspension to release phosphorus back into the water column during high flows. When the condition is anaerobic, the return of phosphorus back to the water column via resuspension is three times greater as in aerobic condition.

2.3. WATER QUALITY

Water, the basis of life, is fundamental for sustaining natural environments and supporting human activities. As a valuable natural resource, it comprises freshwater (river and lakes), marine, estuarine and groundwater environments that stretch across coastal and inland areas. Water has two dimensions that are closely linked: quantity and quality. Water quality is commonly defined by its physical, chemical, biological and aesthetic (appearance and smell) characteristics. Water quality is fundamental for good river health to sustain ecological processes that support native fish populations, vegetation, wetlands and birdlife. Similarly, many of our own uses depend on water quality that is suitable for irrigation, watering stock, industrial processes, drinking, fishing and recreation, and to meet cultural and spiritual needs (OEH NSW, 2012).

2.3.1. WATER POLLUTION

If water quality is not maintained, it is not just the environment that will suffer; the commercial and recreational value of the water resources will also diminish. Water quality is degraded or polluted mainly from two sources; point sources and non-point sources.

2.3.1.1. POINT SOURCE WATER POLLUTION

The point source impurity enters the water resource at an easily identifiable, distinct location through a direct route such as discharge coming from a factory or municipal wastewater treatment plant. These discharges generally enter the river from a pipe or ditch, and are often continuous, and easier to measure. Because of these properties, point sources are relatively easy to identify, quantify and control (Carpenter et al, 1998). Therefore, managing point source pollution is theoretically straightforward through regulatory mechanisms. However, even though point source pollution is under control through tertiary treatments and strict water licenses, the limnological problem has not diminished. Attention has now switched to non-point sources especially from intensive agriculture (Shepherd et al, 1999).

2.3.1.2. NON-POINT SOURCE WATER POLLUTION

Non-point source (NPS) impurities enter the water resource usually through a non-direct route and from sources that are diffusive and chronic in nature. The non-point sources are driven by multiple factors and exclusively a result of human land use activities and land use changes (Novotny, 1999). Discharges from non-point sources are usually intermittent, associated with a rainfall or snowmelt event, and occur less frequently and for shorter periods than point source discharges do. Because of these, non-point sources are often difficult to identify, isolate and control. Therefore, unlike the point source pollution, NPS pollution cannot easily be controlled by issuing licenses. Regulatory approaches have to be more subtle and need to be well connected to the land use planning systems. Some examples of NPS include agricultural drainage, urban runoff, road and building construction runoff, mining discharges and septic tank discharges.

NPS pollution results from release of a variety of substances from the NPS sources of primarily agricultural systems. It includes nutrients (such as nitrogen and phosphorus from fertilisers and silage), pesticides and weedkillers (from agriculture and horticulture), oil (from car maintenance and industrial run-off), acidifying pollutants and chemicals (from the atmosphere, abandoned mines and industrial processes).

Nitrogen, carbon and phosphorus are essential to the growth of aquatic biota. Under favourable conditions of light and temperature, excess amounts of nutrients in water can increase the growth of algae and other plants. The result of this growth is an increase in the rate of eutrophication, which is a natural ecological process of change from a nutrient-poor to a nutrient-rich environment. This results in the depletion of dissolved oxygen (Merriam-Webster Inc., 1996). The most important nutrients in eutrophication are phosphorus and nitrogen (Heathwaite et al, 1990; Harper, 1992). It is well-documented that phosphorus, when in excess, can affect the biological productivity of freshwater ecosystems (Heathwaite, 2003; Davis and Koop, 2006) and that excess nitrogen, in particular nitrate, appears to be detrimental for marine systems (Thomann and Mueller, 1987; Fabricius, 2005; Smith et al, 2006; De'ath and Fabricius, 2010).

Excessive plant growth caused by accelerated eutrophication can lead to stagnation of the water. The stagnation is caused by an increased biological oxygen demand created by decaying plant remains. The result of this increased oxygen demand is a tendency toward anaerobic conditions and the inability of the water body to support fish and other aerobic organisms. By controlling phosphorus loading, accelerated eutrophication of waters can be reduced.

2.3.2. MANAGEMENT OF AGRICULTURAL NON-POINT SOURCE POLLUTION

As discussed in Section 2.1, catchment water quality models are very effective tools to develop water quality management plans through simulation of BMPs. BMPs are effective, practical, structural or non-structural conservation practices which prevent or reduce the movement of sediment, nutrients, pesticides and other pollutants from the land to surface water or groundwater, or which otherwise protect water quality from potential adverse effects of land use activities. Data on how BMP implementation improves water quality would help decision makers to determine a cost/benefit ratio of BMP implementation. Such data also would allow them to choose which BMP combination would produce the maximum benefit.

The proper selection of BMPs should be based on environmental, economical, and social issues. The environmental factor consists of sediment, TN, and TP percent reduction, the economic factor consists of total BMP cost, and the social factor consists of farmer preference in BMP implementation. The preference of BMP selection by farmers depends on the BMP application area in the cropland. For example, BMPs that require a small implementation area are preferred by most of the farmers, whereas BMPs that need a large implementation area are preferred the least.

Identifying areas with high pollution potential and treating these areas first would be a more efficient way to allocate financial and educational resources and to control NPS pollution (Tuppad et al, 2010a). Effective water quality protection should target the BMPs on these high potential pollution areas instead of random distribution of BMPs within a catchment. Tuppad et al (2010a) used a strategic approach (based on simulated average sub-catchment erosion rate) for targeting catchment areas to maximize water quality benefits from three BMPs implementation in the Smoky Hill River catchment, Kansas (USA). They found that the targeted approach required about 2.2 times less catchment area than applying the BMPs randomly. Giri et al (2014) used four targeting methods (pollutant concentration level in the sub-catchment reach, total pollutant load from the sub-catchment reach, total pollutant load from each sub- catchment, and average pollutant load per unit area from each sub- catchment) for identifying high priority areas in the Saginaw River catchment, Michigan (USA) to simulate ten BMPs. Similarly, Tripathi et al (2003), Panagopoulos et al (2011a; 2011b), Giri et al (2012), Tesfahunegn et al (2012) and Giri et al (2014) have also found that the targeting approach is the most cost-effective and efficient way of managing water quality.

2.3.2.1. BEST MANAGEMENT PRACTICES

Regulatory agencies developed different types of BMPs in order to help combat agricultural non-point source pollution. They range from simplistic practices like carefully monitoring the amount of fertilizers and manure applied to more complicated and capital-intensive practices like no-till farming or managed drainage. In the United States, the U.S. Department of Agriculture - National Resources Conservation Service (USDA-NRCS) developed several structural or non-structural conservation practices and their standard.

Structural conservation practices are designed primarily to manage the flow of water in agricultural systems. Because water is a major contributor to soil erosion and nutrient losses to surface waters, slowing water flow over agricultural fields can be highly beneficial to reduce soil erosion and nutrient loss. Structural conservation practices include practices such as edge-of-field buffer and filter strips, parallel terraces, contour farming, cover crops, critical area planting, grade stabilization structure, and grassed waterway (USDA NRSC, 2012).

Filter strips are an area of riparian land that is planted with stiff-bodied grasses or other vegetation. These serve to slow the flow of water over the landscape immediately adjacent to surface water, allowing sediments to settle among the grass or vegetation and thereby filtering the runoff. Parallel Terraces are broad earthen embankments or channels constructed across the slope to intercept runoff water and control erosion. Contour farming, also known as contour tillage, involves constructing crop rows such that the rows stay at the same elevation over their entire length. Van Doren et al (1950) demonstrated that soil losses from non-contour-farmed land were nearly twice as great as contour-farmed land.

Cover crops are grown between production periods and have several advantages to farmers and the ecosystem, including decreased wind and water erosion and increased crop yields (Mannering et al, 1985). Critical area planting means establishing permanent vegetation on sites that have or are expected to have high erosion rates. Grade stabilization structures are used to control the grade and head cutting in natural or artificial channels. Grassed waterway is a shaped or graded channel that is established with suitable vegetation to carry surface water at a non-erosive velocity to a stable outlet.

Non-structural conservation practices, on the other hand**,** are the simple ways for farmers to reduce nutrient loadings to catchments. These include practices such as fertilizer or manure management, and residue and tillage management (USDA NRSC, 2012). Fertilizer or manure management involves applying fertilizer or manure in appropriate amounts and at the optimal time of the season. Historically, farmers relied upon expected yield-based recommendations for guidance on appropriate rates of fertilizer application (Camberato, 2007). Residue and tillage management methods involve leaving crop residues behind on the field after harvest to protect soil from wind and water erosion. Several tillage management practices exist, each of which is defined by the level of crop residue left on the field. Of particular importance are no-till, which leaves all crop residue on the field, and conservation tillage, which leaves behind at least 30% of crop residue (Mask et al, 1994).

Details of different types of BMPs can be found in Narasimhan et al (2007), Arabi et al (2008), Cho et al (2010b), Tuppad et al (2010b), Panagopoulos et al (2011b), Mbonimpa et al (2012), Tesfahunegn et al (2012) and (Giri et al, 2014).

2.3.2.2. STUDIES OF BEST MANAGEMENT PRACTICES

Several studies quantified the effects of BMPs on water quality at multiple spatial scales using modelling approaches. Some applications are discussed in this section. Some other SWAT specific applications are discussed in Section 2.4.3.2.

Maharajan et al (2016) simulated three BMPs using SWAT model in order to conserve soil and water resources as well as to improve crop productivity in the Haean catchment in South Korea. They found that split fertilization gives lower nitrate loss and the cultivation of cover crops showed significant reductions of sediment and nitrate loss when comparing with the conventional practice of leaving the drylands fields fallow after harvesting the main crop. Strauch et al (2013) evaluated the impacts of different BMPs on streamflow and sediment load using the SWAT model in the intensively cropped Pipiripau River catchment, Brazil. They found that parallel terraces reduced sediment loads by up to 31% in the catchment, whereas the combined implementation of terraces and small sediment basins can lead to the highest reduction in sediment loads of up to 40%.

Schmidt and Zemadim (2015) simulated different conservation practices including terraces, bunds, and residue management using SWAT model in the Mizewa catchment of the Blue Nile Basin (Ethiopia). Results showed that a mixed strategy of terracing on steep slopes and residue management dramatically decrease surface runoff and erosion. Moreover, a landscape-wide implementation of terraces and bunds throughout the watershed landscape decrease sediment yield by 85%, decrease surface flow by almost 50% and increase groundwater flow by 15%. Tesfahunegn et al (2012) found that reduction of sediment, TP, TN and runoff losses by 78, 75, 72 and 70% respectively, can be achieved by a combined conservation practices of afforested degraded lands, parallel terraces, grassed waterways and grad stabilization structures in the Mai-Negus catchment, Northern Ethiopia. Betrie et al (2011) simulated filter strips, parallel terraces and reforestation in the upper Blue Nile catchment of Ethiopia for sediment management. The simulation results showed that applying filter strips, parallel terraces and reforestation scenarios reduced the current sediment yields both at the sub-catchments and the catchment outlets.

Ramos et al (2015) simulated the impacts of two BMPs including drainage terraces and vegetative filter strips in a small basin of the municipality of Piera, Barcelona province, North East of Spain using SWAT model. The results showed that the introduction of drainage terraces gave a reduction in soil losses of up to 20%. Implementing filter strips further reduced these soil losses by up to 57%, while a significant reduction of nutrient losses were achieved by the combined implementation of both BMP measures. Panagopoulos et al (2011b) examined BMPs of filter trips and fertilizer reduction with respect to cost-effectiveness in the Arachtos catchment, Western Greece. The study concludes that considerable reductions of several pollutant types at the same time can be achieved, even at low total cost, by combining targeted BMP implementation strategies only in small parts of the catchment. Using SWAT modelling tool, Rocha et al (2015) assessed the potential of sustainable agricultural practices for reducing NO_3-N exportation and water quality improvement in the Vouga catchment, Portugal. The authors found that reduction in N-fertilizer application rates and N-fertilizer application methods lead to a lower crop yields and higher NO_3-N exportation rates compared to split and slow release N-fertilizer application methods.

Panagopoulos et al (2014) simulated the impact of four agricultural management scenarios in the Upper Mississipi River catchment (USA) using the SWAT model for both current climate and a climate change conditions. The results showed that all four scenarios exhibit similar behaviour under the current and future climate leading to reduced erosion and nutrient loadings to surface water bodies. No-till was the most environmentally effective scenario. Mbonimpa et al (2012) found that vegetative buffer strips, 15 to 30 m wide, around corn farms reduced sediment yield by 51% to 70% and TP loss by 41% to 63% in the Upper Rock River catchment of Wisconsin, USA. Tuppad et al (2010b) simulated water quality impacts of BMPs including streambank stabilization, gully plugs, recharge structures, conservation tillage, terraces, contour farming, manure incorporation, filter strips, and PL-566 reservoirs in the Bosque River catchment, Texas (USA). They found that implementing individual BMPs reduced sediment loads from 3% to 37% and TN loads from 1% to 24% at the catchment outlet. However, the changes in TP loads were ranged from 3% increase to 30% decrease.

Liu and Tong (2011) used the HSPF model to predict the hydrologic and water quality impacts under various scenarios of buffer zones in the Upper Little Miami River catchment, a headwater sub-catchment in Ohio, USA. Results indicated that the 60 m, 90 m, and 120 m riparian forest and wetland buffers were able to reduce the mean annual flow by 0.26 to 0.28%, nitrite plus nitrate by 2.9 to 6.1% and total phosphorus by 3.2 to 7.8. Qi and Altinakar (2011) used AnnAGNPS in the Goodwin Creek experimental catchment, Northern Mississippi (USA), and proposed an optimization technique to design a cost effective vegetative buffer strips (VBSs) in the catchment. The results showed that the optimized design of VBS using an integrated approach at the catchment level can provide efficient and cost-effective conservation of the environmental quality by taking into account productivity and profitability.

2.4. CATCHMENT WATER QUALITY MODELLING SOFTWARE

As discussed in Section 2.1, catchment water quality models are cost effective tools to analyze the impacts of various BMPs (individual or integrated effects of several BMPs) and to develop water quality management plans (Wurbs, 1998; Muttiah and Wurbs, 2002). Since this thesis is about management of agricultural non-point source pollution which is mainly involved with overland processes of a catchment, catchment water quality models will be reviewed in this section. River water quality models are out of scope for this thesis.

2.4.1. MODEL TYPES

A wide range of catchment water quality models exists for use in simulating sediment and associated pollutant transport. These models differ in terms of complexity, processes considered, and the data required for model calibration and model use. Models are classified based on their model structure, spatial distribution, stochasticity, and spatial-temporal scale. In general, models fall into three main categories as below, depending on the physical processes simulated by the model, the model algorithms describing these processes and the data dependence of the model (Wheater et al, 1993; Merritt et al, 2003):

- Empirical or statistical/metric

  (Examples: USLE (Wischmeier and Smith, 1978a), WaterCAST (Cook et al, 2009))
- Conceptual

  (Examples: SWRRB-WQ (Arnold et al, 1991), SOURCE (eWater-CRC, 2010), CatchMODS (Newham et al, 2004), SedNet (Prosser et al, 2001b), IHACRES-WQ (Jakeman et al, 1990))
- Physics-based

  (Examples: SWAT (Arnold et al, 1998), CREAMS (Knisel, 1980), ANSWERS (Beasley et al, 1980), ANSWERS-continuous (Bouraoui et al, 2002a), HSPF (Johanson et al, 1980), AGNPS (Young et al, 1987), AnnAGNPS (Bingner and Theurer, 2001), DWSM (Borah et al, 2002), MIKE SHE (Refsgaard and Storm, 1995), CASC2D (Ogden and Julien, 2002), KINEROS (Woolhiser et al, 1990))

Sometimes conceptual and physics-based models are referred as mechanistic models, and empirical models are as data-based models. The distinction between the models is not sharp, and therefore can be somewhat subjective. They are likely to contain a mix of modules from each of these categories. For example, while the rainfall-runoff component of a water quality model may be physics-based or conceptual, empirical relationships may be used to model erosion or sediment transport. Models may also be described as hybrids between two of these classes. For example, the IHACRES rainfall-runoff model (Jakeman et al, 1990) is a hybrid metric-conceptual model. The structure of the model is conceptual in nature, consisting of a number of storages, while the number and configuration of storages used for each catchment is determined using a statistical identification procedure.

Another way to view the range of models is the way in which they represent the area to which the model is applied; that is, whether the model considers processes and parameters to be lumped or distributed. Models can also be classified as deterministic (HSPF) and stochastic models (ANN models (May, 2011)). Based on temporal scale, a model could be event-based (AGNPS) or a long-term continuous simulation model (SWAT). Moreover, based on spatial scale, models may be classified into those of small catchment to large catchment models.

Integrated water quality models consist of catchment and river water quality models. Better Assessment Science Integrating Point and Nonpoint Sources (BASINS), developed by the USEPA Office of Water (USEPA, 1998), consists of a catchment water quality model (such as SWAT, AGNPS) and a river water quality model - QUAL2E (Brown and Barnwell, 1987). One disadvantage of this system is that the data management module is less useful to countries other than USA, since all relevant information and data are only applicable for catchments in USA, which are updated annually.

The different categories of catchment water quality models discussed above are shown as a flow-chart in Figure 2.5. A detail review on model types can be found on Wheater et al (1993), Singh (1995), Merritt et al (2003), Singh and Frevert (2006) and Pechlivanidis et al (2011).

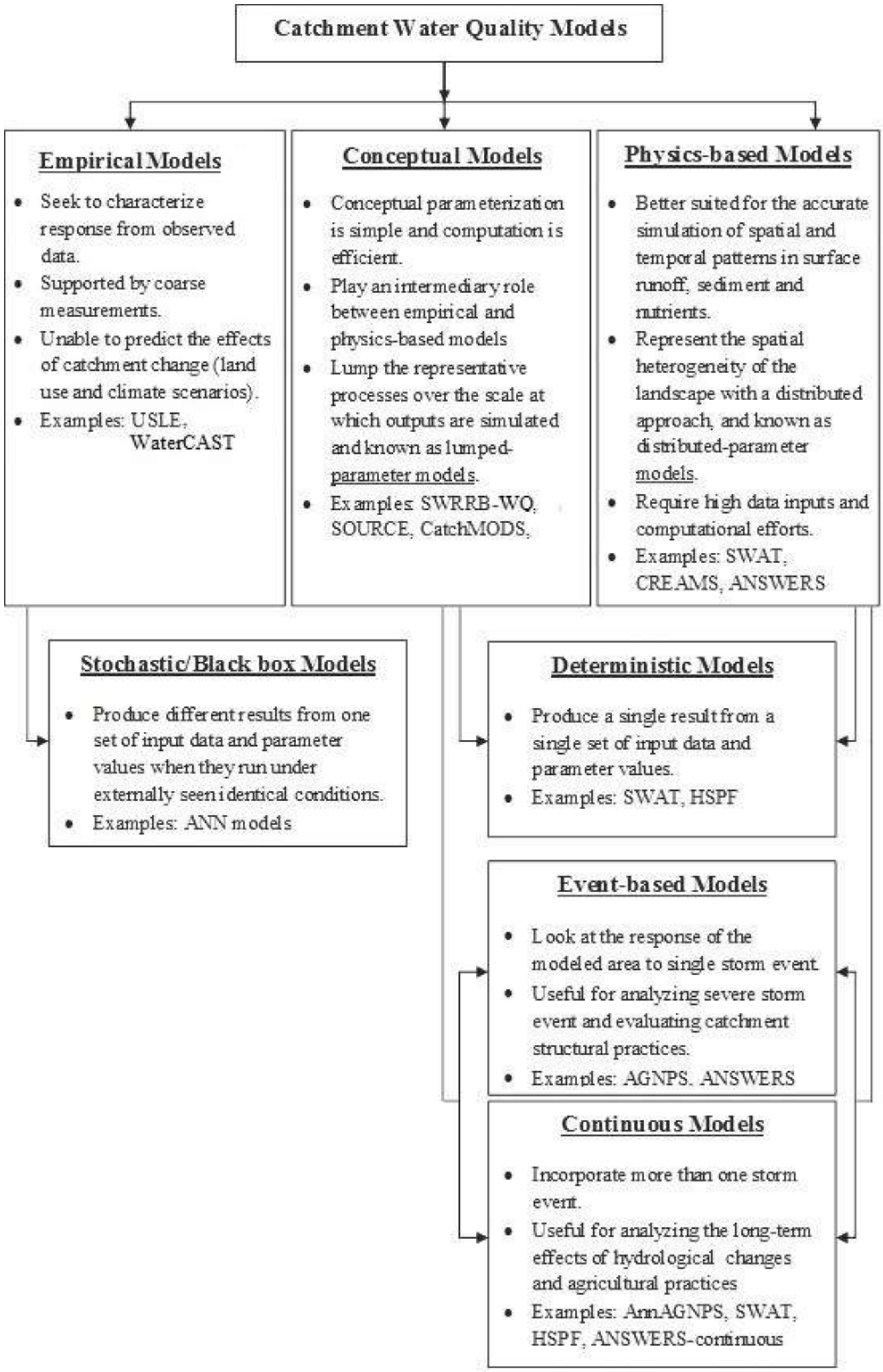


Figure 2.5 Flow-chart diagram for different types of catchment water quality models

2.4.2. WATER QUALITY MODELLING SOFTWARE AND STUDIES IN AUSTRALIAN CATCHMENTS

Australia has a unique hydrological setting that has strongly influenced the development of water-quality models built for Australian catchments (Croke and Jakeman, 2001). For example, there is a high spatial and temporal variability in rainfall, with areas that experience long periods of drought as well as widespread flooding events. Demand for water resources is concentrated in the populated coastal areas where the demand is increasingly exceeding the supply. The impacts of large storage dams and groundwater usage extend from lowering water tables and dryland salinity to impacts on ecosystem from reduced river flows.

In general, Australian catchments are data-rich in terms of hydroclimatic data, but data-poor especially for water quality and land management data compared to Europe or America. In Australia, Grayson et al (1999b) found that there is only limited continuous water quality data available and that much of the spot sample data held is largely inaccessible. Information on erosion, soil properties or spatially referenced land use and ecosystem data is also relatively sparse, complicating the development of water quality models in Australia (Kragt and Newham, 2009). The authors on most water quality studies also emphasized on improved data collection for future better modelling (Letcher et al, 2002). Letcher et al (1999) pointed out that physics-based models and the more complex conceptual models are not particularly appropriate for estimating catchment exports across most Australian catchments because of (i) lack of sufficient spatially distributed input data to drive the models, and (ii) paucity of calibration data in space and time to define an appropriate parameter set for the models and hence reliable output. Therefore, traditionally commonly used water quality models in Australia are either empirical or lumped/semi-distributed conceptual models or hybrid models between any two of these models.

Within these modelling frameworks, nutrients sub-models are mainly generation rate-based (empirical) without considering the detailed physical and biochemical processes. Generation rates-based modellings are appealing because they are inexpensive, easy to implement and the results can be directly linked to land use (McNamara and Cornish, 2005). However, the confidence in the outputs of generation rate-based modelling can be limited by a shortage of locally-relevant nutrient generation rates, inadequate land use data, and the fact that generation rates-based modelling fails to take account of hydrologic factors that determine both the nutrient export and the delivery of nutrients to the receiving water (McNamara and Cornish, 2005).

The Australian models generally have the facility to generate basic scenarios of catchment management change such as land use changes, gully-zone engineering works, riparian-zone revegetation, climate variability and reducing point source pollution. However, the effects of management practices in agricultural areas, e.g. fertilizer and effluent application rates cannot be simulated at the present frameworks of these models, which are potentially important determinants of nutrient generation (Newham and Drewry, 2006). In Australian for managing any catchment, catchment managers ranked riparian zone management as the most important (Drewry et al, 2006). However, important riparian and gully management processes are modelled in a generally empirical manner. In CatchMODS, for example, increases in gully and riparian vegetation reduce nutrient source inputs by fixed proportions of base case estimates only and the trapping efficiency of near-stream vegetated areas is not explicitly considered (Newham and Dowry, 2006). Moreover, many modelling studies did not consider subsurface pathways and soluble nutrient components, and did not have the capability of in-stream nutrient processing with the subsequent likelihood of either underestimating nutrient losses, or potentially overestimating effectiveness of riparian buffers (Newham and Dowry, 2006). Newham and Dowry (2006) proposed the future development of nutrient generation models that should aim to produce models which are able to simulate management practices in agricultural areas and in-stream nutrient process with different forms of nutrients. To achieve acceptable simulation of management practices, improved understanding and quantification of the effects of common management practices is needed. This can only be gained through experimental research.

The most widely used water quality models in Australia are “Source Catchments” (Argent et al, 2009; eWater-CRC, 2010), CatchMODS (Newham et al, 2004), SedNet (Prosser et al, 2001b), EMSS (Vertessy et al, 2001) , CMSS (Davis and Farley, 1997); IHACRES-WQ (Jakeman et al, 1990). Some of these models are discussed below.

2.4.2.1. SOURCE CATCHMENTS MODEL

In Australia, the most recent modelling platform for evaluating catchment scale constituent losses is Source Catchments (Argent et al, 2009; eWater-CRC, 2010), an evolution of earlier models WaterCAST (Cook et al, 2009) and E2 (Argent et al, 2005). This is a lumped, semi-distributed, conceptual catchment modelling framework that operates on a daily time step. It allows for the construction of catchment models by selecting and linking generation and transport component models from a range of options. Source Catchments conceptualizes a range of catchment processes using sub-catchments which are composed of Functional Units (FUs) that generally represent a single land use (Searle and Ellis, 2009).

Each FU can use a range of component models that represent the processes of runoff generation, constituent generation and filtering. These processes are spatially lumped at the sub-catchment nodes which are linked together to represent the flow network to the catchment outlet. The rainfall/runoff component of Source Catchments consists of a choice of lumped conceptual models including AWBM, SimHYD, Sacramento and SMAR. Each FU is characterized by similar pollutant generation processes, which are typically determined using an event mean concentration (EMC), and/or dry weather (i.e. baseflow) concentration (DWC) approach (Chiew and Scanlon, 2002). Runoff and constituents are then transferred from each unit directly to the node and summed with the outputs from the other FUs (Neumann et al, 2007). The Source Catchments model or its previous versions have been applied in many Australian studies, ranging from assessing the impacts of bushfires on water quality (Feikema et al, 2005) to developing a decision support system for water quality improvements in Port Phillip Bay (Argent et al, 2007); supporting water quality improvement plans and management activities in Queensland (Waters and Webb, 2007), and assessing farm dams impacts on surface water in Victoria (Cetin et al, 2009).

Considerable modelling experience and knowledge is needed to develop and use this modelling framework to have confidence in its outputs. Employing a selection of sub-models requires the user to be familiar with the detail, applicability and data requirements of each of the component models and with the challenges of linking multiple component models. The model uses coefficient based nutrient generation rates; It has no detailed in-stream sediment, nutrient and other pollutant decay and transformation processes (DNRW, 2008). Due to the exclusion of in-stream processes, the model assumes the complete transport of pollutants from the source to the outlet. Moreover, soil water processes are not considered explicitly.

2.4.2.2. CatchMODS MODEL

The Catchment Scale Management of Diffuse Sources (CatchMODS) framework is a lumped, semi-distributed, conceptual catchment modelling approach that simulates the effects of different catchment management actions on pollutant loadings to surface waters. CatchMODS aims to identify the critical diffuse sources of erosion, suspended sediments and nutrients, including the appropriate management interventions to address these loads (Newham et al, 2004). Scenarios that can be considered within the framework include land use changes, gully-zone engineering works, riparian-zone revegetation, climate variability and reducing point source pollution.

CatchMODS is based on a series of linked river reaches and associated sub-catchment areas. The modelling is lumped at these stream reach and sub-catchment units (Newham et al, 2004). The topology of the stream network enables the downstream routing of pollutants with the individual sub-models each simulating processes of pollutant attenuation and/or deposition. Reaches and sub-catchments are disaggregated using an area threshold to define reaches. The topology of the stream network defines the associated sub-catchment areas. The size of a sub-catchment in a typical application of CatchMODS averages 30 km^2.

The hydrologic sub-model used is the conceptual IHACRES rainfall-runoff model (Jakeman et al, 1990). It is applied at a daily time step with its temperature and rainfall inputs scaled linear according to sub-catchment mean rainfall and mean elevation, respectively. The quality of predictions using IHACRES is influenced by rain gauge density, stream gauge rating quality, and catchment response dynamics, particularly baseflow. The sediment sub-model of CatchMODS is modified from the SedNet model (Prosser et al, 2001b) but retains several of its underlying algorithms. The focus of CatchMODS is on the simulation of the suspended sediment fraction only. This reflects the importance of suspended sediment as a source and transport medium for many common stream pollutants e.g. phosphorus. It also enables the investigation of contemporaneous SS fluxes and management effects over the more historic perspective of

SedNet. Sediment inputs are estimated from hillslope, gully and streambank erosion sources. Dissolved and particulate nutrient fractions are simulated separately in CatchMODS. The Phosphorus (P) and Nitrogen (N) sub-models of CatchMODS are identical in structure. A generation-rate-based or flow-based approach (or a combination of the two) may be used for to simulate dissolved nutrients. The attenuation of dissolved nutrients through the system is simulated using a simple exponential decay function. CatchMODS is likely to underestimate N and P losses from intensive farmland given the current reliance on the erosion sub-model. The model is limited to provide steady state estimates (reported as average annual loads) of sediment and nutrients.

The costs of management change scenarios are also estimated in CatchMODS. Three types of costs are estimated: fixed, ongoing and land use-related. Fixed costs are those one-off costs which are incurred during the implementation of riparian and gully zone remediation works. Ongoing costs are the maintenance costs required to maintain the effectiveness of riparian and gully zone remediation works for pollutant control. The land use-related costs represent the change in gross margins associated with the conversion between land uses.

CatchMODS was initially developed for application in the Ben Chifley Dam catchment of NSW and has since been applied in several other Australian catchments. Norton et al (2004) described an analysis of uncertainty of the CatchMODS and its application in the Ben Chifley Dam catchment. Newham et al (2008) used the CatchMODS model in the Moruya and Tuross River catchments, NSW as an example of the integration of collateral knowledge in the model development process. Vigiak et al (2009) used the CatchMODS model to compare the spatial distribution of sediment delivery ratio as predicted by four landscape approaches in the Avon-Richardson catchment in the semi-arid Wimmera region in Victoria, south-east Australia. Bende-Michl et al (2009) assessed the CatchMODS model in the context of regional environmental investment planning within the Cradle Coast Natural Resource Management (NRM) region of north western Tasmania.

2.4.2.3. EMSS MODEL

The Environmental Management Support System (EMSS) is a lumped conceptual catchment-scale model used to estimate daily runoff and pollutant loads to receiving waters and to assess the impact of changes in land use and land management. The model is sensitive to changes in climate, reservoir operations, land use and land management practices (Vertessy et al, 2001), and scenarios for implementing these changes can be included in the model. EMSS is composed of three linked sub-models: a runoff and pollutant export model (Colobus); a streamflow and pollutant routing model (Marmoset); and a reservoir model (Mandrill).

The runoff and pollutant export sub-model operates on individual sub-catchments to provide daily estimates of streamflow, suspended sediment, Total Phophorus (TP), Total Nitrogen (TN) and pathogens. In contrast to annual pollutant load reporting in CatchMODS, the pollutant loads in EMSS are predicted daily (Vertessy et al, 2001). The rainfall-runoff component of the model originates from the SIMHYD model (Chiew et al, 2002). Daily rainfall and potential evapotranspiration data are needed to estimate daily runoff, which is partitioned into event and baseflow components. These flow components are multiplied by user specified generation rates to estimate daily loads. Loads are predicted by a generation rates-based approach using estimates of Event Mean Concentration (EMC) for stormflow and the baseflow runoff volume by Dry Weather Concentration (DWC) (Merritt et al, 2003). Different EMC and DWC values can be allocated to sub-catchments, depending on land use (Vertessy et al, 2001). The reservoir model simulates the regulation of river flows, and traps pollutants and accounts for the evaporative losses from large reservoirs.

The model does not recognize spatial variation in runoff or pollutant generation across the catchment. EMC and DWC have been noted to be highly variable. Further research, supported by event-based water quality data collection, is required to further refine this approach. The EMSS was developed for application in the Brisbane River catchment of South East Queensland and has been subsequently applied in several other Australian catchments.

2.4.2.4. CMSS MODEL

The Catchment Management Support System (CMSS) is designed to assist catchment managers to assess the effects of land use and management policies on long term nutrient loads delivered to streams (Marston et al, 1995; Davis and Farley, 1997). CMSS has been widely used in Australia as an initial planning tool because of its simplicity, ease of use and ease of results presentation (Gourley et al, 1996; Richard Davis et al, 1998).

The predictive module calculates the nutrient loads by summation of the area per land use multiplied by a nutrient generation rate per unit area. A single generation rate is assigned to a land use. Many different land uses can be described to capture spatial variability in biophysical factors, for example, ‘grazing on low fertility soils’ can be assigned a different generation rate to ‘grazing on high fertility soils’. CMSS has a sub-catchment network structure where loads are accumulated (and attenuated) through the network to give predictions for each sub-catchment.

A study by Baginska et al (2003b) noted that models like CMSS are indicative of long term nutrient generation, and therefore may not compare well with measured annual loads for a particular year due to high variability of rainfall and runoff. This is particularly important when interpreting short-term nutrient generation studies. Letcher et al (2002) pointed out that, in general, CMSS is not used to provide an accurate estimate of loads, but rather to provide preliminary information of relative source strengths of different land use and management options.

2.4.2.5. SedNet MODEL

The SedNet (Sediment River Network) model was developed in 2003 by CSIRO Land and Water as part of the National Land and Water Resources Audit. SedNet is a conceptual, lumped, semi-distributed model that identifies patterns in erosion rates, sedimentation and nutrient fluxes on a regional catchment scale (Prosser et al, 2001a; Wilkinson et al, 2004).

SedNet defines a stream network as a series of links, and can be used to construct sediment and nutrient budgets for each link. SedNet uses simple conceptual and empirical models of sediment detachment, transport and deposition to describe long-term sediment loads in individual river reaches. Information on material transport processes, soil mapping, vegetation cover, geology and climate are used to estimate sediment and nutrient supply from various sources. This information is combined with measurements of river flows to calculate: the mean annual suspended sediment output from each river link; the depth of sediment accumulated on the river bed in historical times; the relative supply of sediment from sheet wash, gully and bank erosion processes; the mean annual export of sediment to the coast; and the contribution of each sub-catchment to that export (Prosser et al, 2001b). The nutrient budget module of SedNet is known as ANNEX (Annual Network Nutrient Export). ANNEX is used to predict the mean annual loads of phosphorus and nitrogen in each link of the river system (including particulates, organic and inorganic forms of dissolved nutrients) (Wilkinson et al, 2004). ANNEX considers only the physical and not the biological stores of nutrients, and is also primarily concerned with the physical transport processes.

SedNet has been used to identify the relative importance of different processes that supply sediment and nutrients to rivers in catchments throughout Australia (Kinsey-Henderson et al, 2003; Dougall et al, 2005). However, the model offers the user little flexibility in modifying the underlying algorithms. SedNet is also constrained by its requirements to estimate erosion from observed averages over longer time periods, providing insufficient consideration of contemporary erosion rates.

2.4.2.6. NUTRIENT GENERATION STUDIES IN AUSTRALIAN CATCHMENTS

Specific model based water quality studies are discussed in the above sections. A comprehensive summary of Australian catchment water quality or nutrient generation studies undertaken prior to 1996 can be found in the Nutrient Generation Rates Data Book of Marston et al (1995). The Nutrient Generation Rates Data Book includes Australian review studies (published up to 1993) and international studies (published up to 1991). It was compiled to assist users of CMSS to estimate long-term annual average nutrient generation rates under specified land uses and management practices (Davis and Farley, 1997).

Young et al (1996) indicated that land use can be used as a simple predictor of nutrient loads, but that conclusion is based on limited literature. Several studies in the Australian literature show intensive land uses such as dairying to have a relatively high generation of P and that single storm events may be responsible for high loads. Under dairying, for example, 69% of annual loss of TP was reported as lost in a single storm event (Nash and Murdoch, 1997). Fleming and Cox (2001) showed 98% of TP was lost during a three-year period in overland flow, rather than as interflow through the soil. However, the amount of nutrient lost varied depending on rainfall, with most losses occurring during the wettest year.

In the Hawkesbury-Nepean catchment, several studies have measured N and P losses from market gardening, dairying and semi-improved pasture. High nutrient exports, up to 200 kg N/ha/year and 15 kg P/ha/year for market gardens have been reported (Baginska et al, 1998). However, export rates for the whole of the sub-catchment were estimated by the modelling approach to be 19.3 and 3.3 kg/ha/year for N and P, respectively. Losses on dairy farms, reported by Baginska et al (1998) ranged from 2 to 6 kg P/ha/year and 4 to 6 kg N/ha/year depending on intensity of farming. It was also found that semi-improved pasture had much greater exports than bush land (Hollinger and Cornish, 2002). These studies do not take account of factors important at catchment scales (e.g. dilution and in-stream processes).

Although many studies have examined TN and TP exports, and sediment-bound N and P, relatively few have considered the soluble components, particularly for P. Nash and Murdoch (1997) showed that 93% of the P lost annually for a dairy site was in dissolved form. Cox and Ashley (2000) showed that catchment discharge contained 100% dissolved P, and therefore they concluded that estimation of TP loss based on sediment (particles > 45μm) would be inappropriate during periods of low rainfall and flow.

The ratio of soluble to particulate P varies with land management and land use. Hence, the effectiveness of riparian buffers to remove dissolved N and P may not be adequate (Nash and Murdoch, 1997; McDowell et al, 2004). Riparian vegetation and wetlands provide an opportunity for removal of nutrients, although may have a finite lifespan and once saturated they may act as a source (McDowell et al, 2004). McKergow et al (2003) found that in a small agricultural catchment, improved riparian management reduced sediment exports, (a likely result of reduced stream bank erosion), but there was little effect on overall N exports, TP concentration and loads. Although a recent Queensland study showed grass riparian strips were more effective at filtering sediment than forest buffers (McKergow et al, 2004), there has been little detailed research into the effectiveness of N removal by buffer strips in Australian systems.

Much of the available nutrient export data has been derived from small-scale field or plot trials. Plot-scale nutrient generation studies do not take account of many factors important at catchment scales. Vigiak et al (2011) developed and evaluated a modelling framework of coupling a point-scale model (HowLeaky2008) to a catchment scale model (CatchMODS) to enhance modelling of farm management impacts on in-stream phosphorus loads in two catchments of Northern Victoria, Australia. In the Avon-

Richardson catchment, management scenarios showed that alternative farming systems focused on retaining vegetation cover throughout the year would yield a 50 per cent reduction of suspended sediment load. In contrast, fencing and revegetation of connected gullies was estimated to yield the largest reduction in suspended sediment load (44% of current load) in the Avoca catchment. Similarly Vigiak et al (2012) found that perennial pastures in grazing systems and zero-tillage in cropping systems can reduce phosphorus load by 31% in the Avon-Richardson catchment and 19% in the Avoca catchment, relative to current practices (annual pasture and minimum tillage) using the same modelling framework.

2.4.3. SELECTION OF WATER QUALITY MODELLING SOFTWARE FOR THE MIDDLE YARRA CATCHMENT

A wide range of catchment models exist for use in simulating sediment and associated pollutant transport as discussed in Section 2.4.1. These models differ in terms of complexity, processes considered, and the data required for model calibration and model use. These models have different strengths and weaknesses in modelling certain hydrologic and water quality processes. Therefore, it is difficult to choose the most suitable model for a particular catchment to address a particular problem.

As discussed in Section 2.4.2, the Australian models are traditionally empirical or lumped/semi-distributed conceptual models mainly because of the data-poor environment in Australia. Within these modelling frameworks, nutrient sub-models are mainly generation rate-based (empirical) without considering the detailed physical and biochemical processes, and did not have the capability of in-stream nutrient processing. Moreover, the effects of potential management practices in agricultural areas (e.g. fertilizer and effluent application rates) cannot be simulated with these models (Newham and Drewry, 2006). Thorsen et al (2001) pointed out that the predictive capability of empirical and lumped conceptual models with regards to assessing the impacts of alternative agricultural practices is questionable, due to the semi-empirical nature of the process description. Compared to these models, physics-based models are better suited for the accurate simulation of spatial and temporal patterns in surface runoff, sediment, chemicals and nutrients, and their associated transport pathways (Borah and Bera, 2003).

However, because of high data requirement and processing, the applications of these models are limited in many data-poor catchments.

With the advent of computers with high computational power and geographic information system (GIS) software, physics-based models are increasingly being called upon in data-poor regions (Muttiah and Wurbs, 2002; Borah and Bera, 2003). The extensive input data for the physics-based models are often generated from GIS and regional or local surveys (Refsgaard, 1997; Srinivasan et al, 1998; Ewen et al, 2000). GIS and model–GIS interfaces provide an effective tool to generate, manipulate, and organize the spatially disparate data for modelling (Wu et al, 2005). However, modelers' familiarity with the local environmental processes is a prerequisite for avoiding questionable assumptions and significant input errors when modelling poorly monitored catchments (Silgram et al, 2009).

Leyton (2012) assessed a complex model SWAT in the data-poor Huanquisco River catchment in Bolivia. The author developed a method on how to generate soil map using local survey knowledge and resample coarse DEM. Panagopoulos et al (2011a) used SWAT model with data limitations in the Arachtos catchment of Greece in order to identify critical diffuse pollution source areas. The authors used uniform land-use and soil-type in the model, and calibrated the model especially for nutrients based on seasonal data generated from very limited grab samples. Santhi et al (2006) successfully applied the SWAT model in the West Fork catchment of Trinity River Basin in Texas (USA) where NPS pollution was a serious concern. The authors applied their expertise and experience to calibrate sediment and nutrient parameters because of the limitations of sampling data.

Very limited applications of physics-based models have been found in the Australian catchments for water quality analysis. Baginska et al (2003a) examined applicability and predictive capability of the AnnAGNPS model in the Currency Creek catchment, Sydney. The model showed a poor performance for nutrient prediction because of limited data availability for the model development and calibration. The model was optimized only for five runoff events during a three year period. Similarly, Jivajirajah and Rahman (1994) applied the HSPF model in the Upper Nepean catchment, Sydney for diffuse source nutrient modelling, and reported calibration problems due to inadequate water quantity and quality data.

The study area for this research is the agricultural middle segment of the Yarra River catchment which will be discussed in detail in Chapter 3. In the Yarra River catchment, intensive agricultural activities contribute to a significant amount of non-point pollutants into the waterways mainly from the middle Yarra segment. Moreover, the rural land management was given priority in the PortsE2 (Argent et al, 2007) modelling work as discussed later in Section 3.2.3.2, because it is considered cost-effective in reducing pollutant loads through better farm practices (RossRakesh and Pierotti, 2011). Therefore the following criteria were used to select the appropriate modelling software for modelling the agricultural NPS pollution in the Middle Yarra River catchment with a view of using a physics-based model in the context of data-poor environment of Australia.

1. Be capable of simulating long-term effects of land use and management measures on water quality in a predominantly agricultural catchment.
2. Be capable of incorporating in-stream modelling.
3. Have GIS link with a user-friendly Graphical User Interface.
4. Be a public domain modelling software having wider usage.

Based on a review of eleven models (SWAT, AGNPS, AnnAGNPS, ANSWERS, ANSWERS−Continuous, CASC2D, DWSM, HSPF, KINEROS, MIKE SHE, and PRMS), Borah and Bera (2004) recommended that SWAT is a promising model for long-term continuous simulations in predominantly agricultural catchments. Moreover, a review by Kalin and Hantush (2003) on catchment scale hydrologic and water quality models indicated that the SWAT model offers the greatest number of management alternatives for modelling agricultural catchments. The ability to simulate in-stream water quality dynamics is a definite strength of SWAT; In-stream transformations and kinetics of algae growth, nitrogen and phosphorus cycles, carbonaceous biological oxygen demand, and dissolved oxygen are modelled in SWAT based on the modules developed for the QUAL2E model (Gassman et al, 2007). Also, SWAT has a GIS link and a user-friendly Graphical User Interface which provide a straightforward means of translating digital land use, topographic, and soil data into model inputs.

SWAT is a complex model with many parameters that can complicate manual model calibration. SWAT2005 has an automated sensitivity, calibration, and uncertainty analysis component that is based on approaches described by van Griensven and Meixner (2006) and van Griensven et al (2006). Also the autocalibration and uncertainty analysis of SWAT can be performed using the SWAT-CUP software (Abbaspour et al, 2007a). The model has the option of multi-objective calibration for multi-site and multi-variable at a time. This approach reduces the risk of accumulation of the errors (model errors, and errors on the input and output variables) to the end step which is common in step-by-step calibration process for multi-variable as discussed later in Section 2.5.1. A short overview of the SWAT model structure and execution approach is discussed later in Section 2.4.3.1.

The ability of SWAT to replicate hydrologic and/or pollutant loads at a variety of spatial scales on an annual or monthly basis has been confirmed in numerous studies. Some of these applications are discussed briefly in Section 2.4.3.2. SWAT also has been applied in Australia mainly for modelling hydrology, but it has not yet been widely adopted. Sun and Cornish (2005) used SWAT for recharge estimation in the headwaters of the Liverpool Plains in NSW (Australia). Vervoort (2007) applied SWAT2000 for modelling hydrology in the Mooki catchment in NSW (Australia), and found that the model in general underestimates the peak runoff and over predicts many of the lower flows and some of the smaller peaks. Githui el al (2009) applied SWAT to simulate salinity impacts due to irrigation in the Barr Creek Catchment, South East Australia. Watson et al (2003) evaluated SWAT suitability for modelling the water balance of the Woady Yaloak River catchment in Victoria (Australia), and determined if it could be adopted as a planning tool to manage land use change. However, the model overestimated the baseflow, and the authors recommended that groundwater and tree growth components be modified to improve the model performance. Saha et al (2014) applied SWAT model in the Yass River catchment in South Eastern Australia, and found that the model was able to satisfactorily simulate both low and high flows of the river. Recently, Shrestha et al (2016) assessed SWAT model based on the simulation of streamflow and nutrient loads in the semi-arid Onkaparinga catchment in South Australia. The authors found that SWAT was capable to simulate realistically the extreme flow conditions and nutrient loads by means of the multi-site calibration of SWAT.

Based on the above evaluation, the ArcSWAT interface of SWAT2005 modelling software is chosen as it satisfies all the above criteria of model selection for the Agricultural Middle Yarra River catchment. The details of the ArcSWAT interface of the SWAT2005 model are available in Winchell et al (2009). SWAT is a public domain and open source modelling tool which can be downloaded freely from the official SWAT public domain website (http://www.swat.tamu.edu/).

2.4.3.1. THE SOIL AND WATER ASSESSMENT TOOL (SWAT) MODEL

The SWAT model is a non-proprietary hydrologic/water quality tool developed by the United States Department of Agriculture-Agriculture Research Service (USDA-ARS) (Arnold et al, 1998; Neitsch et al, 2005). The SWAT model is a distributed parameter, continuous scale model that operates on a daily time-step. It has the capability to simulate a variety of land management practices. The SWAT model divides the catchment into a number of sub-catchments based on topography and user defined threshold drainage area (minimum area required to begin a stream). Each sub-catchment is further divided into Hydrologic Response Units (HRUs), which are a unique combination of soil, land use, and land management. The HRU is the smallest landscape component of SWAT used for computing the hydrologic processes. The HRUs are represented as a percentage of the sub-catchment area and may not be contiguous or spatially identified within a SWAT simulation. Water balance is the driving force behind all the processes in SWAT because it impacts plant growth and the movement of sediments, nutrients, pesticides, and pathogens. The hydrological processes are divided into two phases: (a) the land phase where the model determines the upland loadings of flow, sediment, nutrients, and pesticides from each HRU and then the loadings are area-weighted to sub-catchment level; and (b) the channel/floodplain phase, where the model routes the upland loadings from each sub-catchment through the channel/stream network. Below is a brief description of the processes simulated by SWAT.

Within each HRU, the major hydrological processes simulated by SWAT include canopy interception of precipitation, infiltration, surface runoff, evapotranspiration, lateral flow or subsurface flow, shallow ground water flow (or baseflow or return flow), soil moisture redistribution, and percolation to deep aquifer (Figure 2.6). The incoming precipitation, snow melt, and irrigation water is partitioned between surface runoff and infiltration. Infiltrated water can be stored in soil profile, percolate deeper to reach shallow and/or deep aquifer, lost via evapotranspiration, or move laterally to feed back to the stream. Weather inputs required in SWAT include precipitation, minimum and maximum temperature, solar radiation, relative humidity, and wind speed depending on the potential evapotranspiration (PET) method selected. The model offers three options for estimating potential evapotranspiration: (a) Penman-Monteith (Monteith, 1965), (b) Priestley-Taylor (Priestley and Taylor, 1972), and (c) Hargreaves (Hargreaves et al, 1985). The three PET methods included in SWAT vary in the amount of required inputs. The Penman-Monteith method requires solar radiation, air temperature, relative humidity and wind speed. The Priestley-Taylor method requires solar radiation, air temperature and relative humidity, whereas the Hargreaves method requires air temperature only.

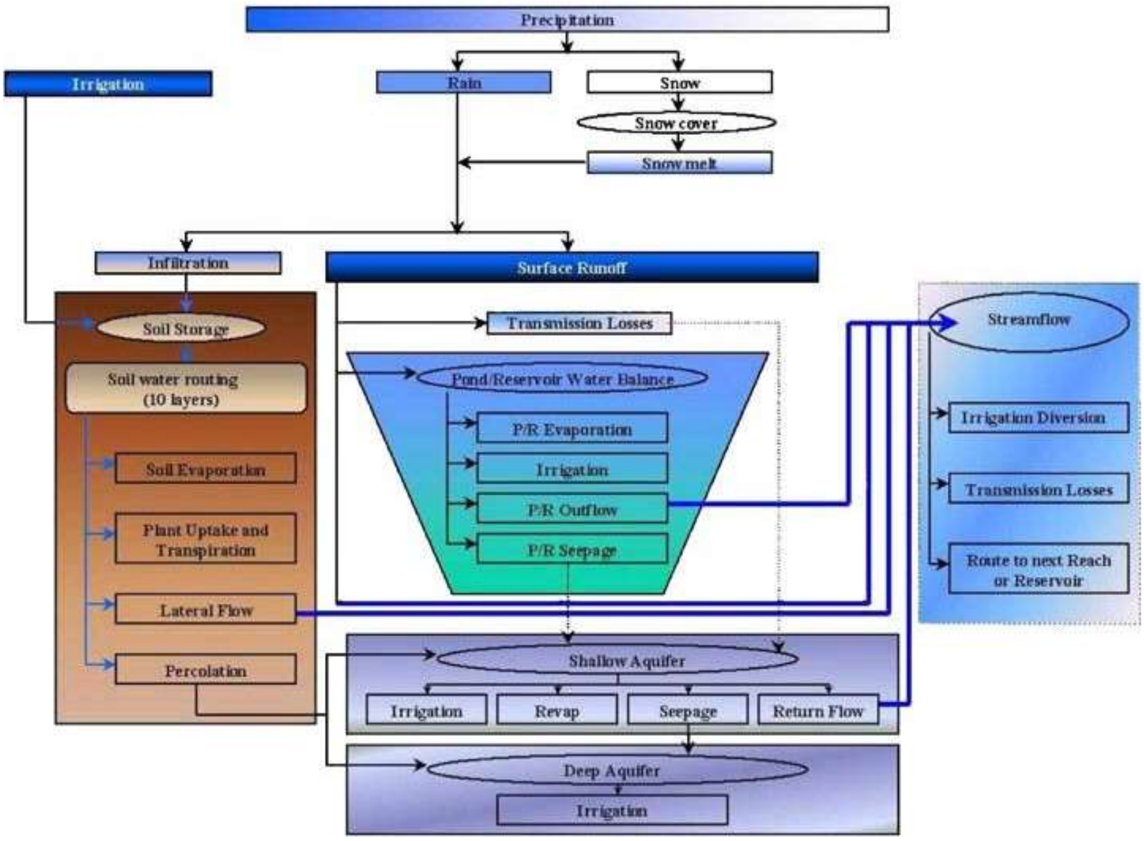


Figure 2.6 Schematics of water movement pathways in SWAT (Neitsch et al, 2005)

Precipitation data could be daily if the curve number (CN) method (USDA-SCS, 1972) is used or sub-daily if the Green-Ampt infiltration (Green and Ampt, 1911) method is used to estimate surface runoff. In the CN method, surface runoff is estimated as a function of daily CN adjusted for the moisture content of the soil on that day. The CN method is widely used due to its simplicity, predictability, and responsiveness to soil type, land use and land condition, and antecedent soil moisture. Some of the disadvantages are that the method has no explicit provision for spatial scale effects and is sensitive to low CNs and low rainfall depths (Ponce and Hawkins, 1996). However, break point rainfall input and streamflow routing at sub-daily time step used by the Green-Ampt infiltration method does not necessarily result in significant improvement in the model prediction for large basins (King et al, 1999).

SWAT allows defining up to 10 soil layers within the routing depth (soil profile) of 2 m. A storage routing technique is used to calculate redistribution of water between layers in the soil profile. Water infiltrated into the soil layer is allowed to percolate into the next deeper soil layer if the water content exceeds the field capacity water content of that layer. Lateral flow (sub-surface flow) is estimated using the kinematic storage model (Sloan and Moore, 1984). Recharge below the soil profile is partitioned between shallow and deep aquifers. The shallow aquifer contributes to baseflow (or return flow) to the main channel (or reach) when the amount of water stored in the aquifer exceeds user specified threshold value. Water in shallow aquifer is also allowed to move up into the soil profile in response to the water deficiency in order to meet the evapotranspiration demands. Also, SWAT allows deep-routed plants uptake water directly from the shallow aquifer. That portion of the water that recharges the deep aquifer is assumed lost from the system.

SWAT estimates crop yields and/or biomass output for a wide range of crop rotations, grassland/pasture systems, and trees. Planting, harvesting, tillage passes, and nutrient and pesticide applications can be simulated for each cropping system with specific dates or with a heat unit scheduling approach. Residue and biological mixing are simulated in response to each tillage operation. Nitrogen and phosphorus inputs can be in the form of inorganic fertilizer and/or manure inputs. An alternative automatic fertilizer routine can be used to simulate fertilizer applications, as a function of user-specified nitrogen stress. Biomass removal and manure deposition can be simulated for grazing operations. The type, rate, timing, application efficiency, and percentage application to foliage versus soil can be accounted for simulations of pesticide applications. Simulation of irrigation water on cropland can be based on five alternative sources: stream reach, reservoir, shallow aquifer, deep aquifer, or a water body source external to the catchment. The irrigation applications can be simulated for specific dates or with an auto-irrigation routine, which triggers irrigation events based on user-specified water stress threshold.

The SWAT model uses the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975) to estimate sediment yield at the HRU level. The model simulates transformation of nitrogen (N) and phosphorus (P) between organic and inorganic pools in the nutrient cycle (Figure 2.7). The loss of both N and P from the soil system of each HRU is accounted for by plant uptake, their transport via surface runoff, eroded sediment, lateral flow and percolation below the soil profile, and by volatilization to the atmosphere.

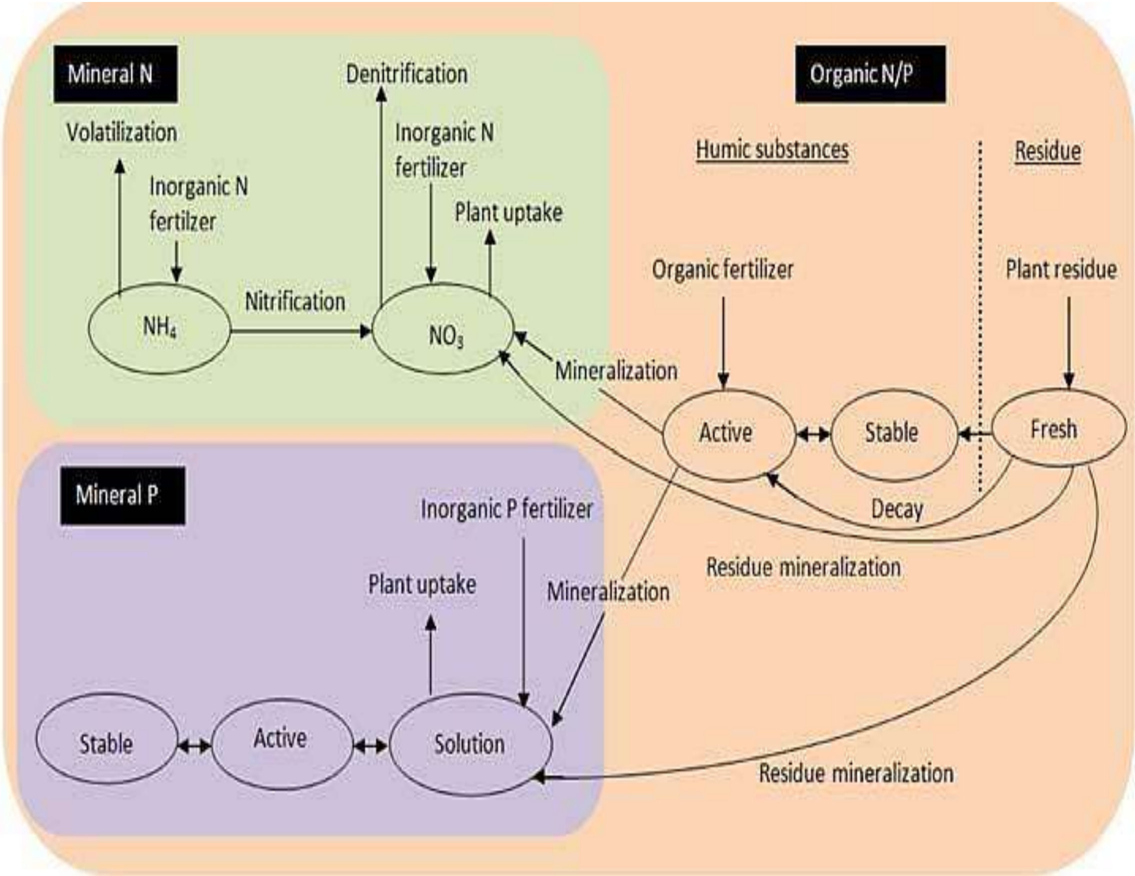


Figure 2.7 Nitrogen and phosphorus transformation in SWAT (Neitsch et al, 2005)

Flow, sediment, nutrients, pesticide and bacteria from all HRUs are summed to the sub-catchment level and then routed through the channels, ponds, reservoirs, and wetlands to the catchment outlet. Flow is routed using either the variable-rate storage method (Williams, 1969) or the Muskinghum method (Overton, 1966). Sediment transport is simulated, using the modified Bagnold's equation (Bagnold, 1977), as a function of peak channel velocity. Sediment is either deposited or re-entrained through channel erosion depending on the sediment load entering the channel. The QUAL2E model (Brown and Barnwell, 1987) has been incorporated into SWAT to process in-stream nutrient dynamics.

Complete theoretical and input/output documentations for SWAT2005 can be found in Neitsch et al (2005) and Neitsch et al (2004) respectively. Model equations are given in the SWAT theoretical documentations (Neitsch et al, 2005) and in Arnold et al (1998). A comprehensive review of SWAT including historic developments and applications can be found in Gassman et al (2007).

2.4.3.2. SPECIFIC SWAT APPLICATIONS

The SWAT has been applied widely during the past decade ranging from hydrological studies to water quality studies along with the climate change impact studies on them. Gassman et al (2007), Douglas-Mankin et al (2010) and Tappad et al (2011) summarized the SWAT applications in the category of hydrologic assessments, pollutant assessments and climate change impacts on them. A complete list of the SWAT peer-reviewed articles is provided at the SWAT website (http://swat.tamu.edu/publications/peer-reviewed-publications/), which is updated regularly. The wide range of SWAT applications underscores that the SWAT software is a very flexible and robust tool that can be used to simulate a variety of catchment problems. Some of the applications are briefly discussed below.

'Sediment studies': Several studies showed the robustness of SWAT in predicting sediment loads at different catchment scales. Saleh et al (2000) conducted a comprehensive SWAT evaluation for the 932.5 km^2 upper North Bosque River catchment in north central Texas (USA), and found that predicted monthly sediment losses matched well measured data but daily output was poor. Srinivasan et al (1998) concluded that the SWAT sediment accumulation predictions were satisfactory for the 279 km^2 Mill Creek catchment, again located in north central Texas. Santhi et al (2001a) found that SWAT-simulated sediment loads matched well with measured sediment loads for two Bosque River (4,277 km^2) sub-catchments in USA, except in March. Arnold et al (1999) used SWAT to simulate the average annual sediment loads for five major Texas river basins (20,593 to 569,000 km^2) and concluded that the SWAT predicted sediment yields compared reasonably well with estimated sediment yields obtained from rating curves.

SWAT sediment simulations have also been evaluated in Asia, Europe, and North Africa. Behera and Panda (2006) concluded that SWAT simulated sediment yield satisfactorily throughout the entire rainy season based on comparisons with daily observed data for an agricultural catchment located in eastern India. Kaur et al (2004) concluded that SWAT predicted annual sediment yields reasonably well for a test catchment in Damodar-Barakar, India, the second most seriously eroded area in the world.

'Nitrogen and Phosphorus Studies': Several published studies from the U.S. showed the robustness of SWAT in predicting nutrient losses. Saleh et al (2000), Saleh and Du (2004), Santhi et al (2001a), Stewart et al (2006), and Di Luzio et al (2002) evaluated SWAT by comparing SWAT nitrogen prediction with measured nitrogen losses in the upper North Bosque River or Bosque River catchments in Texas. They all concluded that SWAT reasonably predicted nitrogen loss, with most of the average monthly validation Nash-Sutcliffe Efficiency (NSE) values greater than or equal to 0.60. Phosphorus losses were also satisfactorily simulated with SWAT in these four studies, with the validation NSE values ranging from 0.39 to 0.93. Chu et al (2004) applied SWAT to the Warner Creek catchment in Maryland (USA) and reported satisfactory annual but poor monthly nitrogen and phosphorus predictions. Hanratty and Stefan (1998) calibrated SWAT nitrogen predictions using measured data collected for the Cottonwood River, Minnesota (USA), and concluded that if properly calibrated, SWAT is an appropriate model to use for simulating the effect of climate change on water quality; they also reported satisfactory SWAT phosphorus results.

In Iowa (USA), Chaplot et al (2004) calibrated SWAT using nine years of data for the Walnut Creek catchment and concluded that SWAT gave accurate predictions of nitrate load. Du et al (2006) showed that the modified tile drainage functions in SWAT-M resulted in far superior nitrate loss predictions for Walnut Creek, as compared to the previous approach used in SWAT2000. However, Jha et al (2007) reported accurate nitrate loss predictions for the Raccoon River catchment in Iowa using SWAT2000. In Arkansas (USA), Cotter et al (2003) calibrated SWAT with measured nitrate data for the Moores Creek catchment and reported an NSE of 0.44. They stated that SWAT's response was similar to that of other published reports.

'Scenarios of BMP and Land Use Impacts on Pollutant Losses': Simulation of scenarios in SWAT has proven to be an effective method of evaluating alternative land use, BMP, and other factors on pollutant losses. SWAT studies in India include identification of critical or priority areas for soil and water management in a catchment (Tripathi et al, 2003; Kaur et al, 2004). Santhi et al (2006) reported the impacts of manure and nutrient related BMPs, forage harvest management, and other BMPs on water quality in the West Fork catchment in Texas. The effects of BMPs related to dairy manure management and municipal wastewater treatment plant effluent were evaluated by Santhi et al (2001b) with SWAT for the Bosque River catchment in Texas.

Kirsch et al (2002) describe SWAT results showing that improved tillage practices could result in reduced sediment yields of almost 20% in the Rock River in Wisconsin. Chaplot et al (2004) found that adoption of no tillage, changes in nitrogen application rates, and land use changes could greatly impact nitrogen losses in the Walnut Creek catchment in central Iowa. Analysis of BMPs by Vache et al (2002) for the Walnut Creek and Buck Creek catchments in Iowa indicated that large sediment reductions could be obtained, depending on the BMP choice. Bracmort et al (2006) presented the results of three 25-year SWAT scenario simulations for two small catchments in Indiana in which the impacts of no BMPs, BMPs in good condition, and BMPs in varying condition were reported for streamflow, sediment, and total phosphorus. Nelson et al (2005) reported that large nutrient and sediment loss reductions occurred in response to simulated shifts of cropland into switch grass production within the 3,000 km^2 Delaware River basin in northeast Kansas (USA).

Recently Sheshukov et al (2016) investigated two widely used BMPs (off-stream watering site and stream fencing) on a livestock pasture for the Pottawatomie Creek catchment in Eastern Kansas (USA). The authors found that application of the BMPs lowered organic phosphorus and nitrogen loads by more than 59% and nitrate loads by 19%. However, total suspended solids and sediment-attached phosphorus loads remained practically unchanged.Wilson et al (2014) simulated a set of alternative conservation management practices in the Root River catchment of Southern Minnesota (USA) using SWAT model, and found that catchment-wide implementation of all conservation management practices resulted in the highest reductions in sediment loads by 52% and total phosphorus loads by 28% from upland crop areas. Gassman et al (2015) evaluated the alternative cropping and nutrient management systems in the Raccoon River catchment in West Central Iowa (USA), and found over 12% reduction in nitrate losses at the catchment scale.

Piniewski et al (2015) investigated the efficiency of riparian buffer zones to mitigate chemical pollution losses using SWAT modelling tool in the Sulejow Reservoir catchment in central Poland. Based on the monitoring data, the authors found that on average, reductions of NO_3-N and total phosphorus can be achieved by 56% and 76%, respectively. Adeogun et al (2016) simulated the impact of different sediment management strategies and cost effectiveness of their application using SWAT model in a catchment located upstream of Jebba Lake, Nigeria. The authors found that implementation of vegetative filter strip, reforestation, and stone bunds to the critical zones of the catchment reduced the sediment yield up to 65.6%, 63.4% and 12% respectively. The authors also found that cost analysis of implementing each of the management options gave 84.9%, 73.3% and 70.5% reduction respectively in the cost to be incurred if sediments are allowed to accumulate in the Jebba dam. Adeogun et al (2014) also successfully validate a SWAT model in the Upstream Catchment of Jebba Dam in Nigeria for Prediction of Water Yield and Water Balance.

2.5. MODEL EVALUATION

2.5.1. SENSITIVITY, CALIBRATION AND VALIDATION, AND UNCERTAINTY ANALYSIS

Physically-based distributed parameter catchment models contain parameters that cannot be measured directly due to measurement limitations and scaling issues (Beven, 2000; Zhang et al, 2008). Complexity in the calibration and validation process increases in these models due to the large number of model parameters needed to achieve calibration, the difficulty associated with calibrating the model at more than one location within the catchment, and the need to calibrate against multiple catchment response variables (e.g. streamflow, sediment, nitrogen and phosphorus) (White and Chaubey, 2005). Therefore, sensitivity analysis methods are needed that can accommodate a large number of parameters while considering several output variables at more than one location within the catchment. Sensitivity analysis methods reducing the number of parameters to be adjusted during calibration are important for simplifying the use of these models (van Griensven et al, 2002). These methods identify parameters that do or do not have a significant influence on the model simulations of output variables.

Model calibration entails the modification of parameter values and comparison of predicted output of interest to measured data until a defined objective function is achieved (James and Burges, 1982). When calibrating a water quality catchment model, one or more objectives are often used to measure the agreement between observed and simulated values. The objectives to be optimized can be the combination of multiple goodness of fit estimators (e.g. Nash-Sutcliffe efficiency and coefficient of determination), multi-variable (e.g. streamflow, sediment, and nutrients), and multi-site (Yapo et al, 1998; Santhi et al, 2001a; Liew and Garbrecht, 2003; White and Chaubey, 2005; Cao et al, 2006; Engeland et al, 2006; Bekele and Nicklow, 2007; Zhang et al, 2008; Zhang et al, 2009; Li et al, 2010; Piniewski and Okruszko, 2011; Niraula et al, 2012).

In most catchment-modelling studies, streamflow, sediment and nutrients are calibrated at one monitoring site, usually at the catchment outlet. If only one calibration site is used, the objective function does not consider how well the model predicts catchment response at all other locations within the catchment, but it is simpler to calibrate the model for that one specific site (White and Chaubey, 2005; Li et al, 2010). However, an increase in the number of calibration sites used for calibrating output variables introduces more constraints on the calibration process.

Correlations between one parameter and multiple output variables (multi-variable) often complicate the multi-variable calibration process. This complication can occur when modification of one parameter causes one predicted variable to more closely coincide with measured values and another predicted variable to less closely coincide with measured values (White and Chaubey, 2005). Often, a step-by-step calibration in a logical order is performed due to correlations between parameters and predicted outputs, and measurement uncertainty (Madsen, 2003). The general order used to optimize the objective function is: (1) total flow, (2) surface runoff and baseflow, (3) sediment, (4) P (phosphorus), and (5) N (nitrogen). Santhi et al (2001a), Cotter (2002), Kirsch et al (2002), and Grizzetti et al (2003) developed multi-variable SWAT models using similar prioritization of the model output variables. A general calibration flowchart for flow, sediment, and nutrients proposed by Santhi et al (2001a) is shown in Figure 2.8 to aid with the manual model calibration process.

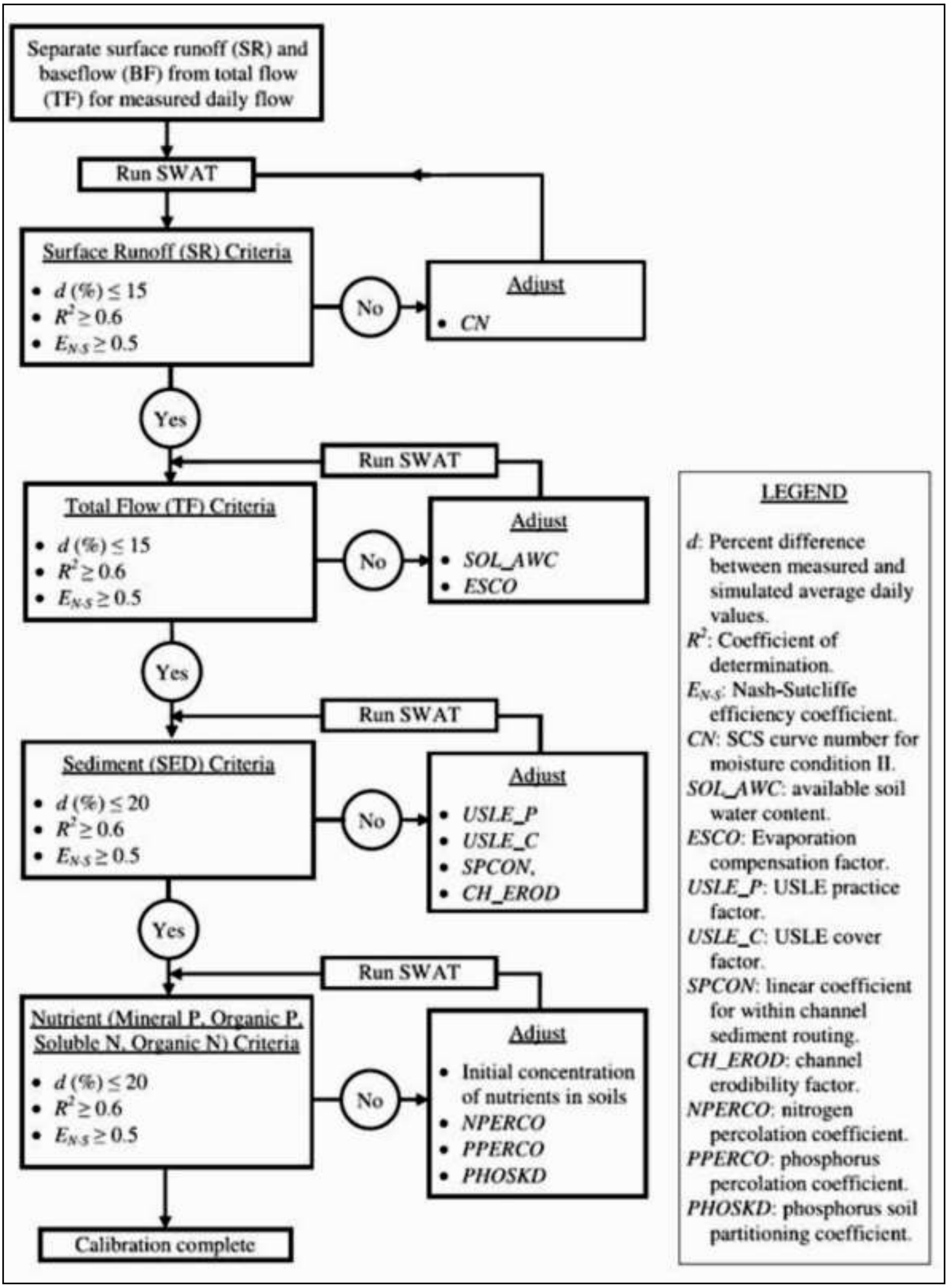


Figure 2.8 General calibration procedure for flow, sediment, and nutrients in SWAT model (Santhi et al, 2001a)

Hydrologic outputs (total streamflow, surface runoff, and baseflow) are calibrated first because of their influence on the other output variables (sediment, nutrients). In addition, measurement uncertainty is assumed to be less with hydrologic data since estimated flow is developed from daily gauge readings, whereas sediment and nutrient yields are estimated from once or twice a month grab samples using some statistical techniques. Hydrologic calibrations are followed by sediment calibration because of the influence sediment can have on phosphorus transport in a catchment (Cambell and Edwards, 2001; Nearing et al, 2001). Phosphorus predictions are calibrated before nitrogen because of the greater uncertainty in phosphorus predictions by the model due to the diverse phosphorus inputs from different sources. Moreover, annual variables are calibrated first followed by monthly variables. In addition, because of greater uncertainty, sediment and nutrients are calibrated at monthly and annual scale.

In each of the steps in the step-by-step calibration process (Figure 2.8), only part of the available information is used. In addition, this approach also incorporates the risk of accumulation of the errors (model errors, and errors on the input and output variables) to the end step. For instance, a bad calibration of the low flows (caused by either a low weight of the low flows in the objective function or by a poor quality of the measurements for the low flows) can be dramatic for the water quality variables. The water quality variables are also highly correlated. To overcome the limitations of the step-by-step calibration process, a multi-site and multi-objective calibration can be performed using all the output variables (multi-variable) simultaneously during the calibration process. This calibration procedure allows the use of all the available information that can contribute to the identification of the parameters (van Griensven et al, 2002; Rasolomanana et al, 2012).

Validation of the model ensues after achieving the objective function for calibration. Validation procedures are similar to calibration procedures in that predicted and measured values are compared to determine if the objective function is met. However, a dataset of measured catchment response selected for validation preferably should be different (split sample approach) than the one used for model calibration, and the model parameters are not adjusted during validation. Validation provides a test of whether the model was calibrated to a particular dataset or the system it is to represent. If the objective function is not achieved for the validation dataset, calibration and/or model assumptions may be revisited.

Model uncertainty analysis aims to quantitatively assess the reliability of model outputs. Many water quality modelling applications used to support policy and land management decisions lack this information and thereby lose credibility (Beck, 1987). Several sources of modelling unknowns and uncertainties result in the fact that model predictions are not a certain value, but should be represented with a confidence range of values (Kuczera, 1983a, 1983b; Beven, 1993; Gupta et al, 1998; Vrugt et al, 2003a). These sources of uncertainty are often categorized as input uncertainties (such as errors in rainfall or pollutant sources inputs), parameter uncertainty resulting from the non-uniqueness of effective model parameters, model structure/model hypothesis uncertainties (uncertainties caused by inappropriateness of the model to reflect reality or the inability to identify the model parameters) and uncertainties in the observations used to calibrate/validate the model outputs, as shown in Figure 2.9.

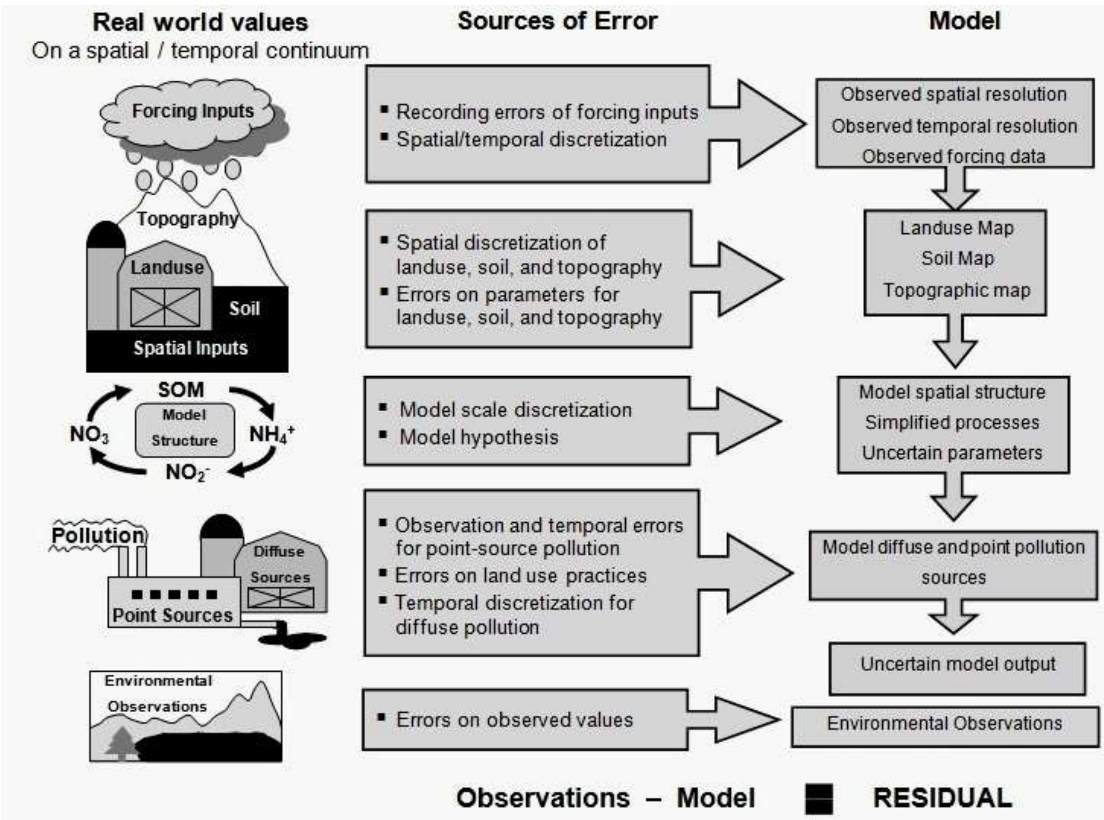


Figure 2.9 Scheme of sources of errors in distributed water quality modelling (van Griensven, 2005)

Abbaspour et al (2004) proposed *p-factor* and *d-factor* originally for quantifying the degree to which uncertainties are accounted for. The *p-factor* is simply the percentage of observed data captured by the 95% prediction uncertainty (95PPU) band, calculated at

2.5^{th} and 97.5^{th} percentiles of cumulative distribution of the simulated variable. The ideal value for *p-factor* is where all of observed values are enclosed by the 95PPU (*p-factor* equals 100%). On the other hand, the *d-factor* is the average distance between upper and lower limits of 95PPU normalized by the standard deviation of observed variables. On the basis of *d-factor* definition, it is obvious that the magnitude of *d-factor* is directly related to the amount of uncertainty in the simulated outputs. In other words, the larger is the d-factor, the larger is the uncertainty. The ideal value for the *d-factor* is when it is close to zero (uncertainty in predicted output is minimum)

2.5.1.1. SENSITIVITY ANALYSIS METHODS

While there are a number of techniques available for conducting sensitivity analysis, all can be broadly grouped as local and global approaches (Saltelli et al, 1999). In local techniques such as the first order second moment method, output responses are determined by sequentially varying each of the input factors and by fixing all other factors to constant nominal values. The further the perturbation moves away from the nominal value, the less reliable the analysis results become (Helton, 1993). Also, the more nonlinear the relationship between inputs and output variables, which is typical in hydrologic models, the more difficult and unreliable it is to employ local techniques. Furthermore, since sampling is performed for one input at a time by fixing all other inputs at constant values, local approaches do not account for any interaction between inputs, if any exists. Unlike the local techniques, the global sensitivity analysis methods explore the entire range of input factors, and all input factors can be simultaneously varied, allowing investigation of output variation as a result of all inputs and their possible interaction (i.e. output uncertainty is averaged over all input factors).

Monte Carlo analysis (also known as a sampling-based method), Latin–Hypercube (LH) simulations, variance-based methods, the response surface methodology, and the Fourier amplitude method are common global sensitivity analysis techniques. A large computational demand is typically a concern of Monte Carlo analysis and is a result of the random and unsystematic generation of inputs from specified distributions. However, the use of more strategic, efficient, and effective sampling approaches, such as importance sampling and Latin-Hypercube sampling, can significantly reduce the computational demand (McKay et al, 1979; Iman and Conover, 1980). The Latin-

Hypercube sampling is commonly applied in water quality modelling due to its efficiency and robustness (Weijers and Vanrolleghem, 1997; Vandenberghe et al, 2001). The main drawback is the assumptions on linearity (i.e. that the model output is linearly related to the changes in the parameter values). If these are not fulfilled, the biased results can be obtained.

An example of an integration of a local method into a global sensitivity method is the One-factor-At-a-Time (OAT) method (Morris, 1991). As in local methods, each run has only one parameter changed, so the changes in the output in each model run can be unambiguously attributed to the input parameter changed. Considering n parameters, this means that this experiment involves performing $n+1$ model runs to obtain one partial effect for each parameter. However, the quantitativeness of this measure of sensitivity is only relative, as the influence of a particular parameter may depend on the values chosen for the remaining parameters. Therefore, this experiment is repeated for several sets of input parameters. The final effect will then be calculated as the average of a set of partial effects. The elementary effects obtained using this procedure allows the user to screen the entire set of input parameters with a low computational requirement. In this way, local sensitivities get integrated to a global sensitivity measure. The OAT design appeared to be a very useful method for modelling (van Griensven and Bauwens, 2001; Francos et al, 2003) as it is able to analyse sensitivity on high number of parameters.

2.5.1.2. CALIBRATION METHODS

Model calibration is typically a form of optimization searching process. It starts by assuming an initial set of variables and calculates its corresponding objective function value. Then this process is repeated many times after changing parameter values to get the most proper parameter values. Optimization algorithms can, in general, be categorized as local and global search methods (Sorooshian and Gupta, 1995). Depending on the hill climbing strategy employed, the local search algorithms may be further divided into "direct" and "gradient-based" methods. Direct search methods only use information on the objective function value, whereas the gradient-based methods also use information about the gradient of the objective function. Local search methods are efficient for locating the optimum of a uni-modal objective function since in this case the hill-climbing search will eventually reach the global optimum, irrespective of the starting point. One of the more popular direct search methods is the simplex method (Nelder and Mead, 1965). The gradient-based methods include the steepest descent method and various approximations of the Newton method (e.g. the Gauss–Marquardt algorithm).

Lumped conceptual rainfall–runoff models may have numerous local optima on the objective function surface (Duan et al, 1992), and in such cases local search methods are inappropriate because the estimated optimum will depend on the starting point of the search. For such multi-modal objective functions, the global search methods should be applied ("global" in the sense that these algorithms are especially designed for locating the global optimum and not being trapped in local optima). Popular global search methods are the so-called population-evolution-based search strategies such as the shuffled complex evolution (SCE) algorithm (Duan et al, 1992) and genetic algorithms (GA) (Wang, 1991). A number of studies have been conducted that compare SCE, GA and other global and local search procedures for calibrating conceptual rainfall–runoff models (Duan et al, 1992; Gan and Biftu, 1996; Cooper et al, 1997; Kuczera, 1997; Thyer et al, 1999). These studies demonstrate that the SCE method is an effective and efficient search algorithm. The SCE method has been widely applied for calibration of various conceptual rainfall–runoff models (Sorooshian et al, 1993; Duan et al, 1994; Gan et al, 1997). The SCE method combines different search strategies, including (i) competitive evolution, (ii) controlled random search, (iii) the simplex method, and (iv) complex shuffling.

2.5.1.3. UNCERTAINTY ANALYSIS METHODS

The uncertainty analysis of hydrological and water quality catchment models in recent years received special attention. Several uncertainty analysis methods have been developed to propagate the uncertainty through the hydrological and water quality models, and to derive meaningful uncertainty bounds of the model simulations. These methods range from analytical and approximation methods (Melching, 1992; Tung, 1996) to Bayesian and Monte Carlo (MC) sampling based methods (Beven and Binley, 1992; Kuczera and Parent, 1998; Vrugt et al, 2003b), methods based on the analysis of model errors (Montanari and Brath, 2004; Shrestha and Solomatine, 2008; Solomatine and Shrestha, 2009), and methods based on fuzzy set theory (Maskey et al, 2004).

The majority of these methods deals only with a single source of uncertainty and consider model uncertainty to be mostly produced by parameter uncertainty assuming that the model structure is correct and the input data is free from errors. Only recently new techniques have been emerging such as data assimilation techniques (Moradkhani et al, 2005; Vrugt et al, 2005), multi model averaging techniques (Ajami et al, 2007; Vrugt and Robinson, 2007), Bayesian approaches (Kavetski et al, 2006; Kuczera et al, 2006), and efficient Markov chain Monte Carlo (MCMC) techniques (Haario et al, 2006; Vrugt et al, 2008) to explicitly treat two or more sources of uncertainty such as input, parameter and structure uncertainty.

Despite the large number of suggested techniques, only rarely more than one technique was applied in the same case study in the literature. Yang et al (2008) compared five commonly used uncertainty analysis methods for a SWAT application to the Chaohe Basin in China. These methods are Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992), Parameter Solution (ParaSol) (van Griensven and Meixner, 2006), Sequential Uncertainty Fitting algorithm (SUFI-2) (Abbaspour et al, 2004; Abbaspour et al, 2007b), and a Bayesian framework implemented using Markov Chain Monte Carlo (MCMC) (Kuczera and Parent, 1998; Yustres et al, 2012) and Importance Sampling (IS) (Kuczera and Parent, 1998) techniques. GLUE, SUFI-2 and ParaSol became the most widely used methods for simultaneous calibration and uncertainty estimation in hydrological and water quality modelling.

In GLUE, parameter uncertainty accounts for all sources of uncertainty, i.e., input uncertainty, structural uncertainty, parameter uncertainty and response uncertainty. GLUE is convenient and easy to implement, and widely used in hydrology (Yang et al, 2008). However, GLUE also has very evident shortcomings such as subjective choice of the likelihood function and truncation threshold used to separate behavioral and non-behavioral models (Zhang et al, 2014). Another drawback of this approach is its prohibitive computational burden imposed by its random sampling strategy (Hossain et al, 2004).

In SUFI 2, parameter uncertainty is expressed as ranges and is sampled using a Latin Hypercube procedure. Two factors quantify the goodness of calibration and uncertainty analysis. The first one is the *p-factor*, quantified the percentage of data captured by the 95% prediction uncertainty (95PPU), and the other one is the *d-factor*, which quantifies the average thickness of the 95PPU. Similarly to GLUE, SUFI-2 represents uncertainties of all sources through parameter uncertainty and convenient to use. The drawback of this approach is that it is semi-automated and requires the interaction of the modeler for checking a set of suggested posterior parameters, hence, requiring a good knowledge of the parameters and their effects on the output. This may add an additional error (i.e. modeler's uncertainty) to the list of other uncertainties (Yang et al, 2008).

ParaSol is based on the global optimization algorithm SCE-UA (Duan et al, 1992). The idea is to use the simulations performed during optimization to derive prediction uncertainty because the simulations gathered by SCE-UA are very valuable as the algorithm samples over the entire parameter space with a focus on solutions near the optimum/optima (van Griensven and Meixner, 2006). ParaSol is very efficient in detecting the area with high objective-function values in the response surface. Implementation of ParaSol is relatively easy and the computation depends only on the convergence of the optimization process (SCE-UA algorithm) (Yang et al, 2008). However, Parasol ignores the other sources of uncertainty except the parameter uncertainty.

Bayesian inference has a sound theoretical foundation and some statistical assumptions. Due to the complicated likelihood function and processing technique, the Bayesian techniques (MCMC and IS) need more effort to be implemented (such as the construction of likelihood function, test of the statistical assumptions etc.). The computationally most expensive technique is the Bayesian inference: MCMC takes 45,000 model runs while the IS is too inefficient to obtain any reasonable result even after 100,000 model runs (Yang et al, 2008). This is certainly the major disadvantage of this technique. The conceptual basis of ParaSol, MCMC and IS is the probability theory. GLUE and SUFI-2 lack a consistent and testable statistical and probabilistic formulation (Mantovan and Todini, 2006).

2.5.1.4. SENSITIVITY, AUTOCALIBRATION AND UNCERTAINTY ANALYSIS IN SWAT2005

(A) SENSITIVITY ANALYSIS IN SWAT2005: LH-OAT

The Latin-Hypercube and One-factor-At-a-Time (LH-OAT) method (van Griensven et al, 2006) has been incorporated in SWAT2005. This method combines the robustness of the Latin-Hypercube (LH) sampling that ensures that the full range of all parameters has been sampled with the precision of an OAT design assuring that the changes in the output in each model run can be unambiguously attributed to the parameter that was changed.

During the sensitivity analysis, SWAT runs (p+1)*m times, where p is the number of parameters and m is the number of LH loops (default value of m=10). For each loop, a set of parameter values is selected such that a unique area of the parameter space is sampled. This given set of parameter values was used to run a baseline simulation for the unique area. Then, using OAT, a parameter was randomly selected, and its value was changed from the previous simulation by a user-defined percentage (default value 5%). SWAT is run on the new parameter set, and then a different parameter is randomly selected and varied. After all the parameters have been varied, the LH algorithm locates a new sampling area by changing all the parameters. Finally, the model ranked the parameters based on the objective function (Sum of the Square of the Residuals) of simulated and observed output variable monthly time series. The parameter producing the highest average percentage change in the objective function value is ranked as most sensitive. The details of LH-OAT sensitivity analysis guidelines can be found on van Griensven (2005), van Griensven et al (2006), and Van Liew and Veith (2010).

The sensitivity analysis tool in SWAT2005 has the capability of performing two types of analyses. The first type of analysis uses only modeled data to identify the impact of adjusting a parameter value on some measure of simulated output, such as average streamflow. The second type of analysis uses measured data to provide overall ‘goodness of fit’ estimation between the modeled and the measured time series. The first analysis may help to identify parameters that improve a particular process or characteristic of the model, while the second analysis identifies the parameters that are affected by the characteristics of the study catchment and those to which the given project is most sensitive (Veith and Ghebremichael, 2009).

(B) AUTOCALIBRATION IN SWAT2005: PARASOL (SCE-UA)

SWAT2005 includes a multi-objective automated calibration procedure ParaSol (Parameter Solutions Method) that was developed by Van Griensven and Bauwens (2003). The calibration procedure is based on a Shuffled Complex Evolution Algorithm

(SCE-UA; Duan et al, 1992). In the first step, the SCE-UA selects an initial population of parameters by random sampling throughout the feasible parameter space for "*p*" parameters to be optimized, based on given parameter ranges. The population is partitioned into several communities, each consisting of "2*p*+1" points. Each community is made to evolve based on a statistical "reproduction process" that uses the simplex method, an algorithm that evaluates the objective function in a systematic way with regard to the progress of the search in previous iterations (Nelder and Mead, 1965). At periodic stages in the evolution, the entire population is shuffled and points are reassigned to communities to ensure information sharing. As the search progresses, the entire population tends to converge toward the neighborhood of global optimization, provided the initial population size is sufficiently large (Duan et al, 1992).

SCE-UA has been widely used in catchment model calibration and other areas of hydrology such as soil erosion, subsurface hydrology, remote sensing and land surface modelling. It was generally found to be robust, effective and efficient (Duan, 2003). The details of ParaSol (SCE-UA) can be found on van Griensven (2005), Green and Van Griensven (2008), and Van Liew and Veith (2010).

(C) UNCERTAINTY ANALYSIS IN SWAT2005: PARASOL (SCE-UA)

SWAT2005 uses ParaSol with uncertainty analysis option (SCE-UA) for calibration and uncertainty analysis in a single run. Once the optimization is done in ParaSol, the uncertainty analysis divided each simulation that has been performed by the SCE-UA optimization into 'good' simulation and 'not good' simulation based on a threshold value of the objective function whether falling or not within a user-defined confidence interval (e.g. 95% probability). Then good simulations are used to estimate the *p-factor* and *d-factor* from the 95PPU band for each simulated variables. Sum of the squares of the residuals (SSQ) is used as the objective function. There are two separation techniques; both are based on a threshold value for the objective function (or global optimization criterion) to select the 'good' simulations by considering all the simulations that give an objective function below this threshold. The threshold value can be defined by χ^2-statistics where the selected simulations correspond to the confidence region (CR) or Bayesian statistics that are able point out the high probability density region for the parameters or the model outputs. The details of ParaSol with uncertainty (SCE-UA) can be found on van Griensven (2005), Green and Van Griensven (2008), and Van Liew and Veith (2010).

2.5.2. DATA PROCESSING FOR MODEL CALIBRATION

For calibration, catchment water quality models need times series data of streamflow along with surface runoff and baseflow component. The models also need continuous sediment and nutrient observed load data for the calibration. This section addresses the data processing techniques for observed streamflow and water quality data especially on how to generate sediment and nutrients loads from sparsely available water quality grab samples for calibration purposes.

2.5.2.1. STREAMFLOW DATA

Accurate estimation of catchment water balance is a vital prerequisite for water quality modelling (Grayson et al, 1999b). An incorrect representation of the baseflow and surface runoff can cause wrong estimates of the diffuse pollution loads to the river, as the erosion and leaching processes depend on this representation. Therefore baseflow and surface runoff are also calibrated along with the streamflow to represent surface and subsurface hydrological processes accurately. Various techniques are available to separate baseflow from gauged streamflow data. These include traditional manual graphical procedures to more recent automated procedures.

Graphical separation methods tend to focus on defining the points where baseflow intersects the rising and falling limbs of the quick flow response. Manual separation of the streamflow hydrograph into surface flow and baseflow is difficult and inexact; often results derived from such manual methods cannot be replicated by different investigators (White and Sloto, 1990). On the other hand, automated data processing or filtering procedures remove some of the subjectivity inherent with the manual methods and substantially reduce the streamflow analysis time. It is fast, consistent, and reproducible (Arnold et al, 1995).

The computer software program Base Flow Index (BFI) (Wahl and Wahl, 1988; Wahl and Wahl, 1995) estimates the baseflow using an automated technique (known as smoothed minima filtering technique) developed by the Institute of Hydrology (Institute of Hydrology, 1980). BFI uses the minimum daily streamflow in five consecutive days, and minimum flows less than 90 percent of adjacent minimum flows are defined as turning points. The turning points are used to interpolate the baseflow hydrograph (White et al, 2004).

The automated procedures predominantly involve the use of recursive digital filters that have their basis in signal analysis and processing, and are used to remove the high-frequency quickflow signal to derive the low-frequency baseflow signal (Nathan and McMahon, 1990). Several studies have shown that the automated digital filter technique compares well with manual and other automatic baseflow separation techniques and with measured results (Nathan and McMahon, 1990; Arnold et al, 1995; Arnold and Allen, 1999; Gonzales et al, 2009). The software “Baseflow Filter Program” is developed by USDA-AES (USDA-ARS, 1999) based on the automated digital filter technique. This software is widely used by SWAT model users to separate the baseflow from the observed streamflow time series data to be used for calibration purposes (Arnold et al, 2000; Santhi et al, 2001a; Zhang et al, 2003; Romanowicz et al, 2005; Santhi et al, 2006; Larose et al, 2007; Geza and McCray, 2008; Panagopoulos et al, 2011a).

2.5.2.2. WATER QUALITY DATA

The load of a water quality pollutant in a stream (i.e. the weight of material transported during specific time period) is a function of the concentration of the pollutant and the stream discharge (Littlewood, 1992). In general, load L (kg), over a time period T, can be represented by the equation

$$L = \int_0^T CQdt \tag{2.1}$$

where C (mg/l) is the pollutant’s concentration and Q (m^3/s) is the water discharge.

The use of automated equipment allows precise discharge measurements economically for short time intervals (e.g. hourly or less), but water quality constituents are generally collected as grab samples at regular intervals (i.e. weekly, monthly or seasonally). The measurement of a pollutant concentration requires water sampling, storing, and costly laboratory analyses, which makes concentration measurement the limiting factor for estimating pollutant loads. Therefore, in most cases, water quality measurements are done sparsely, mainly for compliance purposes. In this case, integrating concentration and streamflow may be inappropriate to calculate the loads.

For calibration of complex models, it needs continuous pollutant load and concentration data which can be generated by data-based techniques from sparsely available grab sample data. There are many different techniques used for estimating pollutant loads, differing in complexity, accuracy and bias. The choice of the technique for estimating pollutant loads depends on the data resolution, the mathematical ability of the operator, the computer technology available, or the relationship within the data and between various constituents' concentrations (Letcher et al, 1999). Ideally, data should be collected to suit a particular river and a particular method of load estimation. However, more often data are collected without clear objectives thus reducing collection efficiency and usefulness. Existing data-based methods for load estimation using field data can be classified into three major classes: (i) averaging techniques, (ii) ratio methods, and (iii) regression methods (Letcher et al, 1999; Letcher et al, 2002; Etchells et al, 2005; Quilbe et al, 2006; Tennakoon et al, 2007; Marsh and Waters, 2009; Joo et al, 2012).

The averaging techniques: The averaging techniques, also called integration or interpolation methods, are based on some form of averaging of concentration or flow data. Estimates of load over a time period are made by using averages of discharge, concentration or load for a given subinterval and then summing these over the entire period. These averages may be over different time periods, such as monthly, quarterly or yearly, and can combine discharge and concentration in a number of different ways (for examples see Letcher et al (1999)).

The Ratio methods: The ratio methods are based on the ratio of flow and concentration, and often modified by a bias correction factor. Generally discharge data is used as an auxiliary variable, x_i, with load data treated as a dependent variable, y_i. The ratio estimate is usually calculated as "$Y_R = (y/x)\ X$" where y and x are the sample means of y_i and x_i respectively, Y_R is the ratio estimate of load and X is the discharge. Preston et al (1989) developed several ratio methods based on the ratio estimator of Beale (1962) (see Letcher et al (1999)).

The regression methods: The regression methods are based on fitting a relationship between flow and concentration for estimating a continuous trace of concentration. Typically this relationship is considered to be log–log, that is, the log of pollutant load or concentration is assumed to be a linear relationship of the log of stream discharge. This relationship is generally applied because both discharge and concentration are often best described by a bivariate log–normal distribution. For commonly used regression methods, see Letcher et al (1999).

Reviews of methods of load estimation techniques using field data can be found in Degens and Donohue (2002); Etchells et al (2005); Littlewood (1992); Littlewood et al (1998); Letcher et al (1999); Marsh and Waters (2009); Mukhopadhyay and Smith (2000); Preston et al (1989); and Quilbe et al (2006). Based on the literature, Quilbe et al (2006) suggested that: (i) averaging techniques are accurate only when concentration measurements are available for the entire flow range; (ii) ratio methods are less sensitive to river and pollutant characteristics than regression methods but require more data to achieve the same level of precision, and they are robust and unbiased under systematic sampling, as well as under stratified event sampling; (iii) regression methods can give the best results if streamflow and concentration data are strongly correlated for a wide range of streamflow values.

The regression methods do not require extensive data but the quality of prediction depends on the quality of the correlation between flows and concentrations (Smith and Croke, 2005). This requirement is often met for sediments, particulate and total P, as well as pesticides, but more rarely for mobile chemicals such as nitrate or chlorides (Robertson and Roerish, 1999; Vieux and Moreda, 2003). Regarding accuracy of load estimation, Walling and Webb (1981, 1988) performed a rigorous evaluation of regression methods, and showed that they can produce an underestimation of 23–83% of the actual load. Since the temporal variability of the relationship between concentration and streamflow can be important (Haygarth et al, 2004), some authors define the regression equation as a function of time in order to take into account nonlinearities as well as seasonal and long-term variability (Cohn et al, 1989).

Preston et al (1989) found that no group of load estimators (i.e. the averaging techniques, the ratio methods and the regression methods) discussed above were better in all cases. In general, the authors found that overall, the ratio estimators were more robust than the other estimation methods, virtually unbiased in all test cases, but slightly less precise than the averaging and regression methods. Tennakoon et al (2007) proposed a decision tree for the selection of load estimation methods taking into consideration of land use category, sampling frequency and number, and correlation between streamflow and pollutant concentrations as shown in Figure 2.10. Figure 2.10 shows that for rural catchments (other than intensive agriculture) and for long term monthly/annual loads, the choice of a load estimation method is: (a) the averaging techniques for high sample number, (b) the regression methods for low sample number, but high correlation between concentrations and streamflow, and (c) the ratio methods for low sample number and low correlation between concentrations and streamflow. This means the choice of technique depended on the characteristics of the catchment being considered, and the availability of data for that catchment.

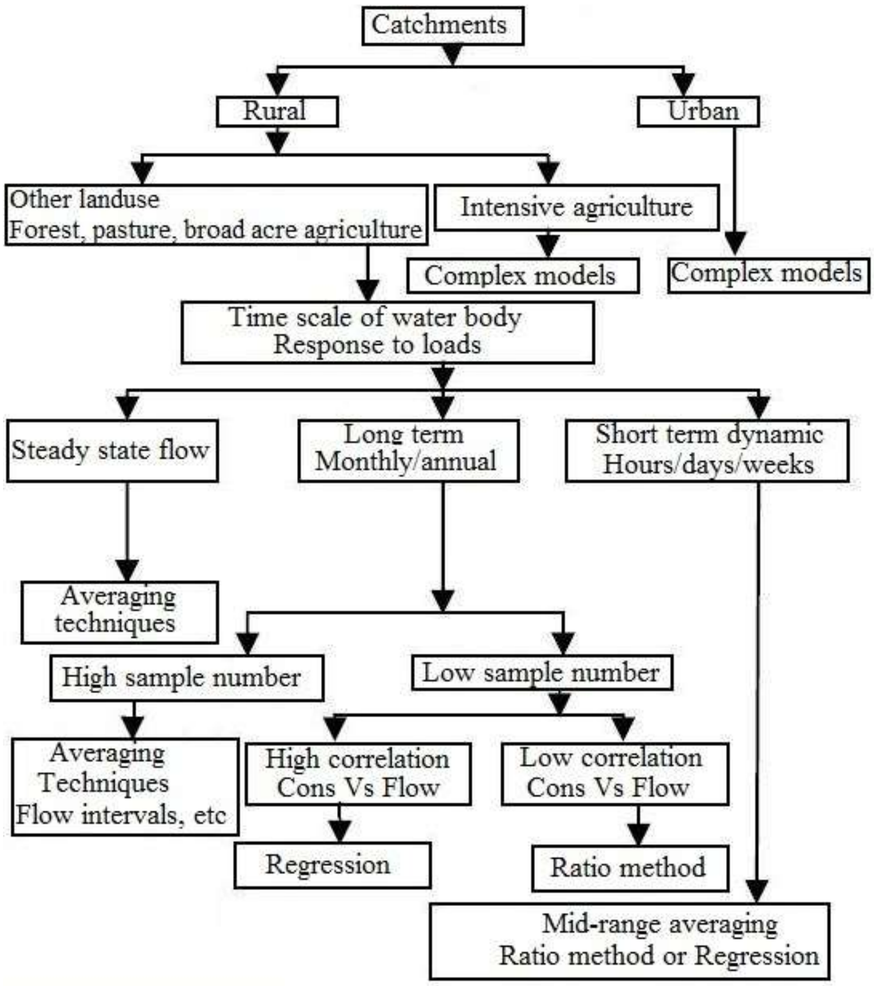


Figure 2.10 Decision tree for the selection of load estimation methods (Tennakoon et al, 2007)

The Queensland Department of Environment and Resource Management (DERM) in collaboration with the eWater Cooperative Research Centre (both in Australia) have designed and developed a software package “Water Quality Analyzer” (Tennakoon et al, 2011) which includes different data based methods to estimate and analysis pollutant loads.

Recently, the U.S. Geological Survey developed a regression based load estimation software tool LOADEST (Runkel et al, 2004) which considers temporal variability of the relationship between concentration and streamflow. LOADEST estimates constituent loads in streams and rivers by developing a regression model, given a time series of streamflow, constituent concentration, and additional data inputs. LOADEST also considers the regression equation as a function of time in addition to the usual streamflow in order to take into account nonlinearities as well as seasonal and long-term variability. It is well documented, and is accepted as a valid means of calculating constituent load from a limited number of water quality measurements (Jha et al, 2007). The LOADEST model has been widely used, particularly by the SWAT model users and the U.S. Geological Survey (Pickup et al, 2003; White et al, 2004; White and Chaubey, 2005; Deacon et al, 2006; Jha et al, 2006; Tortorelli and Pickup, 2006; Jha et al, 2007; Migliaccio et al, 2007; Domagalski et al, 2008; Maret et al, 2008; Debele et al, 2009; Jha et al, 2010; Mukundan et al, 2010; Maringanti et al, 2011; Cerro et al, 2012; Kannan, 2012; Omani et al, 2012).

LOADEST Model: The U.S. Geological Survey developed the LOADEST, a FORTRAN program for estimating pollutant loads in streams and rivers, that accounts for many of the statistical challenges encountered when formulating, calibrating and applying regression models in estimation of pollutant loads (Runkel et al, 2004). LOADEST is based on two previous models: LOADEST2 (Crawford, 1991, 1996) and ESTIMATOR (Cohn et al, 1989). The calibration and estimation procedures within LOADEST are based on three statistical estimation methods. The first two methods, Adjusted Maximum Likelihood Estimation (AMLE) and Maximum Likelihood Estimation (MLE), are appropriate when the calibration model errors (residuals) are normally distributed. Of the two, the AMLE method is considered when the calibration data set (time series of streamflow, additional data variables, and concentrations) contains censored data. The third method, Least Absolute Deviation (LAD), is an alternative to maximum likelihood estimation when the residuals are not normally distributed.

The LOADEST model evaluates the relationships between pollutant loads (dependent variables), and streamflow and time variables (explanatory variables) based on eleven predefined models and a user-defined model. The users can select a model manually or the user can automatically select the best model from the first nine models based on the lowest value of Akaike Information Criterion (AIC) (Akaike, 1974). In statistics, AIC is the most commonly used criterion for model selection from a set of parametric models.

The first nine models include different combinations of time variables and seasonal variables to consider time trend and seasonal trend in a continuous manner. For example, the seven-parameter model is given below;

$$\ln(L) = a_0 + a_1 \ln Q + a_2 \ln Q^2 + a_3 \sin(2\pi dtime) + a_4 \cos(2\pi dtime) + a_5\, dtime + a_6\, dtime^2 \qquad (2.2)$$

where ln = natural logarithm; L = pollutant load in kg/day; a_0 = dimensionless regression constant; a_1, a_2, a_3, a_4, a_5, a_6 = dimensionless regression coefficients; Q = daily mean streamflow in cubic feet per second; and dtime = time parameter in decimal years from the start of the study period. Within the above model, the explanatory variables lnQ and $\ln Q^2$ account for the dependence on streamflow, the sine and cosine terms account for seasonal variability, and the dtime and $dtime^2$ account for the time trend. For abrupt seasonal change, the users can use last two predefined models or develop a user-defined model (for LOADEST details see Runkel et al, 2004).

2.5.3. MODEL EVALUATION STATISTICS

The performance of a model is evaluated using graphical and statistical techniques to determine the quality and reliability of the predictions when compared to observed values. Graphical techniques provide a visual comparison of simulated and measured constituent data and a first overview of model performance (ASCE, 1993). According to Legates and McCabe Jr (1999), graphical techniques are essential to appropriate model evaluation. Two commonly used graphical techniques, hydrographs and percent exceedance probability curves, are especially valuable. Other graphical techniques, such as bar graphs and box plots, can also be used to examine seasonal variations and data distributions.

The quantitative evaluation statistics are divided into three major categories: standard regression, dimensionless, and error index. The standard regression statistics such as Coefficient of Determination (R^2) determine the strength of the linear relationship between simulated and measured data. The dimensionless techniques such as Nash-Sutcliffe Efficiency (E_{NS}^2) provide a relative model evaluation assessment, and the error indices such as, Root Mean Square Error (RMSE) quantify the deviation in the units of the data of interest (Legates and McCabe Jr, 1999). Moriasi et al (2007) discussed 12 statistical techniques along with the graphical techniques for evaluating model performance ratings. A number of other publications have also addressed model evaluation statistics (Willmott, 1981; ASCE, 1993; Legates and McCabe Jr, 1999; Krause et al, 2005). By far, the most widely used statistics reported for calibration and validation of streamflow, sediments and nutrients are R^2 and E_{NS}^2 (Arnold et al, 2012).

To establish guidelines and to determine recommended statistical techniques for catchment water quality model evaluation, Moriasi et al (2007) conducted an extensive review on the published literature related to calibration, validation, and application of catchment models focusing on simulation of streamflow and transport of sediment and nutrients. Based on this analysis, they recommended that three quantitative statistics namely Nash-Sutcliffe efficiency (E_{NS}^2), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR), in addition to the graphical techniques, be used in model evaluation. The authors also developed general model evaluation guidelines, for monthly time step (and that appropriate relaxing and tightening of the standard be performed for daily and annual time step evaluations respectively), based on performance ratings for the recommended statistics and on project-specific considerations as shown in Table 2.1. Model performance can be judged based on these general performance ratings. As shown in Table 2.1, the performance ratings for RSR and E_{NS}^2 are the same for all constituents, but PBIAS is constituent specific. This difference is due to the recent availability of information (PBIAS) on the uncertainty of measured streamflow and water quality.

Table 2.1. General performance ratings of the recommended statistics for monthly time step

Performance Rating	RSR	E_{NS}^2	PBIAS (%)		
			Streamflow	Sediment	N, P
Very good	$0.00 \leq RSR \leq 0.50$	$0.75 < E_{NS}^2 \leq 1.00$	PBIAS < ±10	PBIAS < ±15	PBIAS< ±25
Good	$0.50 < RSR \leq 0.60$	$0.65 < E_{NS}^2 \leq 0.75$	±10 ≤ PBIAS < ±15	±15 ≤ PBIAS < ±30	±25 ≤ PBIAS < ±40
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < E_{NS}^2 \leq 0.65$	±15 ≤ PBIAS < ±25	±30 ≤ PBIAS < ±55	±40 ≤ PBIAS < ±70
Unsatisfactory	$RSR > 0.70$	$E_{NS}^2 \leq 0.50$	PBIAS ≥ ±25	PBIAS ≥ ±55	PBIAS ≥ ±70

The three evaluation statistics E_{NS}^2, PBIAS and RSR as recommended by Moriasi et al (2007) are briefly discussed below. The evaluation statistic R^2 is also discussed below as this has wide application and acceptability.

Coefficient of Determination (R^2): R^2 describes the proportion of the variance in measured data explained by the model. R^2 ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Santhi et al, 2001a; Van Liew et al, 2003). A perfect fit also requires that the regression slope and intercept are equal to 1 and 0, respectively; however, the slope and intercept have typically not been reported in published studies. Although R^2 has been widely used for model evaluation, this statistic is over-sensitive to high extreme values (outliers) and insensitive to additive and proportional differences between model predictions and measured data (Legates and McCabe Jr, 1999). R^2 is computed as shown in Equation 2.3.

$$R^2 = \frac{\left[\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})\right]^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2 \ \sum_{i=1}^{n}(P_i - \bar{P})^2} \qquad (2.3)$$

where O_i is *i*th observation for the constituent being evaluated, P_i is the *i*th simulated value for the constituent being evaluated, $\bar{O}$ and $\bar{P}$ is the mean of observed and simulated data respectively, and n is the total number of observations.

Nash-Sutcliffe efficiency (E_{NS}^2): The Nash-Sutcliffe efficiency is a normalized statistic that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Nash and Sutcliffe, 1970). E_{NS}^2 indicates how well the plot of observed versus simulated data fits the 1:1 line. E_{NS}^2 is computed as shown in Equation 2.4.

$$E_{NS}^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad (2.4)$$

E_{NS}^2 ranges between $-\infty$ and 1.0 (1 inclusive), with $E_{NS}^2 = 1$ being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance. Sevat and Dezetter (1991) found E_{NS}^2 to be the best objective function for reflecting the overall fit of a hydrograph. It is also recommended for use by ASCE (1993) and Legates and McCabe Jr (1999). However, like R^2 it is also biased toward high flows.

Percent bias (PBIAS): Percent bias measures the average tendency of the simulated data to be larger or smaller than their observed counterparts (Gupta et al, 1999). PBIAS is calculated with Equation 2.5.

$$\mathrm{PBIAS} = \left[\frac{\sum_{i=1}^{n}(\mathrm{O}_i - \mathrm{P}_i) * 100}{\sum_{i=1}^{n}(\mathrm{O}_i)}\right] \qquad (2.5)$$

where PBIAS is the deviation of data being evaluated, expressed as a percentage. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias. PBIAS values for streamflow tend to vary more, among different autocalibration methods, during dry years than during wet years (Gupta et al, 1999). This fact should be considered when attempting to do a split-sample evaluation, one for calibration and one for validation. As an evaluation criterion, PBIAS is recommended by ASCE (1993) and Gupta et al (1999), since it has the ability to clearly indicate poor model performance.

RMSE-observations standard deviation ratio (RSR): Root Mean Square Error (RMSE) is one of the commonly used error index statistics (Singh et al, 2004). Based on the recommendation by Singh et al (2004), Moriasi et al (2007) developed a model evaluation statistic, named the RMSE-observations standard deviation ratio (RSR). RSR standardizes RMSE using the observations standard deviation, and it combines both an error index and the additional information recommended by Legates and McCabe Jr (1999). RSR is calculated as the ratio of the RMSE and standard deviation of measured data as shown in Equation 2.6.

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\mathrm{STDEV}_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}(\mathrm{O_i}-\mathrm{P_i})^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}(\mathrm{O_i}-\bar{\mathrm{O}})^2}\right]} \qquad (2.6)$$

RSR varies from the optimal value of zero, which indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. The lower RSR, the lower the RMSE, and the better the model simulation performance is.

2.6. DATA SOURCES FOR CATCHMENT WATER QUALITY MODELS

Physics-based water quality model needs Digital Elevation Model (DEM), land use, soil, climate (precipitation, minimum and maximum temperature, wind speed, solar radiation and relative humidity), and crop and land management practices data for model development. For calibration, the model also needs observed times series data of streamflow, sediment and nutrients. This section discusses about some sources of these data which would enhance the applications and development of physics-based model in data limited conditions.

2.6.1. DIGITAL ELEVATION MODEL (DEM)

Recently relatively high resolution and good quality global scale DEMs have become available in public domain. The CGIAR-CSI GeoPortal is able to provide SRTM 90m Digital Elevation Data for the entire world (http://srtm.csi.cgiar.org/). ASTER 30m Global Digital Elevation Model (GDEM), jointly developed by The Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space Administration (NASA), can be downloaded from NASA's Earth Observing System (EOS) data archive (http://asterweb.jpl.nasa.gov/gdem-wist.asp). In Australia, high resolution DEM can be purchased from Geoscience Australia (http://www.ga.gov.au/topographic-mapping/digital-elevation-data.html).

2.6.2. SOIL DATA

Food and Agriculture Organization (FAO) provides digital soil map and soil properties for most part of the world (http://www.fao.org/nr/land/soils/en/). In Australia, digital soil map and soil properties can be collected from the Australian Soil Resource Information System (ASRIS) (http://www.asris.csiro.au). ASRIS is a product of the Australian Collaborative Land Evaluation Program (ACLEP) developed by CSIRO, and Department of Agriculture, Fisheries and Forestry in collaboration with state and territory agencies.

2.6.3. LAND USE DATA

Land use maps can often be obtained from government agencies or can be downloaded freely from public domains. For example, the European Commission Joint Research Centre has provided 45 classes of global land cover data for year 2000 (http://www.forobs.jrc.ec.europa.eu/products/glc2000/glc2000.php). In Australia, 50m grid raster land use (catchment scale) can be collected from Australian Bureau of

Agricultural and Resource Economics and Sciences (http://www.agriculture.gov.au/abares/aclump/land-use).

2.6.4. CLIMATE DATA

NOAA's National Climatic Data Center (NCDC) provides public access to climate data worldwide (http://www.ncdc.noaa.gov/cdo-web/). In Australia, all climate data can be collected from the SILO climate database (http://www.longpaddock.qld.gov.au/silo/) and the Bureau of Meteorology (http://www.bom.gov.au/climate/data/).

2.6.5. CROP AND LAND MANAGEMENT PRACTICES DATA

The main sources for crop and land management practices data are local catchment management authorities or statistical survey authorities. In Australia, Australian Bureau of Statistics (ABS) provides spatially coarse agricultural management data. In Victoria State of Australia, crop and land management practices data can also be collected from Melbourne Water Corporation (http://www.melbournewater.com.au/) and Department of Environment and Primary Industries (http://www.depi.vic.gov.au/).

In most cases, crop and land management practices data are spatially very coarse and scarce. Correct information on the amount and date of fertilizer or manure or pesticide application does not often exist, while it is expected that such information is crucial for a correct modelling (Neitsch et al, 2002). Moreover, all farmers do not apply fertilizer or manure on the same day and at the same rate. A randomly defined application date may easily coincide with a rainy day leading to overestimation of loads. In reality, farmers do not apply fertilizer or manure on rainy days. A proper development of a model then requires some inverse modelling techniques to tackle this problem (Holvoet et al, 2005) where fertilizer and manure application types, rates and dates can be adjusted based on their effects on the simulated nutrient loads during the calibration process. Inverse modelling techniques mean determining unknown causes or calibration parameters based on observation of their effects (Abbaspour et al, 2004; Abbaspour et al, 2007b).

2.6.6. STREAMFLOW AND WATER QUALITY DATA

Similar like the crop and land management practices data, the main sources for these data are also local catchment management authorities. In most cases, continuous streamflow data are available, but availability of water quality data is very limited. Because water quality measurements are done sparsely as grab samples, mainly for compliance purposes since it requires highly specialized and systematic data collection, and costly laboratory analysis. In Victoria State of Australia, Melbourne Water Corporation provides access to continuous streamflow data.

In Australia, water quality monitoring is carried out by a wide range of organizations from Local, State and Federal Governments, private sector and community groups (Bartley et al, 2012). Data is available on-line via the State Government agencies (e.g. http://data.water.vic.gov.au/monitoring.htm), Regional Groups (e.g. Melbourne Water Corporation, the South East Queensland Ecosystem Health Monitoring Program), and Local Councils (e.g. http://www.hornsby.nsw.gov.au/environment/water-catchments/water-quality). The data housed in State Government data centers, and eventually the Bureau of Meteorology (http://www.bom.gov.au/water), provide important baseline information regarding the health of rivers in Australia.

2.7. SUMMARY

Effective management of an agricultural catchment necessitates basic understandings of numerous processes and interactions between the water resources continuum of a catchment, pollutant loadings, the receiving water bodies and the effects of management practices. Mathematical complex models simulating and simplifying these complex processes are useful analysis tools to understand problems and find solutions through land use changes and best management practices (BMPs) for particular catchments and agronomic settings. Developing reliable catchment simulation models and validating them on real-world catchments with measured and monitored data are also challenging. In this regard, sensitivity analysis, calibration and validation, and uncertainty analysis help to evaluate the ability of the model to sufficiently predict streamflow and constituent yields for specific applications.

Australia has a unique hydrological setting that has strongly influenced the development of water quality models built for Australian catchments. In general, the Australian catchments are data-rich in terms of hydroclimatic data, but data-poor especially for water quality and land management data compared to Europe and America. Therefore, traditionally commonly used water quality models in Australia are either empirical or lumped/semi-distributed conceptual models. Even, within these modelling frameworks, nutrients sub-models are mainly generation rate-based (empirical) without considering the details of physical and biochemical processes.

Physics-based distributed models are better suited for the accurate simulation of spatial and temporal patterns in surface runoff, sediment, chemicals and nutrients, and their associated transport pathways. However, because of high data requirement and processing, the applications of these models are limited in many data-poor catchments like the Australian catchments. Therefore, developing an effective water quality management plan in data-poor catchments still remains as a big challenge for water catchment managers. Recently with the advent of computers with high computational power and GIS software, physics-based models are increasingly being called upon in data-poor regions. The extensive input data for the physics-based models are often generated from GIS and regional or local surveys. Moreover, most of the data are available from many global sources for these models.

SWAT is a promising model for long-term continuous simulations in predominantly agricultural catchments, and offers the greatest numbers of management alternatives for modelling agricultural catchments. The ability to simulate in-stream water quality dynamics is a definite strength of SWAT. Also, SWAT has a GIS link and a user-friendly Graphical User Interface which provide a straightforward means of translating digital land use, topographic, and soil data into model inputs, and it is publicly available free of charge. The SWAT2005 version has an automated sensitivity, calibration and uncertainty analysis component. The model also has the option of multi-objective calibration for multi-site and multi-variable at a time. This approach reduces the risk of accumulation of the errors (model errors, and errors on the input and output variables) to the end step which is common in step-by-step calibration process for multi-variable.

Physics-based models like SWAT need observed data (such as sediment and nutrient loads, surface runoff and baseflow) for calibration and validation. A regression based software tool LOADEST developed by the U.S. Geological Survey was found promising for load estimation from sparsely available water quality grab sample data. Also, the software “Baseflow Filter Program” developed by USDA-AES based on automated digital filter technique was found promising for baseflow separation. Moriasi et al (2007) recommended three quantitative statistics namely Nash-Sutcliffe efficiency (E_{NS}^2), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR), in addition to the graphical techniques, to be used in model evaluation when comparing the observed and simulated data.

The wide range of SWAT applications underscores that the SWAT software is a very flexible and robust tool that can be used to simulate a variety of catchment problems. Therefore, the ArcSWAT interface of SWAT2005 modelling software was chosen for the study area of this research.

3. STUDY AREA AND DATA

3.1. INTRODUCTION

As discussed in Chapter one, the Middle Yarra River catchment was chosen as the study area for this project. Moreover, a physics-based distributed and continuous model, SWAT, was selected for this study area to develop the Middle Yarra Water Quality Model (MYWQM). The steps in the development of a complex model involves selection of modelling software, data collection and processing, assembly of the model, sensitivity analysis, calibration and validation, and uncertainty analysis. The collection of accurate and reliable data, and their proper processing is the most important stage of overall model development. SWAT requires extensive data collection and preparation covering climate, topography, soil, land use, agricultural management, hydrology, long-term water quality data and other information. Where possible, these data should be collected from local organizations to make the model robust.

This chapter first describes the Yarra River catchment in detail with respect to its water quality condition in Section 3.2. Then in Section 3.3, the study area – the Middle Yarra catchment (MYC) is described, followed by sources and processes of data required for developing the SWAT based MYWQM. The streamflow data analysis and the pollutant load estimation technique from water quality grab samples are also presented in Section 3.3. These two sets of data are required for calibration and validation of the model. Finally, a summary is presented at the end of the chapter.

3.2. YARRA RIVER CATCHMENT

3.2.1. DESCRIPTION OF THE YARRA RIVER CATCHMENT

The Yarra River catchment is located in the eastern part of Victoria (Australia), as shown in Figure 3.1. The Yarra River flows from east to west, and has a total catchment area of 4,078 square kilometres, and a stream course of 245 kilometres from its source in the Great Dividing Range to the estuary at Port Phillip Bay as shown in Figure 3.2 (EPA Victoria, 1999). About 21 percent of the catchment retains its natural vegetation, 57 percent is agricultural and 22 percent is urbanized (DSE, 2006a). The Yarra River catchment has three distinct segments: Upper, Middle and Lower Yarra, as shown in Figure 3.2 (EPA Victoria, 1999).

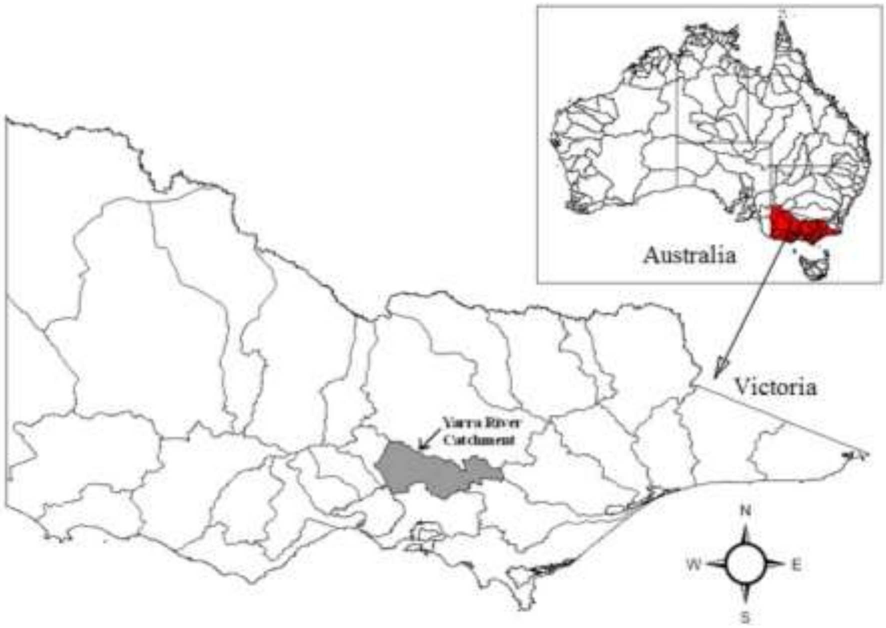


Figure 3.1 Yarra River catchment

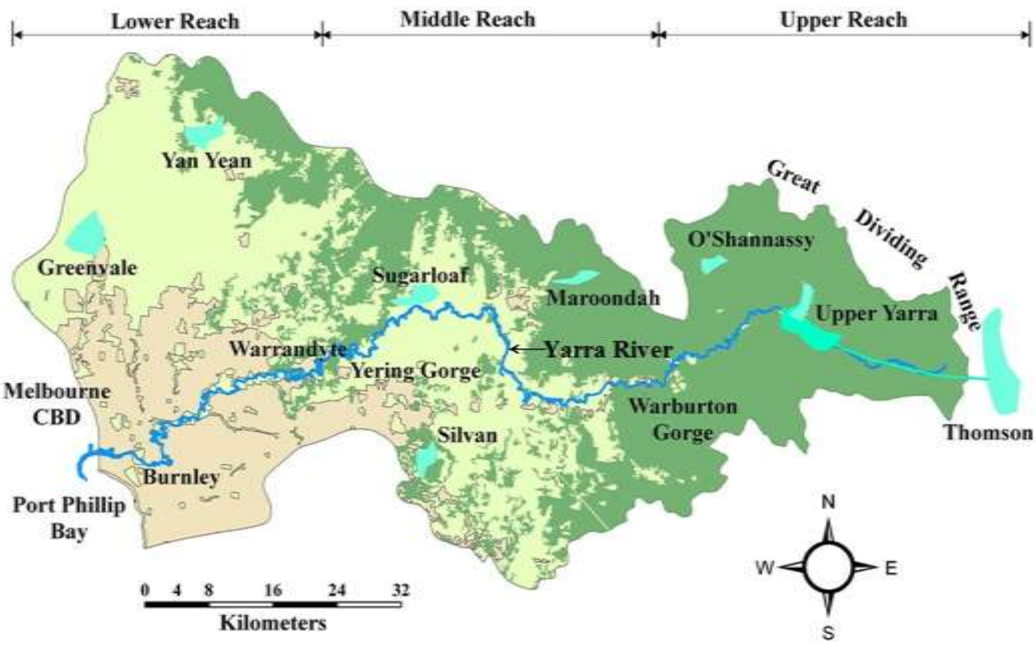


Figure 3.2 Details of Yarra River catchment (Melbourne Water, 2010a)

The Upper Yarra segment, from the Great Dividing Range to the Warburton Gorge at Miligrove, consists of mainly dense and extensive forested area with minimum human population. Water quality in this segment is excellent, and reserved for urban water supply purposes for more than 100 years (Melbourne Water, 2015).

The Middle Yarra segment, from the Warburton Gorge to Warrandyte Gorge, flows mainly through rural floodplains and valleys with limited urban development. There are several significant gorges in this segment, and majority of the land are used for agricultural purposes (Gardner, 1994). The extensive clearing of land in this part has resulted in high runoff during storms with the consequence of erosion on stream banks and increase in sediment loading, causing major non-point source pollution in terms of high nutrient runoff.

The Lower Yarra segment, downstream of Warrandyte, flows through mainly urbanized floodplains, and has the poorest water quality because of urban runoff.

The Yarra River catchment has a temperate climate. The average annual rainfall of the catchment varies from approximately 1,080 mm at Upper Yarra Reservoir near Warburton to about 615 mm at Burnley, near Melbourne, contributing to higher flows during winter and spring (Melbourne Water, 2015). However, the annual average rainfall has declined during the last decade compared to the long-term historical average (Muttil et al, 2009). Figure 3.3 shows the annual average rainfall for the Yarra River catchment based on the 22 rainfall measuring stations for the period of 1960 to 2008 as analyzed by Barua (2010). The figure shows that the average annual rainfall after 1997 is 831.1 mm whereas it was 1031.9 mm before 1997. The mean annual streamflow at the catchment outlet is approximately 1,100 GL/year. A major diversion of approximately 51.3 GL/year (on average) occurs at Yering Gorge (Davis et al, 1998).

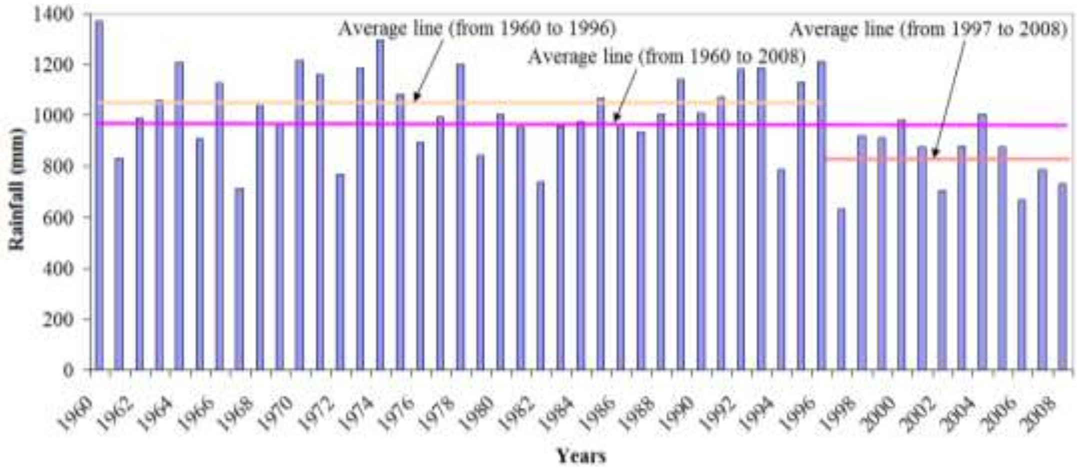


Figure 3.3 Annual average rainfalls in the Yarra River catchment

3.2.2. IMPORTANCE OF THE YARRA RIVER CATCHMENT

The Yarra River catchment is an important water resources catchment for Victoria, where over one-third of Victoria's population (approximately 2 million) lives in this catchment. Although the Yarra River is not large by Australian standards, it is a very productive catchment as it generates the fourth highest water yield per hectare of catchment in Victoria (Melbourne Water, 2015). The catchment water resources support a range of uses valued by the Melbourne's community, including urban water supply, agricultural, horticultural industries and downstream user requirements as well as flow requirements for maintaining environmental flows.

There are seven major reservoirs in the catchment, and one reservoir (Thomson) is outside the catchment as shown in Figure 3.2. These reservoirs are used mainly for urban water supply and storage purposes. There are many farm dams and licensed water extraction points in the catchment. A range of recreational activities, parks and biodiversity conservation is also located around the catchment waterways.

3.2.3. WATER QUALITY STATUS OF THE YARRA RIVER CATCHMENT

3.2.3.1. PAST WATER QUALITY MANAGEMENT IN THE YARRA RIVER CATCHMENT

Ever since the early years of European settlement, human development has altered Melbourne's rivers and creeks. Gone is the time when the Yarra was used as an open drain for household waste and a dumping ground for industry. However, several key milestones have resulted in significant protection or improvements in water quality in the Yarra River. Early planners showed considerable foresight in closing the upper reaches of the Yarra River and its major tributaries as water catchments for urban water supply, and for dedicating large tracts of land for parks. These have made a positive long term contribution to water quality.

Since the early 1970s, with the introduction of the *Environment Protection Act 1970* and the establishment of Australia's first Environment Protection Authority (EPA), industrial discharges to rivers and creeks have been significantly reduced. In the 1980s, minor wastewater treatment plants were constructed replacing many septic systems.

Later, some of these plants that were discharging to waterways were closed and wastes diverted to major plants such as the Eastern and Western treatment plants. This way the point-source pollution in the Yarra River catchment has become under control through protective legislation such as the Environment Protection Act 1970.

In spite of the above actions, the catchment's waterways and its bay is still threatened by diffuse (non-point source) pollution, urban expansion and climate change, each of which presents significant management challenges. The catchment is facing the increasing pollutant loads, particularly carried by stormwater and rural run-off due to increases in population, intensive agricultural practices and rapid urban growth.

3.2.3.2. CURRENT CONDITION OF THE YARRA RIVER CATCHMENT

The Victorian State Government published its third Index of Stream Conditions (ISC) for the Yarra River in September 2013. Five aspects of river condition – flow, water quality, physical form, streamside zone and aquatic life – are combined to give an overall measure of the environmental condition. The results show that only a small proportion of the Yarra River and its tributaries (12% of their length) is in good or excellent condition and over half (57%) is in poor or worse condition as shown in Figure 3.4 (DEPI, 2013). The forested upper reaches of the catchment have excellent water quality, and the condition deteriorates progressively downstream due to poor quality run-off from urban and agricultural land. Further downstream in metropolitan Melbourne, stormwater affects water quality and severely diminishes the river health.

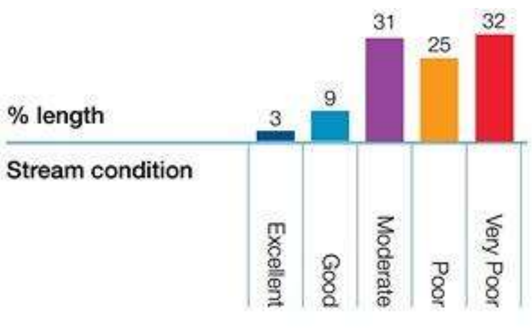


Figure 3.4 Waterway condition in the Yarra River catchment as per the third ISC (DEPI, 2013)

There are many different sources of the contaminants to the Yarra River that impact water quality. The diverse profile of land management and agricultural industries within the Yarra catchment ranges from livestock grazing through to highly productive horticultural or intensive animal enterprises. Urban areas and rural pastures generate the major nutrients and sediment loads in the Yarra River catchment. Argent and Mitchell (2003) used a simple screening model FILTER in NPS pollution modelling in the catchments of Port Philip Bay. The FILTER model suggests that in the Yarra catchment, the generation of both phosphorus and nitrogen was shared equally between urban and rural pasture areas as shown in Table 3.1 (DSE, 2006a). Over half of the total annual sediment transport was derived from the urban areas, and about one third was derived from rural pasture sources.

Table 3.1 Major sources of nutrients and sediments in the Yarra River catchment

Source	TP (ton/year)	TN (ton/year)	Sediment (ton/year)
Urban	41	537	22,930
Rural (pasture)	42	524	12,496
Rural (horticulture/broad-acre)	14	102	1,039
Forested	3	96	4562
Wastewater treatment plants	3	62	--

Melbourne Water Corporation used the PortsE2 (Argent et al, 2007) decision support system for the Port Phillip and Western Port region for water quality modelling. The Yarra River catchment is found as the largest generator of contaminants, both in terms of total load and load per unit area, contributing 50-62% of the total contaminant load in the Port Phillip Bay (Melbourne Water and EPA Victoria, 2009a). Rural land management across the regions was given priority in reducing loads through better farm practices (RossRakesh and Pierotti, 2011). Figure 3.5 shows the distribution of non-point source pollution by land use for Port Phillip Bay (Melbourne Water and EPA Victoria, 2009a).

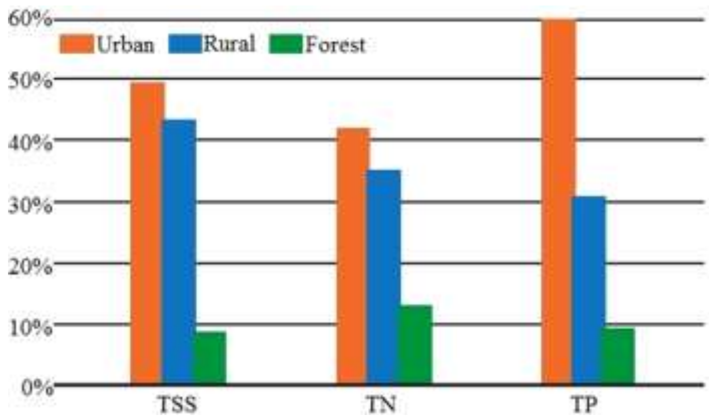


Figure 3.5 Distribution of non-point loads in Port Phillip catchments

As waterways flow to the bay, they transport these pollutants into Port Phillip Bay affecting marine ecosystems. Moreover, nutrients attached to soil particles are transported with sediments to the streams especially phosphorus. These pollutants affect in-stream ecosystems. Nutrients in rivers and creeks, mainly nitrogen and phosphorus, have a vital role in providing organisms with food for growth. However, excessive levels can result in problems such as nuisance weed and algal growth, and reduced biodiversity. In the Yarra River catchment, phosphorus is the key pollutant in the waterways whereas in Port Phillip Bay, nitrogen is the key nutrient affecting algal growth and must be managed to maintain the health of the bay (Harris et al, 1996; Yarra Valley Water, 1997; DSE, 2006a; Melbourne Water and EPA Victoria, 2009a).

The Victorian Government has taken various initiatives to improve Yarra River health mainly through Melbourne Water Corporation, EPA Victoria, and former Department of Sustainability and Environment (DSE). In early 2000s, the Government has spent around $140 million on Yarra projects mainly to improve the sewerage system and stormwater quality (DSE, 2006a). In addition, local government has spent in the order of $3.5 million implementing priority actions in local government stormwater management plans. In January 2006, the Victorian Government released the Yarra River Action Plan, which announced around $600 million to tackle stormwater pollution, leaking sewers, litter, and agricultural run-off to further protect and improve the health and amenity of the Yarra River (DSE, 2006b). Throughout the last few years, the ongoing program of improvement works has managed at least in holding the water quality levels on some extent in the face of expansive urban development and population growth, and intensification of agriculture (DSE, 2006a).

Based on the CSIRO Port Phillip Bay Environmental Study (Harris et al, 1996) and State Environment Protection Policy (SEPP) objectives, Melbourne Water Corporation and EPA Victoria set different short-term and long-term targets for rivers and creeks in the Port Phillip Bay (DNRE, 2002; Melbourne Water and EPA Victoria, 2009a, 2009b). Some of these include: (1) 350 tons per year nitrogen reduction from non-point sources of Yarra River catchment to meet SEPP objectives, and (2) by 2025, all natural rivers and creeks to be in good or better condition.

The existing water quality improvement plans as discussed above provide some guidance on water quality priorities. They are either broadly focus on a single specific issue and do not cover the range of water quality contaminants across the catchment in an integrated manner (such as nutrients) or are area specific (stormwater management plans). Also the current gaps in these plans include limited research and extension programs targeting diffuse pollution sources on intensively managed farms in hot spot areas (DSE, 2006a). Managing water quality, then, remains a major challenge for Melbourne, as continued urban growth and intensification of agriculture increase the risk of further deterioration of water quality.

Despite some success of existing programs, there is still a need for more to be done to overcome the current limitations in the programs and to invest funds efficiently in priority basis. Therefore this research project aims to develop a water quality management plan targeting agricultural based non-point source pollution in the Yarra River through simulation of best management practices (BMPs).

3.2.3.3. PREVIOUS WATER QUALITY MODELLING STUDIES IN THE YARRA RIVER CATCHMENT

The Yarra River catchment is the most dominant and significant catchment in the Port Phillip Bay region in terms of importance and pollution (mainly non-point source). It is the largest generator of contaminants, both in terms of total load and load per unit area, contributing 50-62% of the total contaminant load in the Port Phillip Bay (Melbourne Water and EPA Victoria, 2009a). However, no water quality model was developed specifically for this catchment considering non-point source pollution.

Pettigrove (1997) investigated the major sources of nutrients and suspended solids in different segments of the Yarra River catchment simply analysing observed water quality data of 1993 and 1994. Ng et al (2001; 2006) developed the Yarra River Water Quality Model (YRWQM) based on QUAL2E (Brown and Barnwell, 1987) for the Yarra River to investigate the effect of different management strategies on Yarra River water quality. However, this model is a river water quality model and considers only point source pollution.

Argent and Mitchell (2003) used a simple screening model FILTER in non-point source (NPS) pollution modelling in the catchments of Port Philip Bay. As a simple screening model, FILTER contained no explicit assessment of in-stream processing of pollutants or any effects of groundwater. The Melbourne Water Corporation used the PortsE2 decision support system for the Port Phillip and Western Port region to identify sources of nutrients, sediments, toxicants, and pathogens. The PortsE2 study provided two key reports. The Melbourne Water (2009) report is based on the initial model; and the BMT WBM (2009) report is based on the calibrated model.

3.2.3.4. CLIMATE CHANGE IMPACT ON WATER QUALITY OF THE YARRA RIVER CATCHMENT

The annual average rainfall has declined during the last decade within the Yarra River catchment compared to the long-term historical average (Muttil et al, 2009). As depicted in Figure 3.3, the average annual rainfall after 1997 is 831.1 mm whereas it was 1031.9 mm before 1997. Hence streamflow has become significantly lower than the long-term average in Yarra River catchment after 1997. This significant reduction in rainfall and streamflow has affected water quality in the waterways and bays.

The reduction in rainfall has had a positive effect on pollutant loads as less runoff from rural and urban catchments means fewer pollutants are washed into waterways and drains. Therefore, there was no significant change in concentration trends of pollutants in the last few years except slight higher nitrogen concentration trend in the lower Yarra (DSE, 2006a). However, the reduction in rainfall also reduces flows in waterways resulting in low dissolved oxygen (DO) levels.

A return to either higher average rainfall (signaling the end of a drought) or a move towards more frequent high rainfall events (storms) as is predicted as a result of climate change will result in increased loads being delivered to the waterways and bays. There is an increasing body of scientific evidence that gives a collective picture of a warming world and other climate changes. This will have significant implications for the water resources systems. As per the CSIRO climate study, the consistent trends for Melbourne include more extreme events with more hot days, more dry days and increased rainfall intensity during storm events (Howe et al, 2005). The major potential risks because of this climate change on receiving water include:

- Reduced health of waterways due to changes in baseflows
- Potential for negative water quality impacts in waterways and Port Phillip Bay due to increased concentration of pollutants (longer periods between runoff events and then high intensity events leading to concentrated pollutant runoff) and higher ambient Bay water temperatures.

3.3. STUDY AREA - MIDDLE YARRA CATCHMENT (MYC) AND DATA

The main aspect of this research project is the management of agricultural non-point source pollution. As discussed in Section 3.2.3.2, the Yarra River catchment is the largest generator of contaminants, both in terms of total load and load per unit area in the Port Phillip Bay region. In the Yarra River catchment, intensive agricultural activities contribute to a significant amount of non-point pollutants into the waterways mainly from the middle Yarra River segment. Moreover, the rural land management was given priority in the PortsE2 (Argent et al, 2007) modelling work described in Section 3.2.3.2, because it is considered cost-effective in reducing pollutant loads through better farm practices (RossRakesh and Pierotti, 2011). Therefore, the middle Yarra River segment as shown in Figure 3.6 is chosen as the study area for this research project. The study area is referred to as Middle Yarra Catchment (MYC) in this thesis.

3.3.1. DESCRIPTION OF THE STUDY AREA

The Middle Yarra Catchment (MYC) covering a total area of about 1511 km^2 is mainly rural floodplains and valleys with limited urban development. As discussed in Section 3.2.1, there are several gorges in this area which restrict the flow of the river, in particular Yering Gorge. Majority of the land in the MYC are used for agricultural purposes (Gardner, 1994; Carty and Pierotti, 2010). The extensive clearing of land in this area has resulted in high runoff during storms with the consequences of erosion on stream banks and increases in sediment loading, causing major non-point source pollution in terms of high nutrient runoff.

The river gradient decreases and valley widens as the river approaches downstream. Surface relief of the catchment converges from the east, north and south towards the central portion of the catchment. Figure 3.7 shows that the elevation in the MYC ranges from 9 to 1232 m. The highest values occur in the eastern portions of the catchment, while the lowest are found across the central and western part towards its outlet. The elevation difference along the cross section AB (Figure 3.7) that goes from the eastern side of the catchment to its outlet over 40 km away is 1170m. As shown in the profile graph of Figure 3.7, the streams flow in deep incised mountainous stream channels in the headwaters and then they flow through rolling landscapes from centre part to the outlet. The slope steepness of up to 10% covers about 43% of the catchment area, and the 57% of the catchment area is under the slope greater than 10% as shown in Figure 3.8.

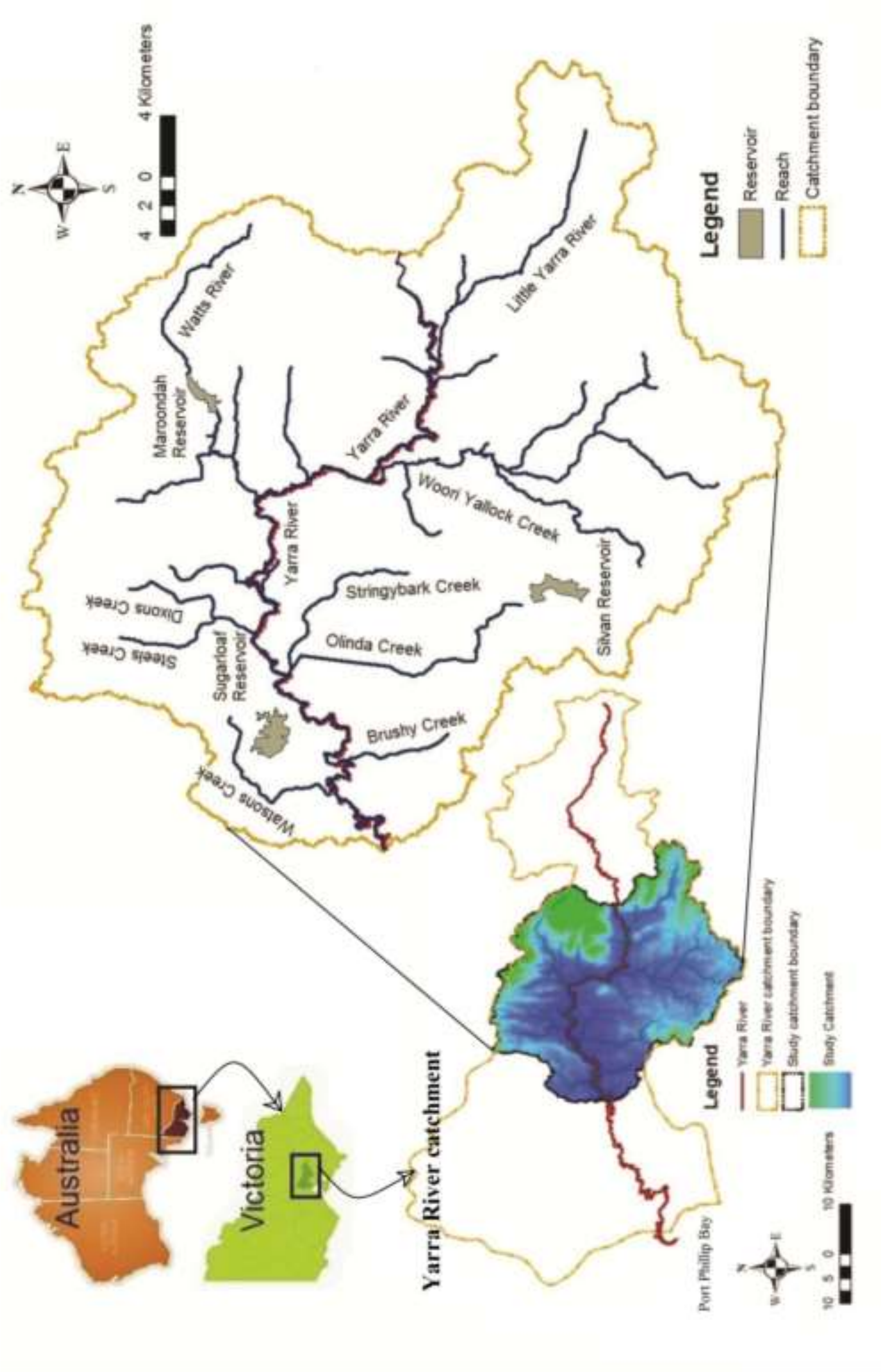


Figure 3.6 Location map of the Middle Yarra Catchment with major waterways and reservoirs

The major waterways and reservoirs in the catchment are shown in Figure 3.6. Maroondah, Sugarloaf and Silvan reservoirs are located in the MYC. Only Maroondah receives natural streamflow, while Sugarloaf and Silvan are offstream storage reservoirs. The major outflow from Maroondah is to Sugarloaf reservoir and a minor amount is to the Yarra River which is usually pumped back into the Sugarloaf reservoir at Yering Gorge Pump station. Sugarloaf and Silvan reservoirs do not contribute to downstream water flow in the Yarra River. Water from these reservoirs flow out to the urban water supply systems of Melbourne.

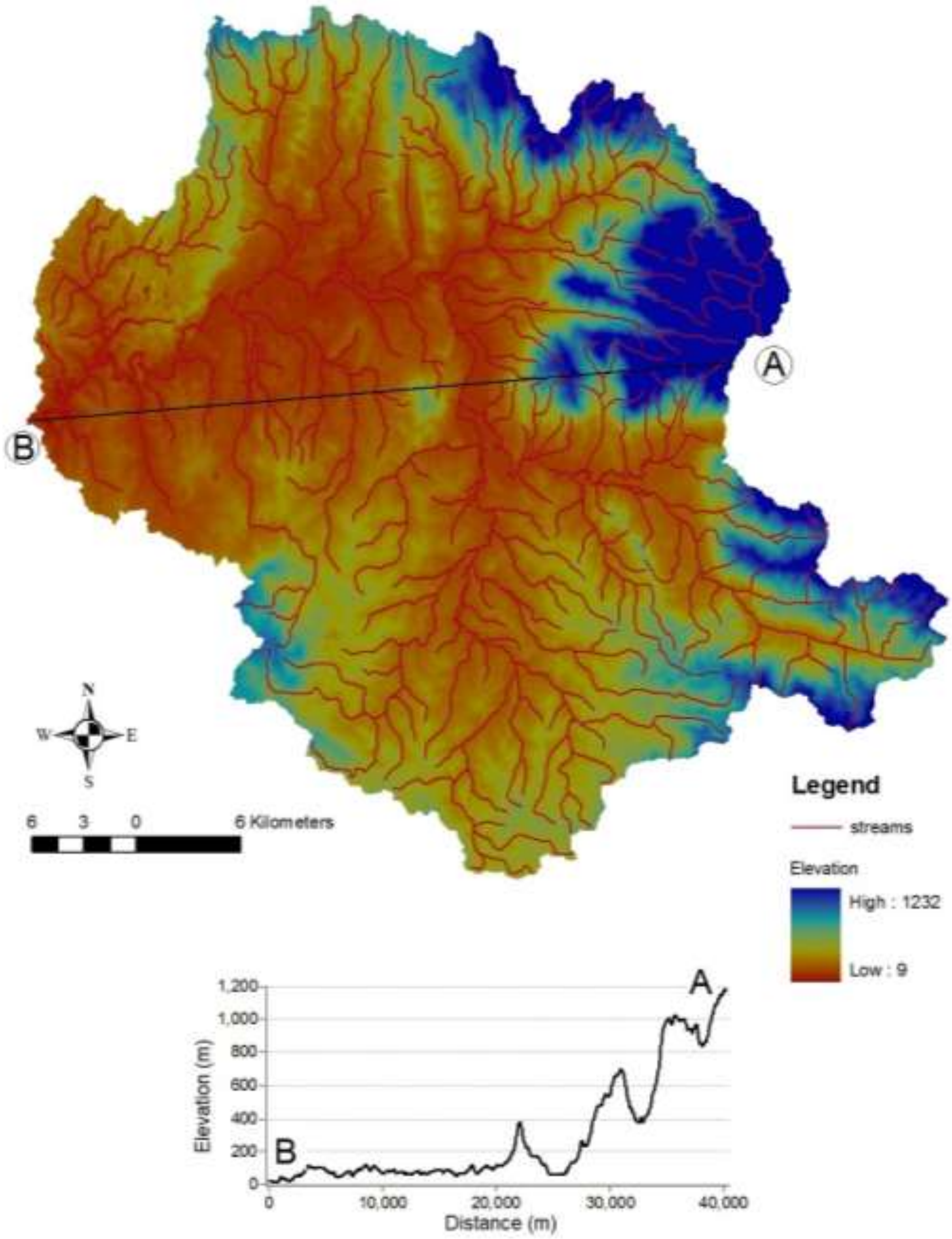


Figure 3.7 DEM of the Middle Yarra Catchment with a cross-section A-B

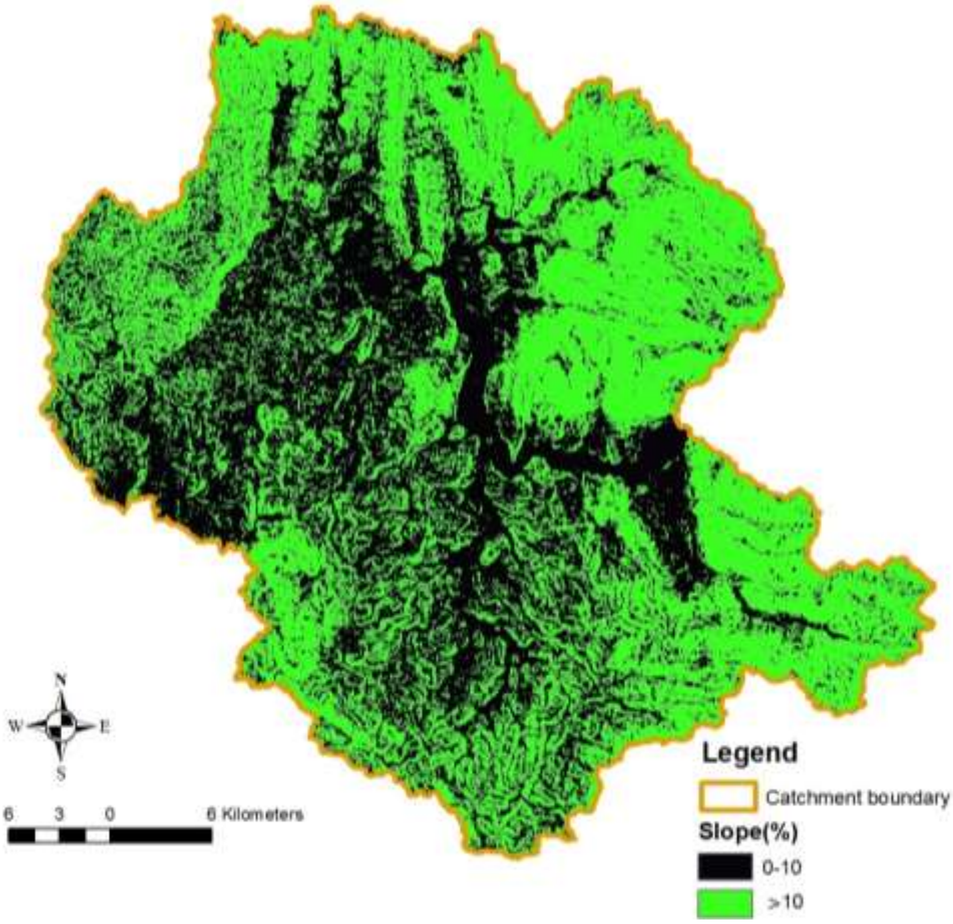


Figure 3.8 Distribution of land slope in the MYC

3.3.2. DATA SOURCES AND ANALYSIS

The ArcSWAT 2.3.4 interface for SWAT2005 modelling software was chosen for this research project as discussed in Section 2.4.3. To create a SWAT dataset, the interface ArcSWAT will need to access ArcGIS compatible raster (GRIDs) and vector datasets (shapefiles and feature classes) and database files which provide certain types of information about the catchment.

3.3.2.1. DATA REQUIRED FOR DEVELOPMENT OF THE SWAT BASED MIDDLE YARRA WATER QUALITY MODEL (MYWQM)

Mandatory GIS spatial input files needed for the ArcSWAT model include the digital elevation model (DEM), and land use and soil layers. The model also needs climate data (daily temperature (max and min), precipitation, solar radiation, wind speed and relative humidity), and crop and land management data. Table 3.2 shows the required data types with their sources of collection.

Table 3.2 Data sources for the MYWQM

Data Type	Source
Digital Elevation Model (DEM)	ASTER 30m GDEM, jointly developed by The Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space Administration (NASA) (http://asterweb.jpl.nasa.gov/gdem-wist.asp)
Soil	Australian Soil Resource Information System (ASRIS) developed by CSIRO and Department of Agriculture, Fisheries and Forestry (DAFF) (http://www.asris.csiro.au)
Land use	50m grid raster data collected from Australian Bureau of Agricultural and Resource Economics and Sciences http://www.agriculture.gov.au/abares/aclump/land-use
Climate	SILO climate data, Bureau of Meteorology (http://www.longpaddock.qld.gov.au/silo and http://www.bom.gov.au/climate/data/)
Crop and land management practices	Australian Bureau of Statistics, Melbourne Water Corporation (http://www.abs.gov.au and http://www.melbournewater.com.au/)

(A) DIGITAL ELEVATION MODEL (DEM)

Terrain analysis based on digital elevation models (DEMs) is being increasingly used in hydrology. The topographic attributes extracted from DEMs are used to determine the slope and flow directions, which are used to determine sub-catchment outlets and areas contributing discharge to the outlets (Catlow, 1986).

As discussed in Section 2.6.1, relatively high resolution and good quality global scale DEMs have become available recently in public domain. ASTER 30m Global Digital Elevation Model (GDEM), jointly developed by The Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space

Administration (NASA), can be downloaded from NASA's Earth Observing System (EOS) data archive (http://asterweb.jpl.nasa.gov/gdem-wist.asp). Leyton (2012) found that 30 m DEM proved to adequately balance the level of uncertainty and the quality of input datasets. Therefore publicly available ASTER 30m GDEM is used in this research project as shown in Figure 3.7.

(B) SOIL DATA

The great variety in Australian soils, combined with the natural limitations of many soils, has made it difficult to develop sustainable land management practices. The Atlas of Australian Soils (Northcote et al, 1960-68) was compiled by CSIRO in the 1960's to provide a consistent national description of Australia's soils. Soil classification for the Atlas is based on the Factual Key. The Factual Key (Northcote, 1979) was the most widely used soil classification scheme prior to the Australian Soil Classification (Isbell, 2002). It is a hierarchical scheme with 5 levels, the most detailed of which is the principal profile form (PPF). The Australian Soil Classification (ASC) is now the national standard for soil classification. Figure 3.9 shows a schematic summary of the Australian Soil Orders as per the ASC (Isbell, 1996; Isbell et al, 1997; Isbell, 2002). The hierarchy in the ASC is Order, Suborders, Great groups, Subgroups and Family. More details about Australian soils and their distinctive features can be found on Isabell (2002).

For this project, a digital soil map and soil properties were collected from the Australian Soil Resource Information System (ASRIS) (http://www.asris.csiro.au). ASRIS is a product of the Australian Collaborative Land Evaluation Program (ACLEP) developed by CSIRO and Department of Agriculture, Fisheries and Forestry (DAFF) in collaboration with state and territory agencies. Figure 3.10 shows the soil map prepared for the MYWQM. The soil names as shown in Figure 3.10 are as per the ASC system (Isbell, 2002) with dominant PPF in brackets as per the Factual Key system (Northcote, 1979). The associated soil properties required for the MYWQM are shown in Table 3.3. The dominant soil types in the catchment were Sodosol (about 54%) and Dermosol (about 35%). As shown in Table 3.3, the major soil hydrologic group in the MYC was "B" (soils having moderate infiltration rate when thoroughly wetted, having moderate runoff potential). The other soil hydrologic group in the catchment was "C" (soils having low infiltration rate when thoroughly wetted, having high runoff potential). The USLE equation soil erodibility (K) factor values in Table 3.3 were determined following the proposed equation of William (1995) as described by Nietsch et al (2004). The soil albedo values were taken from various scientific research literatures (Kalma and Badham, 1972; Piggin and Schwerdtfeger, 1973)

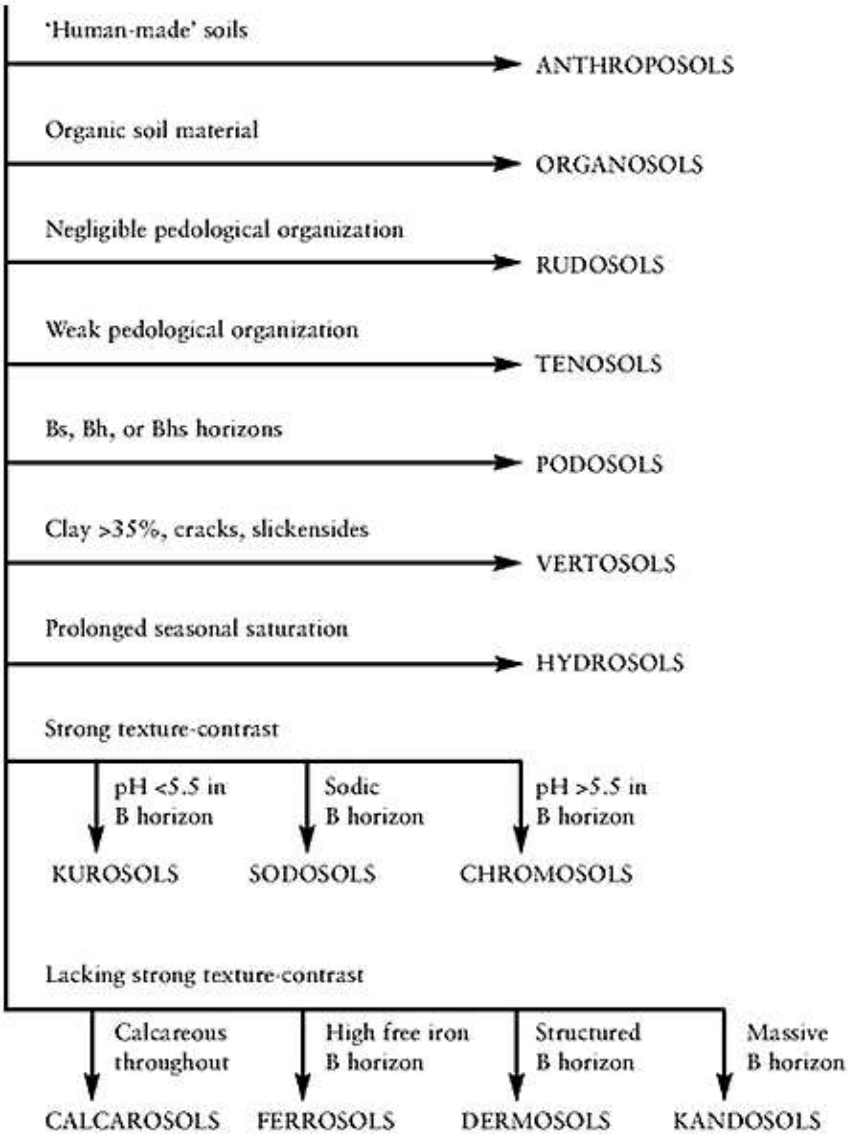


Figure 3.9 Schematic summary of the Australian Soil Orders (Isbell, 2002)

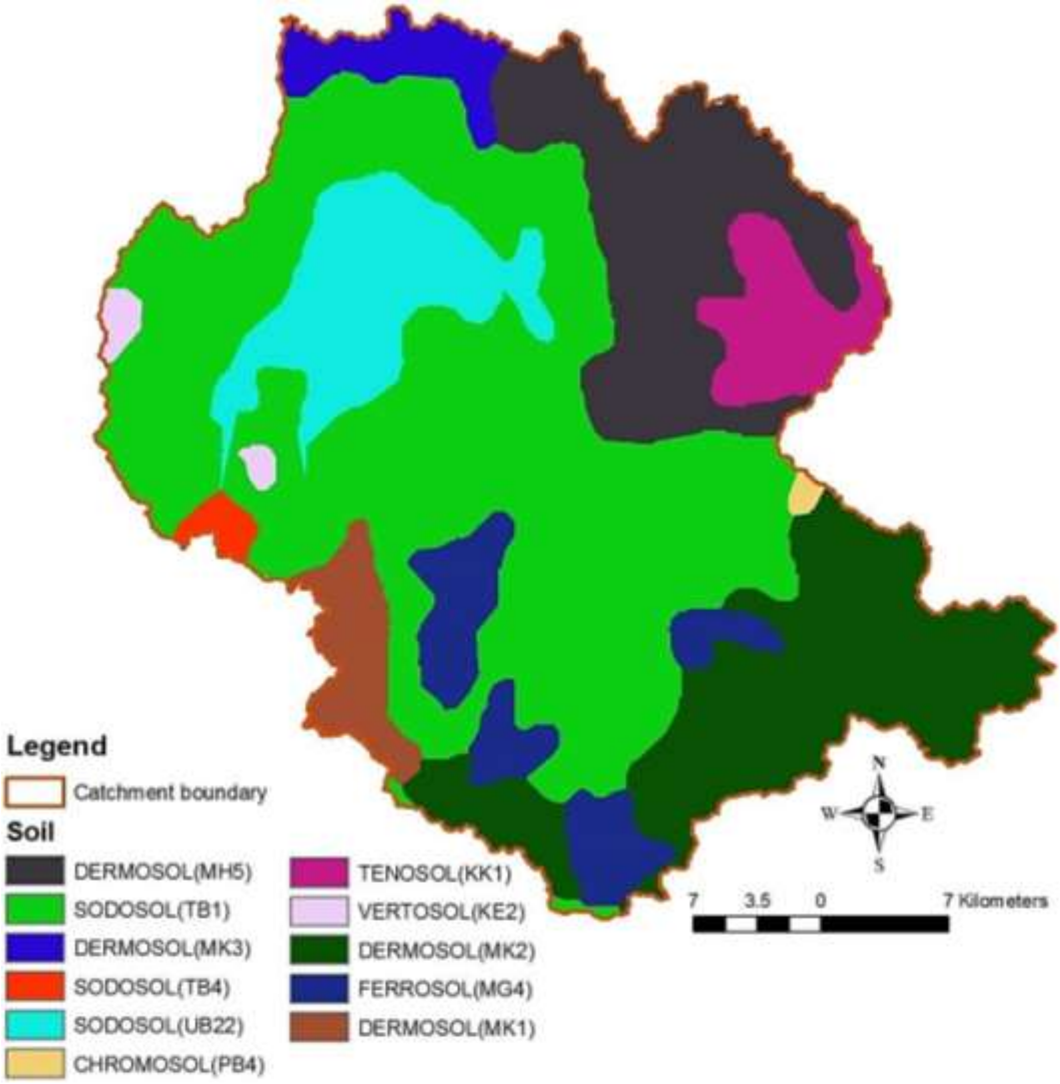


Figure 3.10 Soil map of the MYC

Table 3.3 Soil types and their properties used in MYWQM

SOL_NAME	LAYER	SOL_Z (mm)	TEXTURE	SOL_BD (g/cm^3)	SOL_AWC (mm/mm)	SOL_CBN (%wt.)	SOL_K (mm/hr)	CLAY (%wt.)	SILT (%wt.)	SAND (%wt.)	SOL_ALB (fraction)	USLE_K	HYDGRP	Catchment area (%)
CHROMOSOL (PB4)	1	318	S-L	1.50	40.00	4.45	98.75	16.00	15.00	69.00	0.12	0.12	C	0.22
	2	625		1.61	55.00	0.39	22.00	55.00	15.00	29.00	0.15	0.13		
DERMOSOL (MH5)	1	218	SICL-L	1.01	43.00	4.30	250.00	30.00	28.00	43.00	0.12	0.12	B	13.36
	2	975		1.25	150.00	0.96	91.25	40.00	23.00	36.00	0.15	0.14		
DERMOSOL (MK1)	1	175	SICL-L	1.00	34.00	4.82	300.00	39.00	33.00	29.00	0.16	0.12	B	3.07
	2	1000		1.25	140.00	1.33	100.00	42.00	13.00	44.00	0.19	0.11		
DERMOSOL (MK2)	1	187	SICL-L	0.95	40.00	4.80	300.00	39.00	33.00	29.00	0.19	0.12	B	16.19
	2	1024		1.20	155.00	1.27	100.00	42.00	13.00	44.00	0.22	0.11		
DERMOSOL (MK3)	1	250	SICL-L	1.23	38.00	4.44	150.00	34.00	32.00	35.00	0.12	0.12	B	2.68
	2	1100		1.45	120.00	1.06	42.50	47.00	14.00	38.00	0.15	0.12		
FERROSOL (MG4)	1	150	SICL-L	0.90	33.00	5.61	300.00	39.00	33.00	29.00	0.16	0.12	B	6.02
	2	1000		1.20	149.00	1.65	100.00	42.00	13.00	44.00	0.19	0.10		
SODOSOL (TB1)	1	225	L-L	1.46	32.00	3.74	182.50	18.00	13.00	69.00	0.16	0.11	B	44.45
	2	425		1.59	34.00	0.50	55.75	38.00	14.00	48.00	0.19	0.13		
SODOSOL (TB4)	1	366	S-L	1.48	52.00	3.76	119.17	15.00	12.00	74.00	0.16	0.11	B	0.64
	2	541		1.71	38.00	0.45	15.03	45.00	14.00	40.00	0.19	0.13		
SODOSOL (UB22)	1	300	L-L	1.53	41.00	3.02	23.33	18.00	13.00	69.00	0.16	0.11	C	8.45
	2	533		1.70	23.00	0.48	2.10	55.00	15.00	29.00	0.19	0.12		
TENOSOL (KK1)	1	218	SICL-SL	1.28	59.00	6.06	91.25	29.00	27.00	44.00	0.12	0.12	B	4.22
	2	899		0.98	142.00	1.63	133.33	31.00	30.00	39.00	0.15	0.13		
VERTOSOL (KE2)	1	183	SICL-L	1.10	31.00	4.27	100.43	54.00	22.00	24.00	0.16	0.10	C	0.70
	2	1066		1.27	139.00	1.10	33.40	55.00	15.00	29.00	0.19	0.11		

SOL_NAME: Soil name; SOL_Z: Depth from soil surface to bottom of the layer; SOL_BD: Moist bulk density; SOL_AWC: Available water capacity; SOL_CBN: Organic carbon content; SOL_K: Saturated hydraulic conductivity; SOL_ALB: Moist soil albedo; USLE_K: USLE equation soil erodibility factor; HYDGRP: Soil hydrologic group

(C) LAND USE DATA

The establishment of western civilization in Australia has left a seemingly indelible 'footprint' on the national landscape, flora and fauna. Of all the land uses in the state of Victoria, dryland agriculture and horticulture comprise approximately around 53%, whereas irrigated agriculture and horticulture is less than 4% (DPI, 2011). An understanding of the use of land and management practices within a land use category provides valuable information about the reasons for change in the condition of natural resources. In general, forest, agriculture, grassland and urban are the predominant land use types which are significantly related to pollutant loadings.

Land use mapping in Australia is conducted broadly at two scales: national scale (1:2,500,000) and catchment scale (1:25,000 to 1:1,000,000). Both land use mapping methods use the Australian Land Use and Management (ALUM) Classification system (ABARES, 2012). The ALUM Classification system provides a nationally consistent method to collect and present land use information for a wide range of users across Australia. However, the current land use data is static, that is, it is a snapshot of land use at a moment in time. The ALUM classification has six primary classes of land use (each further divided into two extra tiers) that are distinguished in order of generally increasing levels of intervention or potential impact on the natural landscape. The detail classification is shown in Figures 3.11a (1st three primary classes) and 3.11b (other three primary classes).

The land use map for the MYC was prepared from a 50m grid raster data (catchment scale) collected on 17th August 2010 from the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES, 2012). Figure 3.12 shows details of land use types in the MYC. The map covers data for the period of 1997 to May 2006. The percentages of major six land use categories in Port Phillip and Westernport region, and in the MYC are shown in Figure 3.13. In both regions, “Production from Dryland Agriculture and Plantations” is the dominant land use category, where the main land use type is pasture. Since SWAT has pre-defined land use types through which it creates link with the land use map, the land use classes generated for the MYC were re-classified and made compatible with the requirements of the SWAT model (Figure 3.12). The upstream of the MYC is mainly mountainous forest, and the most downstream part is developed rural and urban area. The mid portion is predominantly agricultural, dominated by pasture and covering around 32% of the total catchment area.

1 Conservation and Natural Environments

1.1.0	Nature conservation
1.1.1	Strict nature reserves
1.1.2	Wilderness area
1.1.3	National park
1.1.4	Natural feature protection
1.1.5	Habitat/species management area
1.1.6	Protected landscape
1.1.7	Other conserved area

1.2.0	Managed resource protection
1.2.1	Biodiversity
1.2.2	Surface water supply
1.2.3	Groundwater
1.2.4	Landscape
1.2.5	Traditional indigenous uses

1.3.0	Other minimal use
1.3.1	Defence
1.3.2	Stock route
1.3.3	Residual native cover
1.3.4	Rehabilitation

2 Production from Relatively Natural Environments

2.1.0	Grazing natural vegetation

2.2.0	Production forestry
2.2.1	Wood production
2.2.2	Other forest production

3 Production from Dryland Agriculture and Plantations

3.1.0	Plantation forestry
3.1.1	Hardwood production
3.1.2	Softwood production
3.1.3	Other forest production
3.1.4	Environmental

3.2.0	Grazing modified pastures
3.2.1	Native/exotic pasture mosaic
3.2.2	Woody fodder plants
3.2.3	Pasture legumes
3.2.4	Pasture legume/grass mixtures
3.2.5	Sown grasses

3.3.0	Cropping
3.3.1	Cereals
3.3.2	Beverage & spice crops
3.3.3	Hay & silage
3.3.4	Oil seeds
3.3.5	Sugar
3.3.6	Cotton
3.3.7	Tobacco
3.3.8	Legumes

3.4.0	Perennial horticulture
3.4.1	Tree fruits
3.4.2	Oleaginous fruits
3.4.3	Tree nuts
3.4.4	Vine fruits
3.4.5	Shrub nuts fruits & berries
3.4.6	Flowers & bulbs
3.4.7	Vegetables & herbs

3.5.0	Seasonal horticulture
3.5.1	Fruits
3.5.2	Nuts
3.5.3	Flowers & bulbs
3.5.4	Vegetables & herbs

3.6.0	Land in transition
3.6.1	Degraded land
3.6.2	Abandoned land
3.6.3	Land under rehabilitation
3.6.4	No defined use

The ALUM Classification is based on a scheme developed by Baxter and Russell (1994). It has been refined collaboratively by partners in the Western Australia Department of Agriculture; New South Wales Department of Natural Resources; Northern Territory Department of Lands, Planning and Environment; South Australia Department of Water, Land and Biodiversity Conservation; Queensland Department of Natural Resources and Mines; Tasmanian Department of Primary Industries, Water and Environment; the Victorian Department of Primary Industries; the National Land and Water Resources Audit; the Murray-Darling Basin Commission; the Australian Government Bureau of Rural Sciences and Department of Agriculture, Fisheries and Forestry.

Figure 3.11a Australia Land use and Management Classification Version 6 (ABARES, 2012)

4	Production from Irrigated Agriculture and Plantations
4.1.0	**Irrigated plantation forestry**
4.1.1	Irrigated hardwood production
4.1.2	Irrigated softwood production
4.1.3	Irrigated other forest production
4.1.4	Irrigated environmental
4.2.0	**Irrigated modified pastures**
4.2.1	Irrigated woody fodder plants
4.2.2	Irrigated pasture legumes
4.2.3	Irrigated legume/grass mixtures
4.2.4	Irrigated sown grasses
4.3.0	**Irrigated cropping**
4.3.1	Irrigated cereals
4.3.2	Irrigated beverage & spice crops
4.3.3	Irrigated hay & silage
4.3.4	Irrigated oil seeds
4.3.5	Irrigated sugar
4.3.6	Irrigated cotton
4.3.7	Irrigated tobacco
4.3.8	Irrigated legumes
4.4.0	**Irrigated perennial horticulture**
4.4.1	Irrigated tree fruits
4.4.2	Irrigated oleaginous fruits
4.4.3	Irrigated tree nuts
4.4.4	Irrigated vine fruits
4.4.5	Irrigated shrub nuts fruits & berries
4.4.6	Irrigated flowers & bulbs
4.4.7	Irrigated vegetables & herbs
4.5.0	**Irrigated seasonal horticulture**
4.5.1	Irrigated fruits
4.5.2	Irrigated nuts
4.5.3	Irrigated flowers & bulbs
4.5.4	Irrigated vegetables & herbs
4.6.0	**Irrigated land in transition**
4.6.1	Degraded irrigated land
4.6.2	Abandoned irrigated land
4.6.3	Irrigated land under rehabilitation
4.6.4	No defined use (irrigation)

5	Intensive Uses
5.1.0	**Intensive horticulture**
5.1.1	Shadehouses
5.1.2	Glasshouses
5.1.3	Glasshouses (hydroponic)
5.2.0	**Intensive animal production**
5.2.1	Dairy
5.2.2	Cattle
5.2.3	Sheep
5.2.4	Poultry
5.2.5	Pigs
5.2.6	Aquaculture
5.3.0	**Manufacturing and industrial**
5.4.0	**Residential**
5.4.1	Urban residential
5.4.2	Rural residential
5.4.3	Rural living
5.5.0	**Services**
5.5.1	Commercial services
5.5.2	Public services
5.5.3	Recreation and culture
5.5.4	Defence facilities
5.5.5	Research facilities
5.6.0	**Utilities**
5.6.1	Electricity generation/transmission
5.6.2	Gas treatment, storage and transmission
5.7.0	**Transport and communication**
5.7.1	Airports/aerodromes
5.7.2	Roads
5.7.3	Railways
5.7.4	Ports and water transport
5.7.5	Navigation and communication
5.8.0	**Mining**
5.8.1	Mines
5.8.2	Quarries
5.8.3	Tailings
5.9.0	**Waste treatment and disposal**
5.9.1	Stormwater
5.9.2	Landfill
5.9.3	Solid garbage
5.9.4	Incinerators
5.9.5	Sewage

6	Water
6.1.0	**Lake**
6.1.1	Lake - conservation
6.1.2	Lake - production
6.1.3	Lake - intensive use
6.2.0	**Reservoir/dam**
6.2.1	Reservoir
6.2.2	Water storage - intensive use/farm dams
6.2.3	Evaporation basin
6.2.4	Effluent pond
6.3.0	**River**
6.3.1	River - conservation
6.3.2	River - production
6.3.3	River - intensive use
6.4.0	**Channel/aqueduct**
6.4.1	Supply channel/aqueduct
6.4.2	Drainage channel/aqueduct
6.5.0	**Marsh/wetland**
6.5.1	Marsh/wetland - conservation
6.5.2	Marsh/wetland - production
6.5.3	Marsh/wetland - intensive use
6.6.0	**Estuary/coastal waters**
6.6.1	Estuary/coastal waters - conservation
6.6.2	Estuary/coastal waters - production
6.6.3	Estuary/coastal waters - intensive use

Figure 3.11b Australia Land use and Management Classification Version 6 (ABARES, 2012)

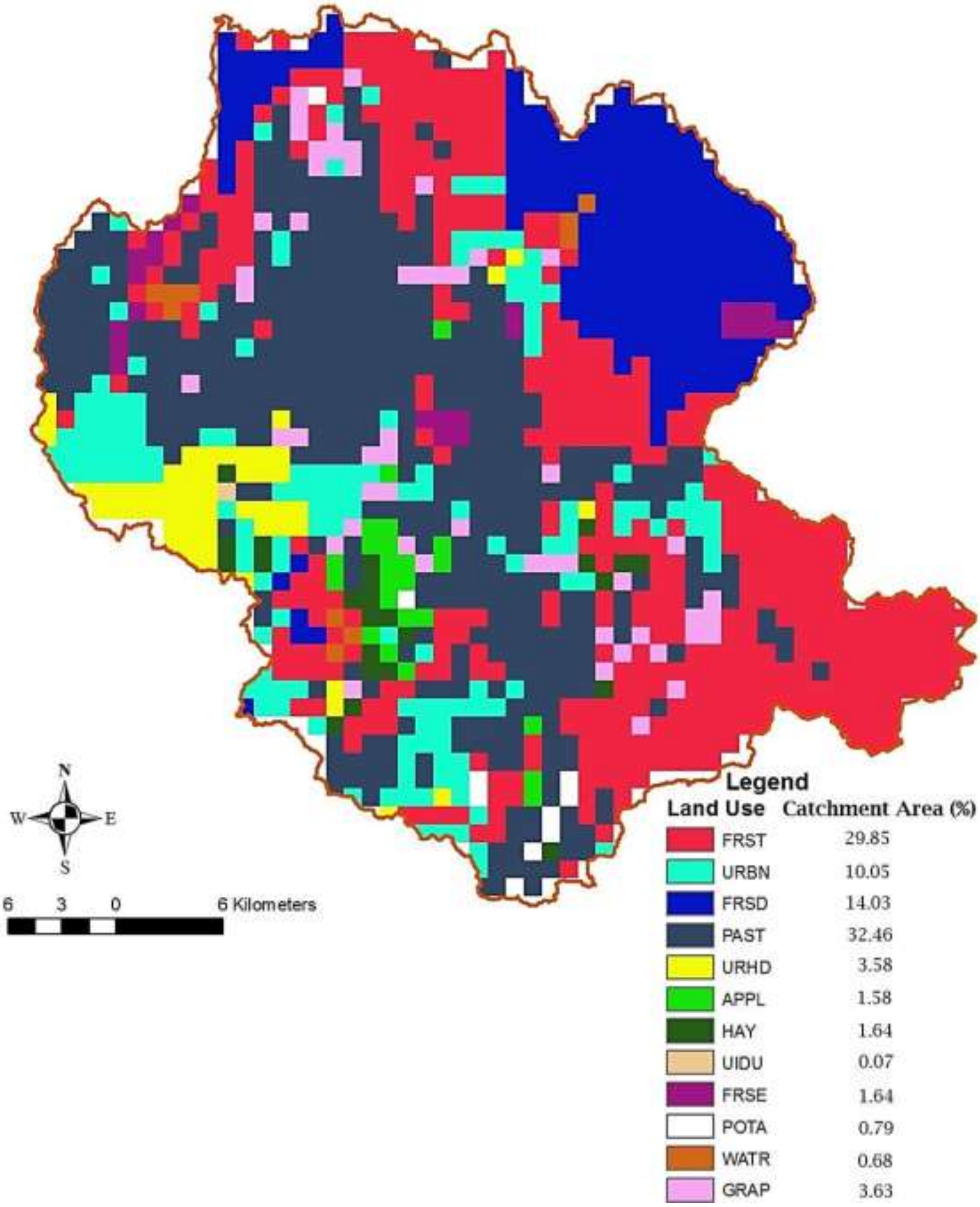


Figure 3.12 Land use map of the MYC

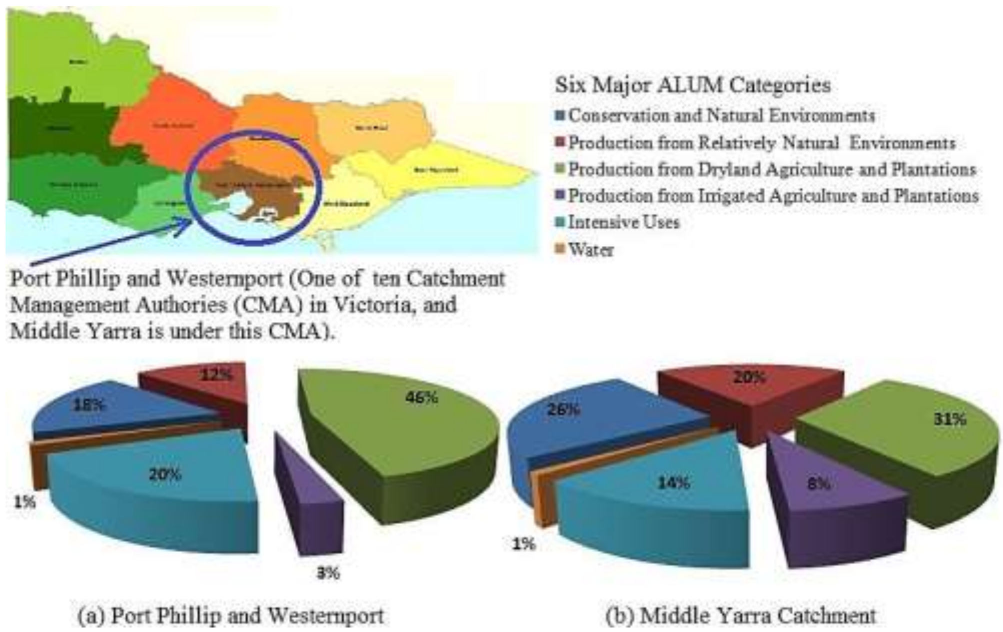


Figure 3.13 Percentages of six major land uses in (a) Port Phillip and Westernport region (b) the Middle Yarra Catchment

(D) CLIMATE DATA

SWAT requires climatic data at the daily time step. The required climatic variables include precipitation, minimum and maximum temperature, wind speed, solar radiation and relative humidity. For this project, all measured climate data were collected from the SILO climate database (Jeffrey et al, 2001) and the Bureau of Meteorology, as listed in Table 3.2.

Figure 3.14 shows all climate data stations along with streamflow and water quality monitoring stations. Precipitation data was used from sixteen rainfall stations located within and around the catchment as shown in Table 3.4 for the period of 1980–2008. The selected stations are distributed all over the catchment to effectively capture the spatial variability of precipitation. Temperature, wind speed, solar radiation and relative humidity data were used from four weather stations located within and around the catchment as shown in Table 3.5 for the period of 1980–2008.

The modelling feature “Inland” in the SWAT model indicates the upstream part of the Yarra River catchment above the study area as shown in Figure 3.14. Similarly the modelling feature “upstream inlet point” indicates the point through which the streamflow and water quality contaminant loads are added as point source loads from the upstream part of the Yarra River catchment (the “Inland” feature) to the study area MYC as shown in Figure 3.14. More details about these features are discussed in Section 3.3.2.2.(B).

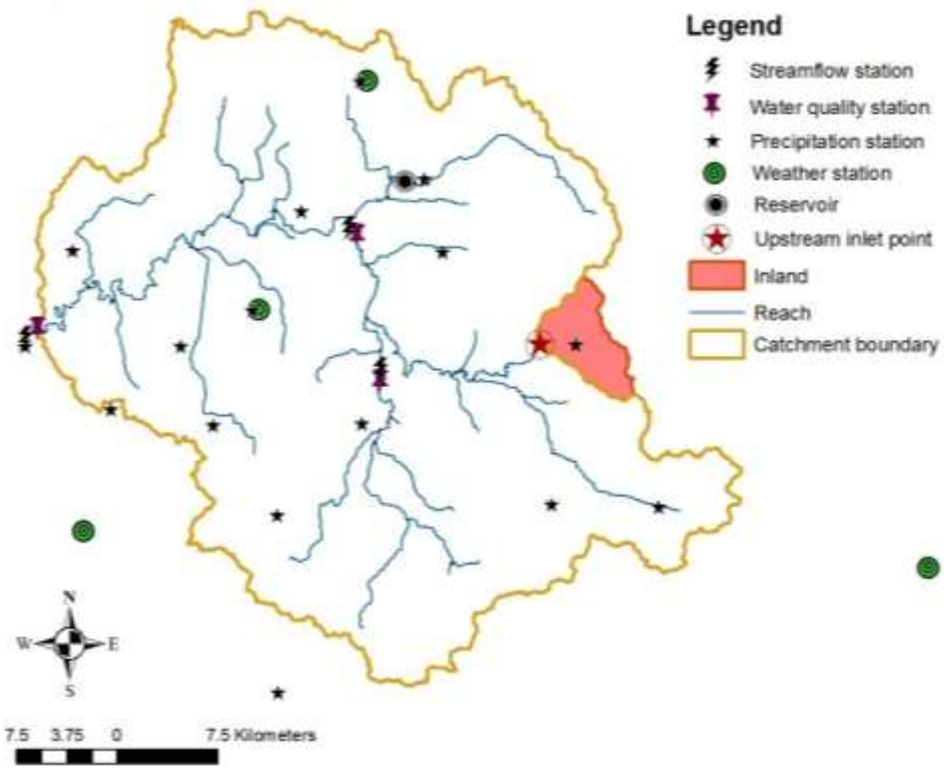


Figure 3.14 Climate, streamflow and water quality monitoring stations in the MYC

Table 3.4 Rainfall stations in the MYC

Station No.	Station Name	Latitude (°S)	Longitude (°E)	Elevation (m)
86027	Croydon (Samuel Street)	-37.790	145.281	117
86059	Kangaroo Ground	-37.683	145.252	196
86066	Lilydale	-37.749	145.342	113
86070	Maroondah Weir	-37.639	145.550	149
86076	Montrose	-37.802	145.368	170
86094	Powelltown Dnre	-37.862	145.744	189
86121	Warburton	-37.752	145.676	170
86142	Mount St Leonard DPI	-37.572	145.501	620
86219	Coranderrk Badger Weir	-37.689	145.564	360
86261	Beaconsfield Upper	-37.982	145.419	221
86313	Warrandyte	-37.747	145.210	126
86358	Gladysdale (Little Feet Farm)	-37.859	145.653	193
86359	Monbulk (Bulb Farm)	-37.863	145.421	298
86364	Tarrawarra Monastery	-37.659	145.446	100
86367	Seville	-37.803	145.494	171
86383	Coldstream	-37.724	145.409	199

Table 3.5 Weather (Temperature, Solar radiation, Wind speed and Relative humidity) stations in the MYC

Station No.	Station Name	Latitude (^oS)	Longitude (^oE)	Elevation (m)
85277	Noojee (Slivar)	-37.904	145.972	275
86104	Scoresby Research Institute	-37.871	145.256	80
86142	Mount St Leonard Dpi	-37.572	145.501	620
86383	Coldstream	-37.724	145.409	199

In Table 3.6, monthly average and standard deviation of all climate data are shown. Figure 3.15 shows the average monthly precipitation and temperature (max and min) in the MYC. The average monthly maximum precipitation occurs in September, and minimum precipitation occurs in February. In general, the summer (December to February) is very dry compared to the winter (June to August) and spring (September to November). The average monthly maximum temperature varies from 11.4^{0}C (July) to 25.3^{0}C (February), and minimum temperature varies from 4.4^{0}C (July) to 12.3^{0}C (February). Figure 3.16 shows the annual rainfall, and maximum and minimum temperatures in the MYC, and shows that there is an abrupt drop in annual rainfall (from 1140mm to 922mm) from 1997 onwards. This abrupt change is similar to what has been seen in Figure 3.3 for the whole Yarra River catchment.

Table 3.6 Monthly average and standard deviation of all climate data for the period of 1980 to 2008 in the MYC

Month	Precipitation (STDEV) (mm)	Temp. Max. (STDEV) (°C)	Temp. Min. (STDEV) (°C)	Wind Velocity (STDEV) (m/s)	Solar Radiation (STDEV) (MJ/m^2)	Rela. Hum. (STDEV) (%)
January	68.0 (14.2)	24.8 (1.8)	12.2 (1.2)	3.0 (0.3)	22.8 (0.3)	68.2 (2.1)
February	51.8 (7.8)	25.3 (1.8)	12.3 (1.3)	2.7 (0.4)	20.9 (0.4)	67.9 (2.1)
March	62.2 (13.2)	22.7 (2.0)	11.0 (1.2)	2.6 (0.4)	16.7 (0.3)	71.0 (2.0)
April	81.2 (14.6)	18.7 (2.1)	8.8 (1.0)	2.4 (0.4)	12.3 (0.2)	74.0 (1.4)
May	86.4 (16.3)	15.0 (2.1)	7.2 (1.1)	2.2 (0.6)	8.5 (0.1)	78.2 (1.0)
June	104.2 (24.7)	12.1 (2.2)	5.2 (1.2)	2.6 (0.7)	7.0 (0.2)	79.6 (1.5)
July	98.4 (28.1)	11.4 (2.3)	4.4 (1.2)	2.8 (0.7)	7.7 (0.3)	79.3 (1.7)
August	105.7 (28.6)	12.8 (2.3)	5.0 (1.3)	3.0 (0.6)	10.4 (0.3)	76.3 (1.5)
September	109.2 (27.3)	15.0 (2.2)	6.3 (1.2)	3.2 (0.5)	14.1 (0.2)	74.5 (1.5)
October	99.7 (21.3)	17.7 (2.0)	7.5 (1.1)	3.2 (0.4)	18.3 (0.2)	72.4 (1.5)
November	93.1 (16.7)	20.4 (1.9)	9.2 (1.2)	3.0 (0.3)	21.1 (0.3)	70.9 (2.0)
December	90.2 (18.1)	22.6 (1.9)	10.6 (1.2)	2.9 (0.3)	22.6 (0.3)	69.8 (1.9)

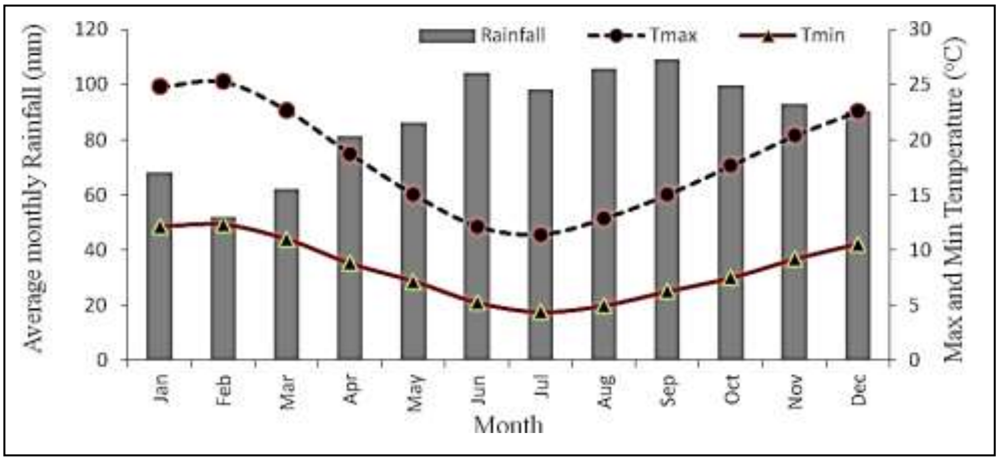


Figure 3.15 Average monthly rainfall and temperature (max and min) in the MYC

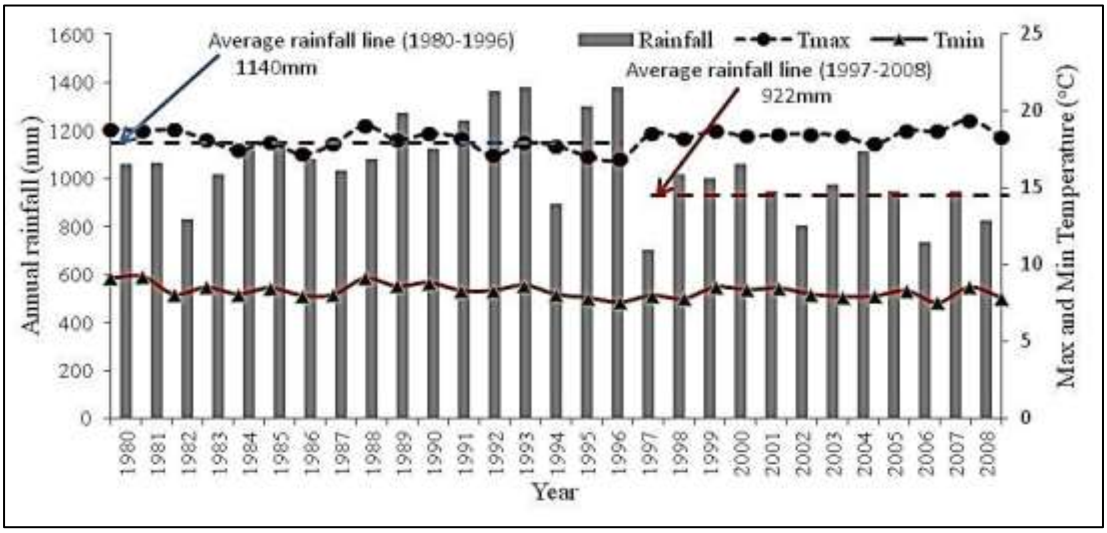


Figure 3.16 Annual rainfall and temperature (max and min) in the MYC

(E) CROP AND LAND MANAGEMENT PRACTICES DATA

For this project, the crop and land management data were collected from the Australian Bureau of Statistics (ABS). These data were spatially very coarse and were not available at the MYC level. As shown in Figure 3.17, the MYC is located in Melbourne Statistical Division (SD), and seven Statistical Local Areas (SLAs) (shown with code numbers in Figure 3.17) cover the MYC. The available data for fertilizer type and application rate are shown in Table 3.7. The most common time for applying fertilisers is at tillage and sowing time (Oliver et al, 2009). The two common sowing times for pasture and other crops are early autumn (March to May) and spring (September to November). Livestock data were available at SLA level for 2007-2008 periods. Based on these livestock, animal manures were applied in the MYC. Manure deposition during grazing was calculated as per the livestock data and literature data (Azevedo and Stout, 1974; He and Croley II, 2006; DA, 2008; DAF, 2016).

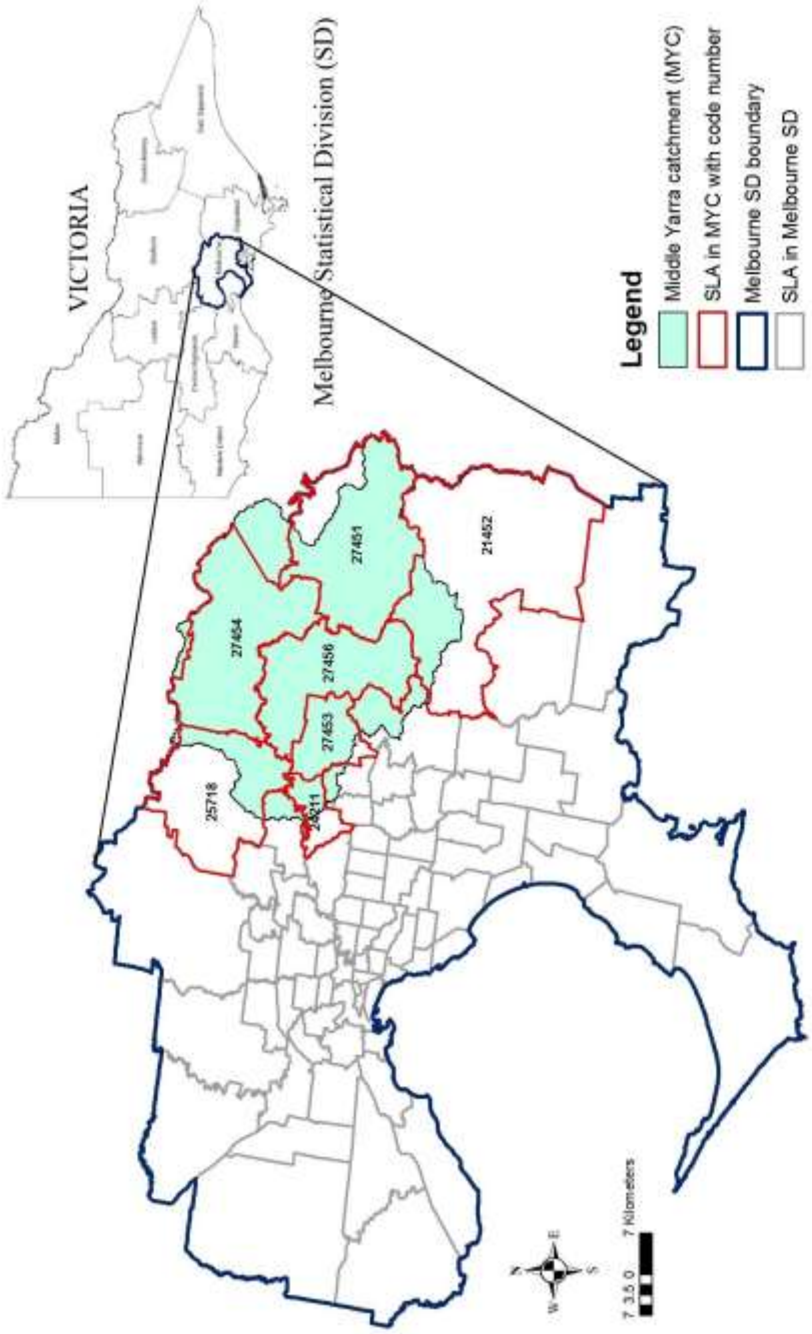


Figure 3.17 Melbourne SD and seven SLAs in which the MYC located in

The tillage practices data were available at Victorian State, and Port Phillip and Westernport (PPW) region level. In the PPW region, tillage practices for crops and pastures were "no cultivation (42% area)", "one or two cultivations (48% area)" and "three or more cultivations (10% area)". Valzano et al (2005) divided the current tillage practices in Australia into three categories, from least to most soil disturbance: (1) No tillage or zero tillage (2) Reduced tillage, and (3) Conventional tillage. Most stubble in PPW- Natural Resources Management region was removed by ploughing into the soil (48%) and by baling or heavy grazing (32%). Specific data about crop rotation were not available. The irrigation water application rate in PPW region was 2.8 ML/ha for the year of 2005-2006, and the main source of irrigation water (about 85%) was surface water.

Table 3.7 Fertilizer type and application rate collected from ABS

<table>
<tr><th colspan="2" rowspan="2">Fertilizer</th><th rowspan="2">Labelling of Fertilizer</th><th colspan="2">2007-2008</th><th colspan="2">2000-2001</th></tr>
<tr><th>VIC (ton/ha)</th><th>Port Phillip and Westernport (ton/ha)</th><th>VIC (ton/ha)</th><th>Melbourne (SD) (ton/ha)</th></tr>
<tr><td rowspan="6">N based</td><td>Urea</td><td>46-0-0</td><td>0.12</td><td>0.26</td><td>0.11</td><td>0.20</td></tr>
<tr><td>Ammonium sulphate</td><td>21-0-0</td><td>0.08</td><td>--</td><td>0.13</td><td>0.36</td></tr>
<tr><td>Urea ammonium nitrate</td><td>32-0-0</td><td>0.09</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Anhydrous ammonia</td><td>82-0-0</td><td>0.06</td><td>0.00</td><td>0.06</td><td>0.20</td></tr>
<tr><td>Potassium nitrate</td><td>13-0-46</td><td>0.16</td><td>0.92</td><td>0.17</td><td>0.34</td></tr>
<tr><td>Ammonium nitrate</td><td>33.5-0-0</td><td>--</td><td>--</td><td>0.23</td><td>0.55</td></tr>
<tr><td rowspan="2">P based</td><td>Single superphosphate</td><td>0-9-0</td><td>0.15</td><td>0.21</td><td>0.19</td><td>0.23</td></tr>
<tr><td>Double or triple superphosphate</td><td>0-21-0</td><td>0.11</td><td>0.23</td><td>0.13</td><td>0.24</td></tr>
<tr><td>Both</td><td>Ammonium phosphates</td><td>10-22-0</td><td>0.08</td><td>0.12</td><td>0.10</td><td>0.13</td></tr>
<tr><td>Manure</td><td>Animal manure</td><td>--</td><td>2.24</td><td>4.89</td><td>--</td><td>--</td></tr>
<tr><td rowspan="2">Others</td><td>Muriate of potash or sulphate of potash</td><td>0-0-50</td><td>0.13</td><td>0.18</td><td>0.14</td><td>0.16</td></tr>
<tr><td>All other manufactured fertilisers</td><td></td><td>0.21</td><td>0.65</td><td>0.19</td><td>0.56</td></tr>
</table>

3.3.2.2. DATA REQUIRED FOR CALIBRATION AND VALIDATION OF THE MYWQM

The major streamflow and water quality monitoring program of the Yarra River catchment is the Melbourne Water Corporation’s monitoring network. The entire Yarra River catchment contains 33 water quality monitoring stations and 70 streamflow gauging stations, and they are of variable quality. From these stations, three sites were selected for multi-site, multi-variable and multi-objective calibration purposes of the MYWQM as shown in Figure 3.18. They are called site-1, site-2 and site-3. At each site, streamflow and water quality monitoring stations (Tables 3.8 and 3.9) were close to each other. These sites were also shown in Figure 3.14. Site-1 is situated in the Woori Yallock Creek, while site-2 and site-3 are situated in the Yarra River. These sites were selected based on the data availability and quality. Moreover, these three sites are spatially distributed over the whole MYC where site-3 is the catchment outlet. Generally, it is uncommon that every water quality monitoring station is installed with a discharge measuring equipment. In such cases, observed streamflow data is taken from nearby streamflow monitoring stations, as was also the case for this project.

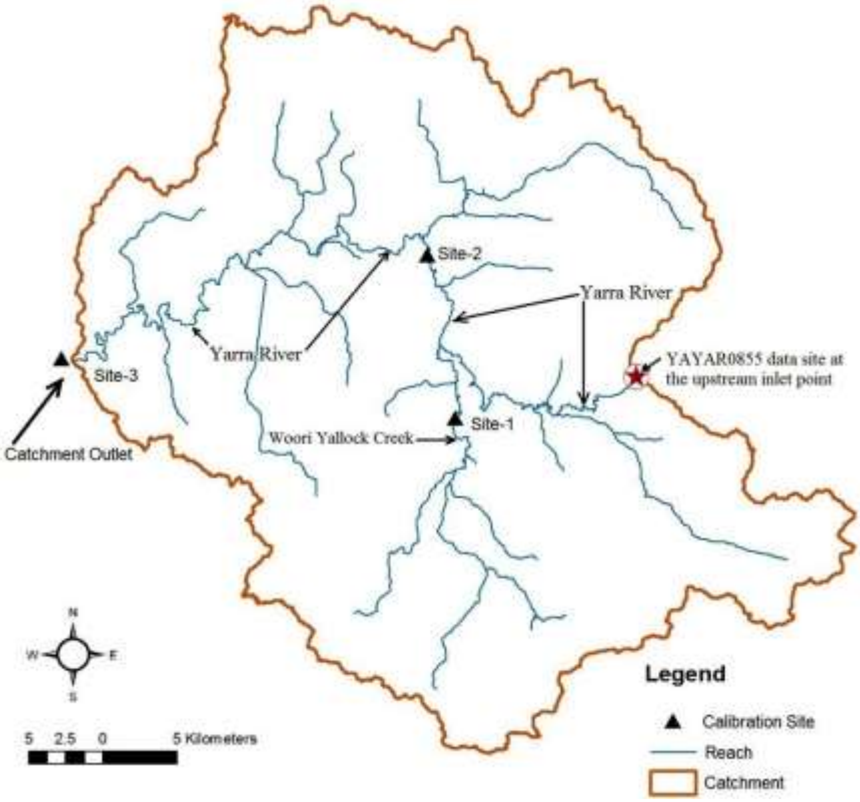


Figure 3.18 Calibration sites in the MYC

Table 3.8 Streamflow monitoring stations in the MYC

Data Site	Station Location (code)	Latitude (°S)	Longitude (°E)
Site-1	Woori Yallock Creek at Woori Yallock (229215B)	-37.765	145.512
Site-2	Yarra River at Yarra Grange (229653)	-37.667	145.476
Site-3	Yarra River at Warrandyte (229200B)	-37.740	145.212

Table 3.9 Water quality monitoring stations in the MYC

Data Site	Station Location (code)	Latitude (°S)	Longitude (°E)
Site-1	at Warburton Highway, Woori Yallock (YAWOO0330)	-37.777	145.508
Site-2	at Maroondah Highway, Healesville (YAYAR1569)	-37.678	145.491
Site-3	at Kangaroo Ground-Warrandyte Road, Warrandyte (YAYAR2356)	-37.738	145.219

(A) STREAMFLOW DATA

Accurate estimation of catchment water balance is a vital prerequisite for water quality modelling (Grayson et al, 1999a). For this reason, hydrologic data, particularly streamflow, is a key data set enabling the catchment-scale modelling of water quality.

The mean daily streamflow data was available for more than thirty years at all sites (Table 3.8), and data quality was good. Therefore for streamflow calibration, a longer calibration period was chosen compared to the water quality constituents so that the model can capture all possible variations in stremflow pattern (wet and dry years). The chosen calibration period for streamflow was 1990 to 2002, and validation period was 2003 to 2008. Water pumped out at Yering Gorge Pumping Station in the Yarra River was included in the streamflow data at Site-3. Figures 3.19 and 3.20 show that there is an abrupt drop in the streamflow pattern in 1997. The calibration period contains both wet and dry years, whereas validation period contains only dry years.

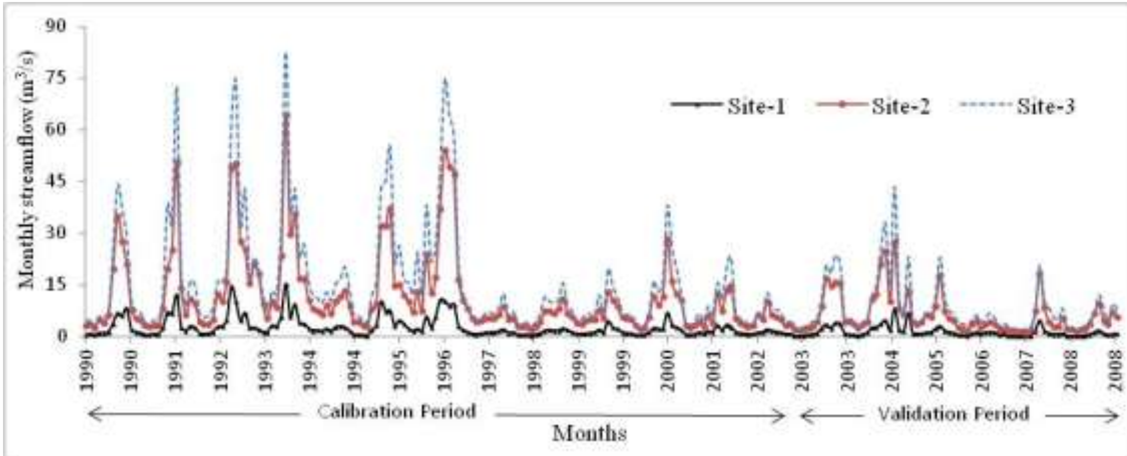


Figure 3.19 Monthly streamflow at the data sites of the MYC

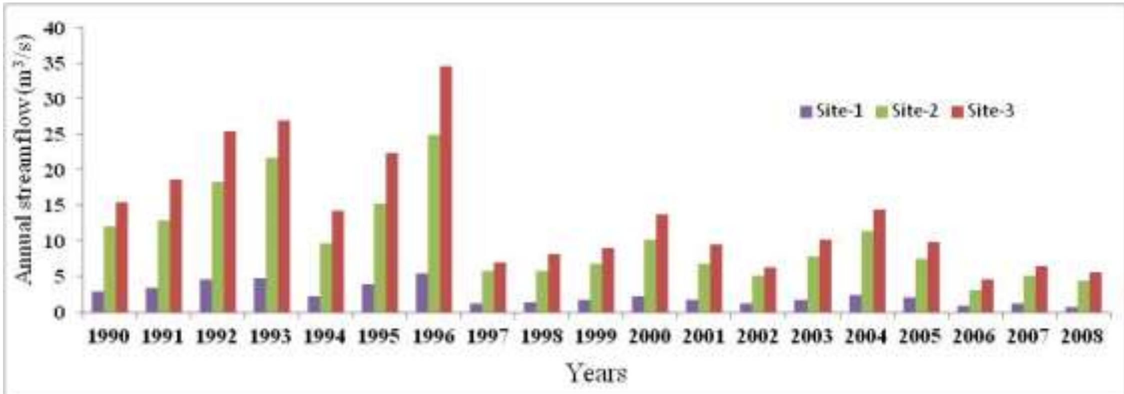


Figure 3.20 Annual streamflow at the data sites of the MYC

Table 3.10 shows that the mean daily streamflow at the three sites is higher in calibration period, but much lower in validation period compared to the total period or record period's mean. At the catchment outlet (site-3), the mean annual streamflow in calibration and validation period were 16.21 m^3/s and 8.46 m^3/s respectively, and for the entire period (1990-2008) it was 13.77 m^3/s.

Table 3.10 Streamflow statistics at the data sites

Data Site	Record period of data available	Mean daily streamflow (m^3/s)									
		Total period (1990-2008)			Calibration period (1990-2002)			Validation period (2003-2008)			Record period
		Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.	Mean
Site-1	1975-2008	0.09	2.37	82.3	0.31	2.79	63.7	0.09	1.47	82.3	2.53
Site-2	1980-2008	0.96	10.20	194.1	1.78	11.89	194.1	0.96	6.53	103.7	10.08
Site-3	1970-2008	1.55	13.77	209.7	2.16	16.21	209.7	1.55	8.46	102.6	13.70

Figure 3.21 shows mean monthly streamflow at the three sites in the MYC. This figure also shows that the streamflow rate in the calibration period was much higher than in the validation period. Peak streamflows occurred during the months of August to October, and low streamflows occurred during the months of January to May. The maximum and minimum streamflow occurred in September and March respectively.

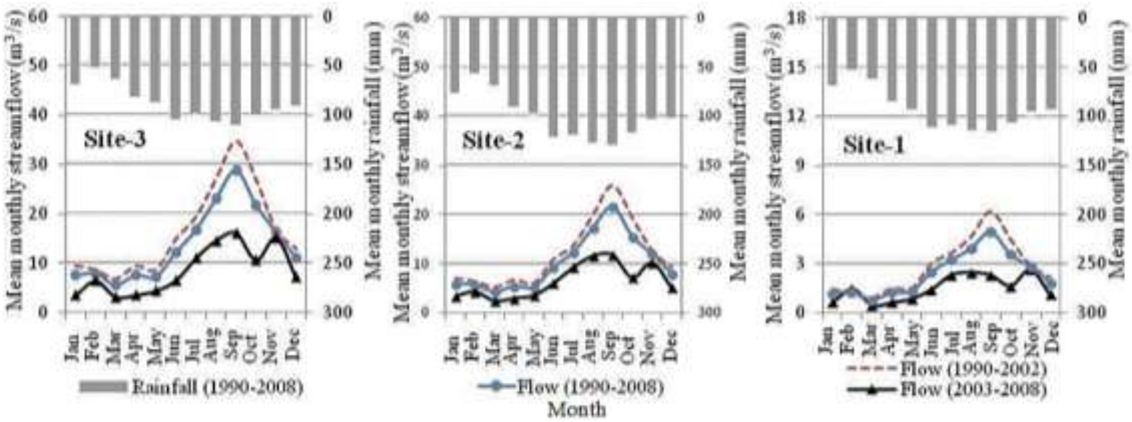


Figure 3.21 Mean monthly streamflow at the data sites of the MYC

Baseflow Separation

As discussed in Section 2.5.2.1, an incorrect representation of the baseflow and surface runoff can cause wrong estimates of the non-point pollution loads in the river, as the erosion and leaching processes depend on this representation. Therefore baseflow and surface runoff were also calibrated along with the streamflow to represent surface and subsurface hydrological processes accurately in the MYC. Different types of techniques are available to separate baseflow from gauged streamflow data. These include traditional manual graphical procedures to more recent automated procedures. Details about baseflow separation techniques were discussed in Section 2.5.2.1.

At the three sites of the MYC, baseflow was separated from mean daily streamflow using automated baseflow separation software “Baseflow Filter Program” (USDA-ARS, 1999). The software “Baseflow Filter Program” is based on the digital filter method for baseflow separation, and widely used by SWAT model users (Arnold et al, 2000; Santhi et al, 2001a; Zhang et al, 2003; Romanowicz et al, 2005; Santhi et al, 2006; Larose et al, 2007; Geza and McCray, 2008; Panagopoulos et al, 2011a). Figures 3.22 and 3.23 show mean daily streamflow and baseflow for the entire 1990-2008 periods and on average year respectively at the three sites.

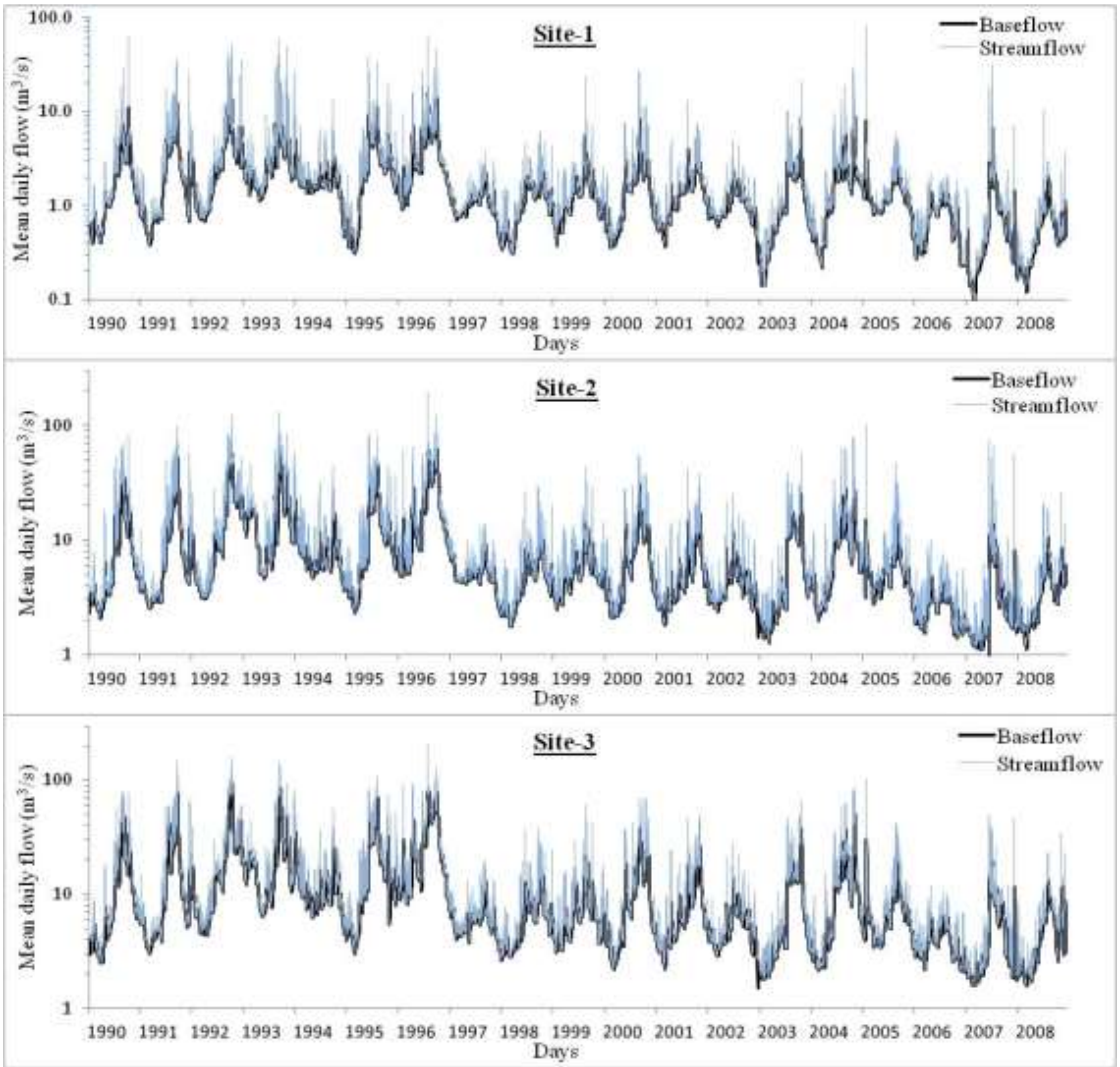


Figure 3.22 Mean daily streamflow and baseflow at the three sites of the MYC

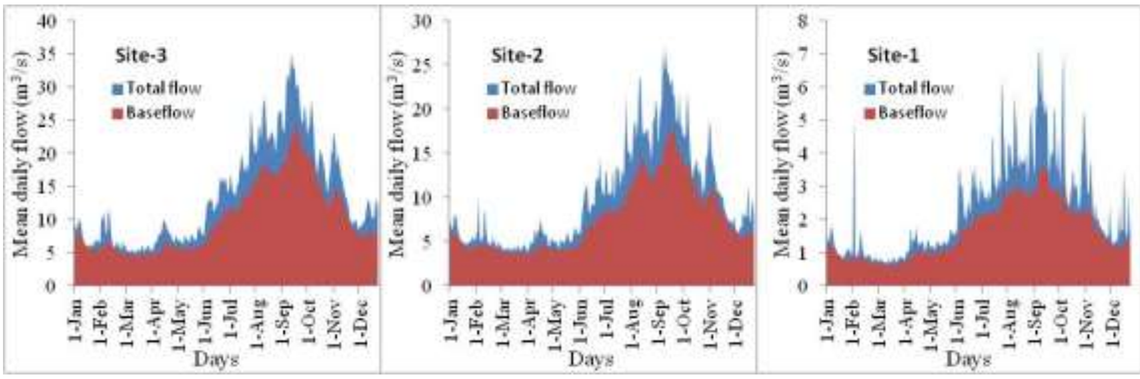


Figure 3.23 Mean daily streamflow and baseflow in a year at the three sites of the MYC

The distribution of baseflow at the three sites is consistent. Baseflow separation for the three sites showed that about 75% of the streamflow was contributed by baseflow. About sixty four percent of the total baseflow occurred in the five months from July to November, where the same period accounts for 65% of the total streamflow. The month of September has the largest baseflow (about 15%), while March has the smallest (about 4%). The high baseflow of the site-3 and site-2, compared to the site-1 is due to the large contributing area that increases baseflow. Relative contribution of baseflow to the streamflow is higher in calibration period than to the validation period at the three sites.

(B) WATER QUALITY DATA

Monthly water quality grab samples data were available from 1994 to 2008 at the three selected data sites (Table 3.9) monitored by Melbourne Water Corporation. The water quality constituents - Sediment (Total Suspended Solid-TSS), Total Nitrogen (TN), and Total Phosphorus (TP) were considered for this project. These water quality constituents were considered for their significant impacts on waterways in the Yarra River catchment and in the Port Phillip Bay (Harris et al, 1996; Yarra Valley Water, 1997; DSE, 2006a; Melbourne Water and EPA Victoria, 2009a).

The MYC for this project is mid part of the Yarra River catchment, and hence it receives streamflow and water quality contaminant loads from the upstream part of the Yarra River catchment. This is addressed with the SWAT modelling feature “Inland” and “upstream inlet point” in the MYWQM as discussed in Section 3.3.2.1(D), and shown in Figure 3.14. The “upstream inlet point” is selected at station YAYAR0855 in the Yarra River at Millgrove (-37.753^{0}S, 145.645^{0}E) where monthly grab samples data were available from 1998 to 2008. Therefore, TN, TP and TSS loads were estimated for 1998-

2008 period at the three data sites and at the upstream inlet point site YAYAR0855 by the method as discussed in the following sections. These constituent loads were then used for calibration and validation of the MYWQM. The calibration period was considered from 1998 to 2004, and the validation period was considered from 2005 to 2008 for the constituents at the three sites. For the constituents, both calibration and validation periods are dry years, where as in case of streamflow, calibration period (1990 to 2002) includes wet and dry years, and validation period (2003 to 2008) includes only dry years (Figure 3.19). How to split data sets for calibration and validation are discussed in Section 4.4.

Constituent Concentrations

Concentration statistics of monthly grab sample constituents are shown in Table 3.11. As can be seen from this table, the mean constituent concentrations in the calibration period are higher than in the validation period. Figure 3.24 shows the water quality grab sample collection time in the hydrograph. The grab samples were not collected targeting storm events as can be seen in the Figure 3.24. Only few samples were on storm events during the calibration period. This is because the data were collected mainly for routine monitoring and compliance checks or ecological research. The most extreme rainfall event or streamflow occurred on 3rd March 2005 in the validation period, and grab sample was collected on that date in case of site-3 only (Figure 3.24). This is why maximum concentrations are reported in the validation period for site-3 opposed to other two sites. These patterns of grab samples collection point on the hydrographs have significant impact on the constituent load especially for the validation periods.

Table 3.11 Constituent concentrations statistics at the data sites

Data Sites	Constituent	Constituent concentrations (mg/l)											
		Total period (1998-2008)				Calibration period (1998-2004)				Validation period (2005-2008)			
		Min.	Mean	Max.	Obs	Min.	Mean	Max.	Obs	Min.	Mean	Max.	Obs
Site-1	TN	0.58	1.19	2.71	129	0.72	1.25	2.71	82	0.58	1.09	1.51	47
	TP	0.01	0.04	0.15		0.01	0.04	0.15		0.01	0.03	0.08	
	TSS	1	12	75		2	14	75		1	8	32	
Site-2	TN	0.33	0.79	2.29	131	0.37	0.83	2.29	83	0.33	0.72	1.32	48
	TP	0.01	0.03	0.12		0.01	0.03	0.12		0.01	0.03	0.07	
	TSS	1	11	54		4	13	54		1	8	48	
Site-3	TN	0.42	1.13	2.93	133	0.42	1.17	2.52	85	0.53	1.07	2.93	48
	TP	0.01	0.06	0.35		0.03	0.06	0.16		0.01	0.05	0.35	
	TSS	1	15	310		1	16	120		1	14	310	

Obs = observations (number of available grab samples)

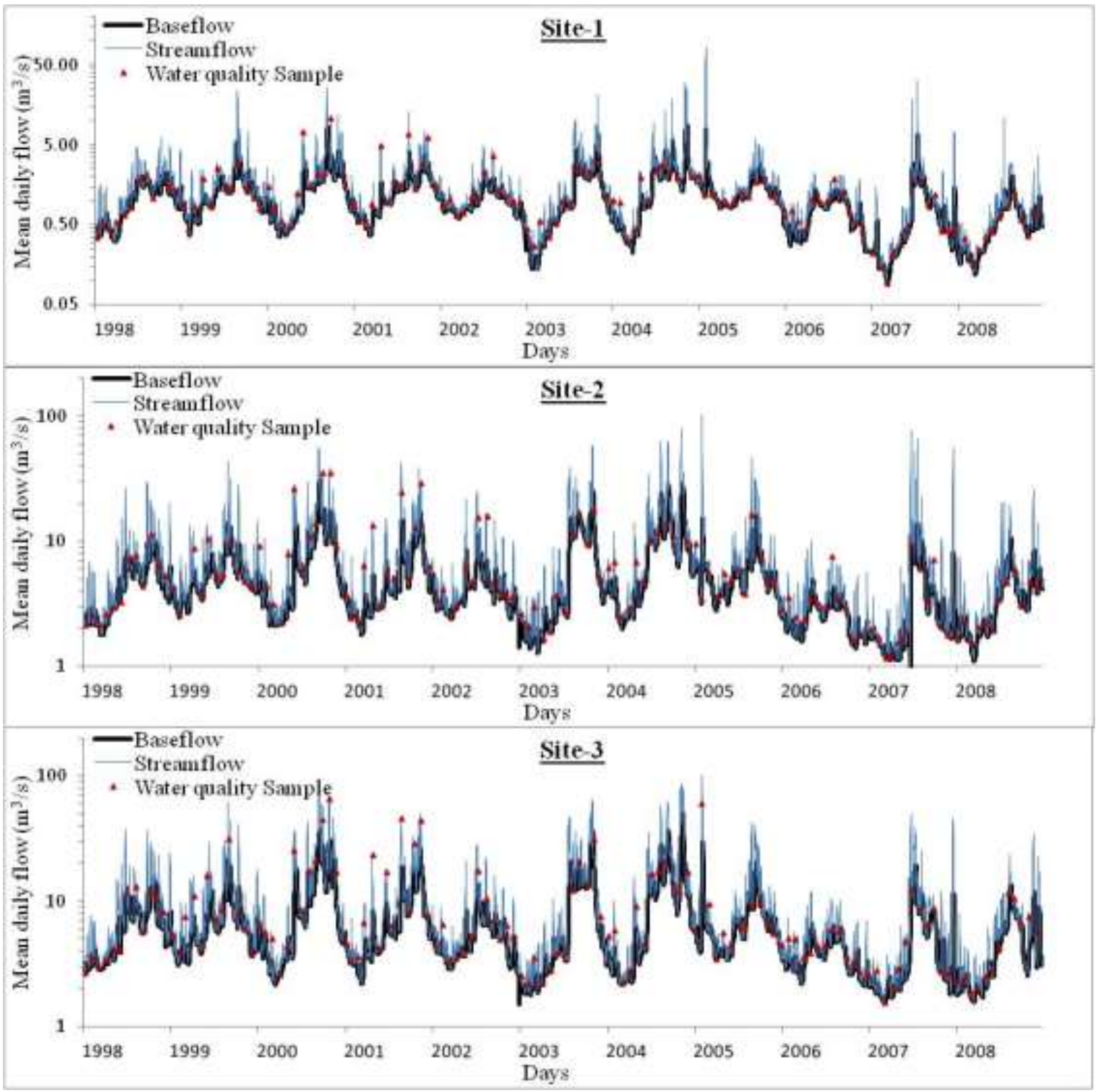


Figure 3.24 Water quality grab samples collection time on the hydrograph in the MYC

The correlations between concentrations of TN, TP, TSS and streamflow were determined for the three sites in the MYC as shown in Figure 3.25. At the three sites, the correlations of TN, TP and TSS were 0.71 to 0.78, 0.58 to 0.76, and 0.65 to 0.76 respectively which were statistically significant ($p<0.01$). Since the correlations were found strong (Dummies, 2017; Statisticsolutions, 2017), the regression method was chosen to estimate constituent loads from the grab sample data. Continuous constituent loads are required for water quality model calibration. The detailed data-based load estimation techniques from grab sample data were discussed in Section 2.5.2.2.

The regression method based modelling tool LOADEST (Runkel et al, 2004) was then used to estimate constituent loads. LOADEST estimates constituent loads in streams and rivers using a regression model, given a time series of streamflow, constituent concentration, and additional data inputs. LOADEST also considers regression equation as a function of time variable in addition to the usual streamflow variable in order to take into account nonlinearities as well as seasonal and long-term variability. The LOADEST model is well documented, and is accepted as a valid means of calculating constituent load from a limited number of water quality grab samples (Jha et al, 2007). The LOADEST model has been widely used, particularly by the SWAT model users and the U.S. Geological Survey (White et al, 2004; White and Chaubey, 2005; Deacon et al, 2006; Jha et al, 2006; Tortorelli and Pickup, 2006; Jha et al, 2007; Migliaccio et al, 2007; Domagalski et al, 2008; Maret et al, 2008; Debele et al, 2009; Jha et al, 2010; Mukundan et al, 2010; Maringanti et al, 2011; Cerro et al, 2012; Kannan, 2012; Omani et al, 2012). The details about LOADEST was described in Section 2.5.2.2.

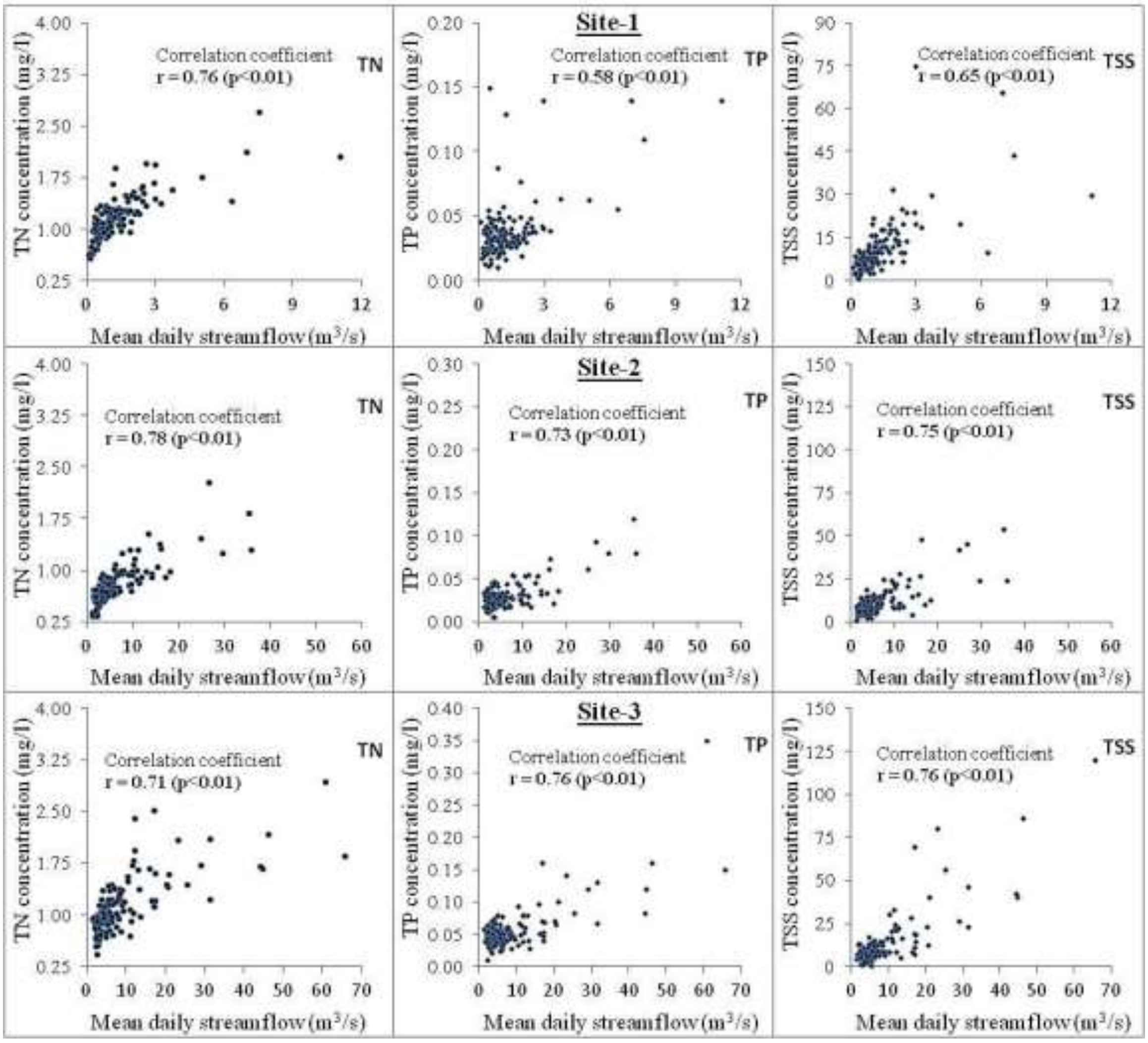


Figure 3.25 TN, TP and TSS correlations with Streamflow at the three sites of the MYC

Constituent Load Estimation

As discussed in Section 2.5.2.2, the LOADEST estimates constituent loads by developing regression models through the relationships between pollutant loads (dependent variables), and streamflow and time variables (explanatory variables). To fit the relationship between the dependent variable and explanatory variables, LOADEST first calculates constituent loads for grab sample collection days. This is calculated as per the Equation 2.1, since for those grab sample collection days, constituent concentration and daily streamflow data are available. This way LOADEST gets constituent load and streamflow data pairs for each grab sample collection date (generally once in a month and twelve in a year for the MYC). Using all these data pairs (during the whole 1998-2008 period), LOADEST develops and select the best regression model for each water quality constituent based on the Akaike Information Criterion (AIC) value. Since daily streamflow data is continuously available at each data site, LOADEST then can generate continuous daily load for each water quality constituent (TN, TP and TSS) using the best regression equation (for example Equation 2.2).

The TN, TP and TSS loads for the study area were estimated at the three data sites and at the upstream inlet point water quality station YAYAR0855 by the LOADEST model following the same procedure as discussed above. The constituent loads estimated at YAYAR0855 were added like point source loads through the upstream inlet point while developing the MYWQM. The details of constituent loads estimation for the three data sites are discussed below.

The models in LOADEST were developed for the total period (1998-2008) at each site. The AMLE calibration and estimation option (described in Section 2.5.2.2) was selected in the model as residuals approximated a normal distribution, and sometimes data were censored (at site-1, one TSS sample, and at site-2, one TP and TSS sample). The best models of TN, TP and TSS at each site were selected automatically based on the AIC value. LOADEST analysis showed that data from all sites generally fit the models well for TN, TP and TSS. Figure 3.26 (a, b and c) shows plotting of residuals against the explanatory variables (streamflow and time) and against the predicted variable (estimated load) at Site-3 (MYC outlet) as a typical case for TN; they are reasonably homoscedastic. Similarly, the goodness of fit in estimation was also tested by normal probability plot of the residuals, and found to be normally distributed as shown in Figure 3.26d.

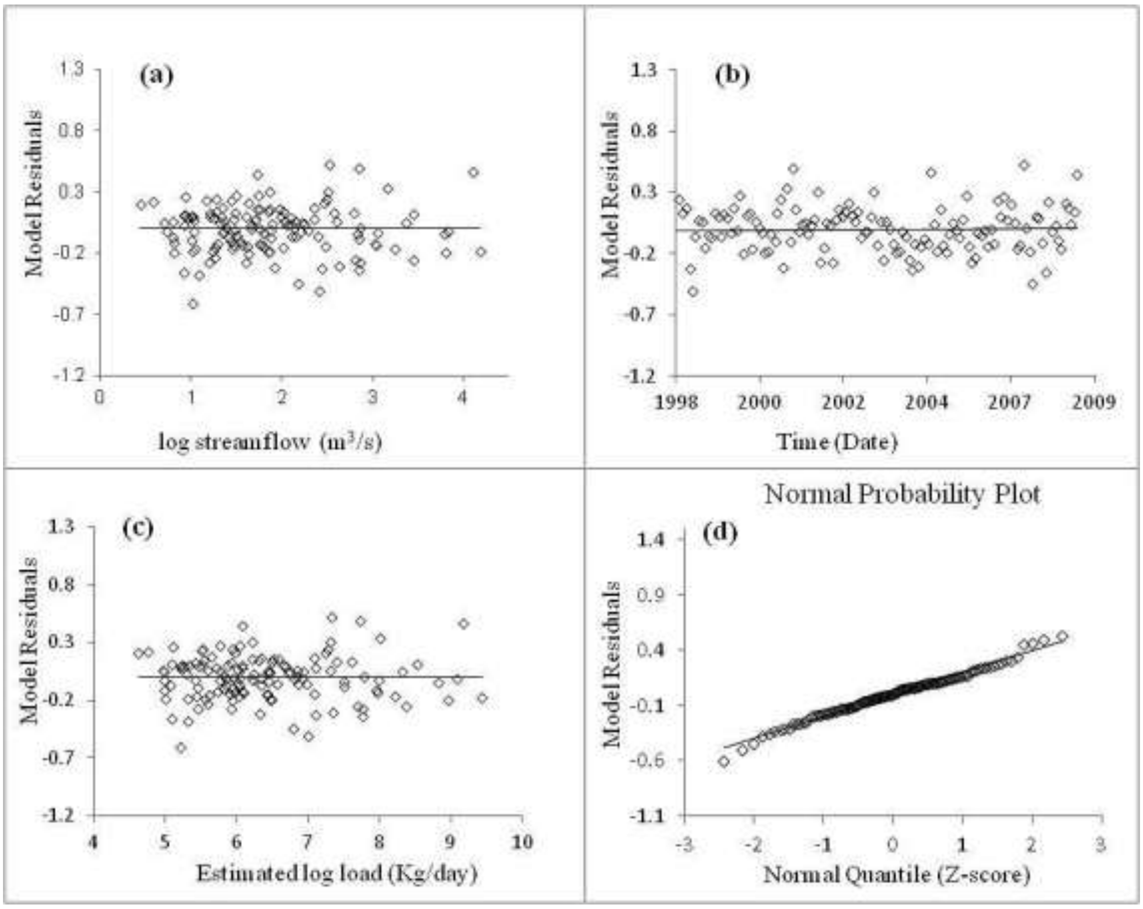


Figure 3.26 Model residuals against (a) log streamflow, (b) time, (c) estimated log load; and (d) normal probability plot of the residuals; all plots are for TN at Site-3

The regression performance statistics are shown in Table 3.12 and Table 3.13. Coefficients of determination (R^2) for the models were evaluated for model performance, and they were greater than 0.85 at all sites for all pollutants as shown in Table 3.12. In general, the residual variance and standard error were found low, and the models performed well for TN.

Table 3.12 Regression statistics at the data sites

	TN			TP			TSS		
	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3
Coefficient of determination (R^2)	0.98	0.97	0.97	0.86	0.86	0.93	0.88	0.85	0.89
Residual variance	0.020	0.037	0.038	0.199	0.166	0.086	0.256	0.272	0.287
PPCC[a]	0.977	0.977	0.993	0.935	0.938	0.974	0.986	0.946	0.978

PPCC[a]: Probability Plot Correlation Coefficient – a linear correlation coefficient between residuals and normal quantile where a value of 1.00 represents perfect normality.

Table 3.13 Constituent Loads statistics at the data sites (period 1998-2008)

Data Sites	Constituent	Mean Load (kg/day)	95% confidence interval		Standard error
			Lower	Upper	
Site-1	TN	185.43	176.17	195.05	4.70
	TP	8.72	5.88	12.47	1.61
	TSS	3130	2470	3900	330
Site-2	TN	566.85	537.54	597.33	14.87
	TP	24.00	20.70	27.66	1.73
	TSS	10830	9150	12740	890
Site-3	TN	1074.00	1012.00	1139.00	32.00
	TP	58.83	52.61	65.58	3.23
	TSS	29170	20870	39690	4650

By default, LOADEST calculates the mean load for the entire estimation period. Users also may request mean load estimates for seasonal and/or monthly time periods. It generates daily load values for each day of the study period for all the constituents. Table 3.14 shows that estimated mean annual load in the calibration period is higher than in the validation period at all sites which is consistent with the constituent mean concentrations (Table 3.11). Moreover, the mean annual load increased from upstream (site-1) to downstream (site-3) which is also expected.

Table 3.14 Constituent mean annual loads at the data sites

Constituent	Constituent mean annual load (ton/year)								
	Total period (1998-2008)			Calibration period (1998-2004)			Validation period (2005-2008)		
	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3
TN	70.27	213.37	392.48	80.72	250.52	466.70	52.00	148.34	262.58
TP	3.28	9.76	22.65	3.37	10.53	26.89	3.12	8.42	15.23
TSS	1191	4101	10655	1338	5098	13045	934	2357	6472

Figure 3.27 shows that monthly TN, TP, and TSS load generation trends are consistent with streamflow. Figure 3.28 show annual TN, TP and TSS load at the three sites in the MYC. In general, 2006-2008 periods generated comparatively low loads, because this period is comparatively drier in the 1998-2008 periods.

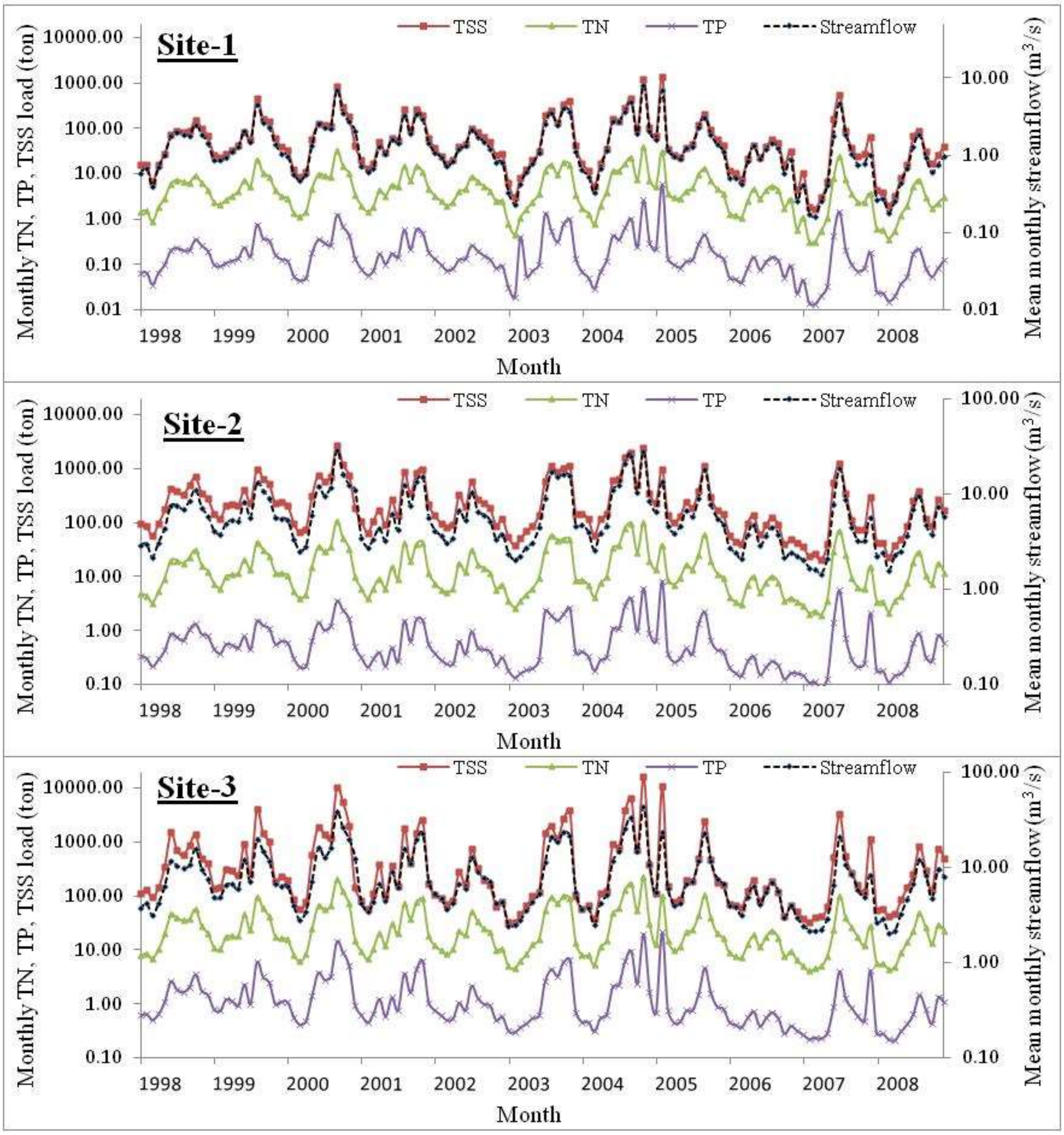


Figure 3.27 Monthly TN, TP and TSS load trend with streamflow at all sites in the MYC

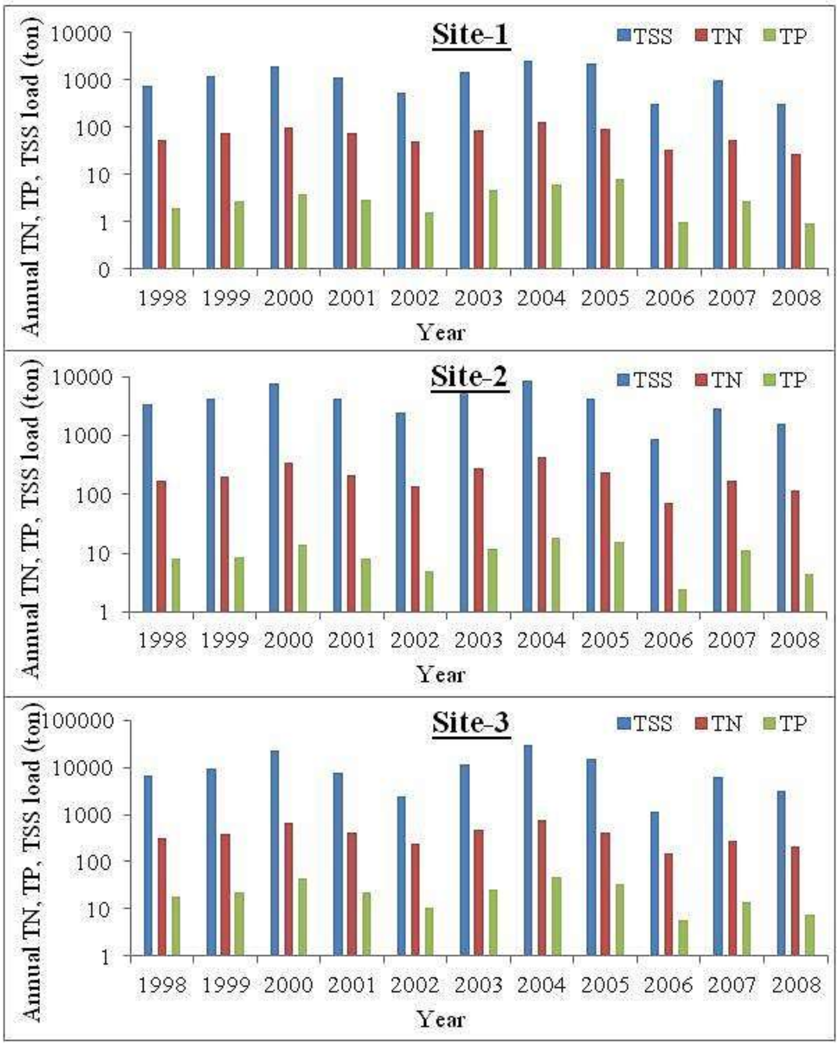


Figure 3.28 Annual TN, TP and TSS load at all sites in the MYC

Figures 3.29, 3.30 and 3.31 are drawn to understand the water quality patterns at all sites in the MYC. In general, the figures show that mean monthly constituent loads are consistent with the rainfall and streamflow pattern. Moreover, higher mean monthly loads are generated in the calibration period than in the validation period. However, loads in February and November months are significantly different in the validation period than in the calibration period. This is because of the extreme rainfall events which occurred in the validation period as shown in Table 3.15. As the most extreme rainfall event occurred in 3rd February 2005 (Table 3.15), it affects the constituent loads significantly in February month. Minimum loads were generated in March and peak loads were generated in August, September and November months. On average 46 % of TN, 42% of TP and 52% of TSS loads in the catchment were generated in the three months of August, September and November.

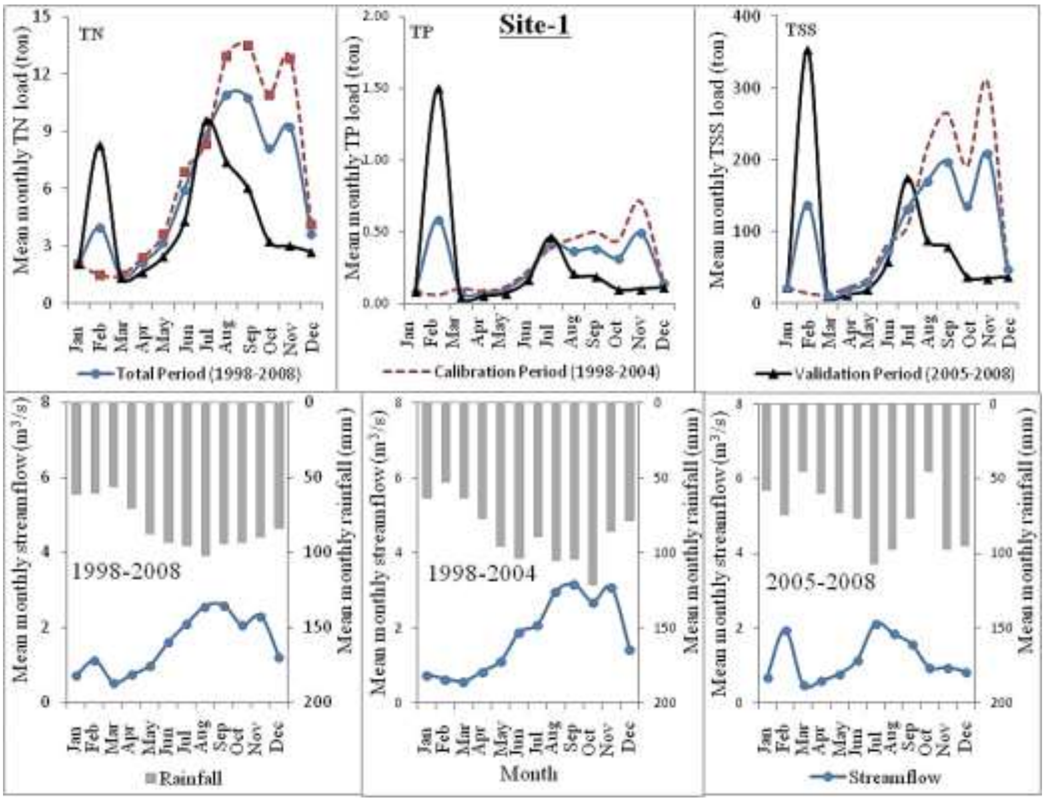


Figure 3.29 Mean monthly TN, TP and TSS loads with streamflow and rainfall at site-1 in the MYC

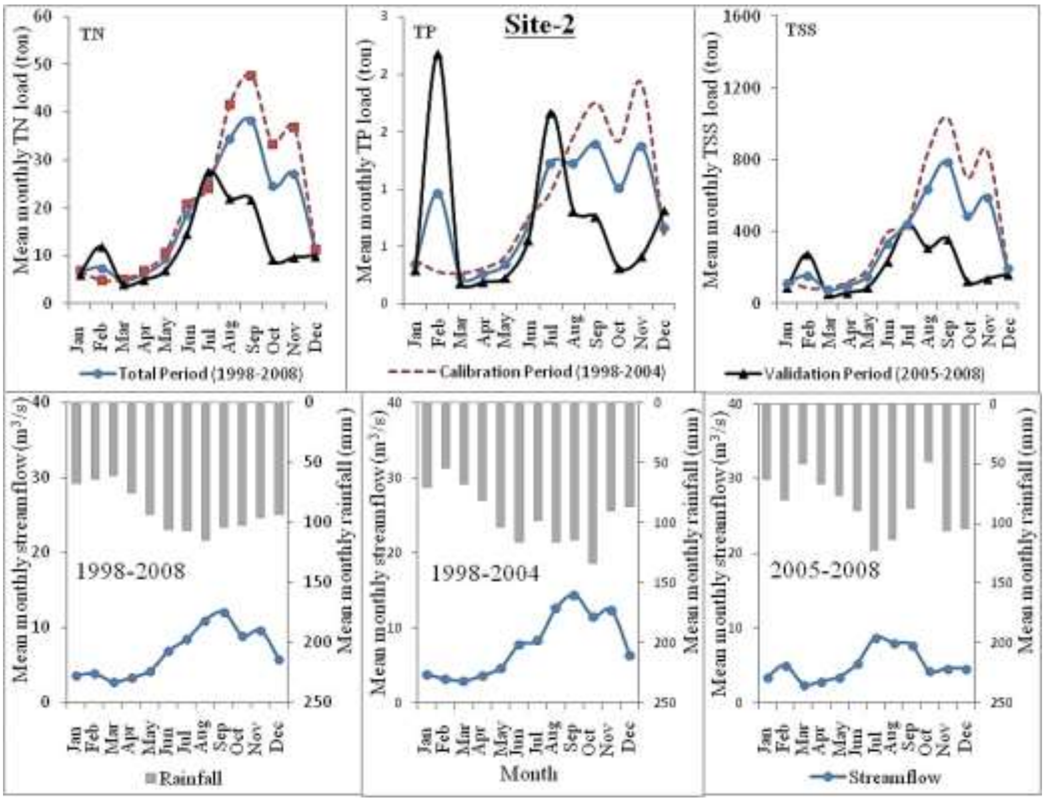


Figure 3.30 Mean monthly TN, TP and TSS loads with streamflow and rainfall at site-2 in the MYC

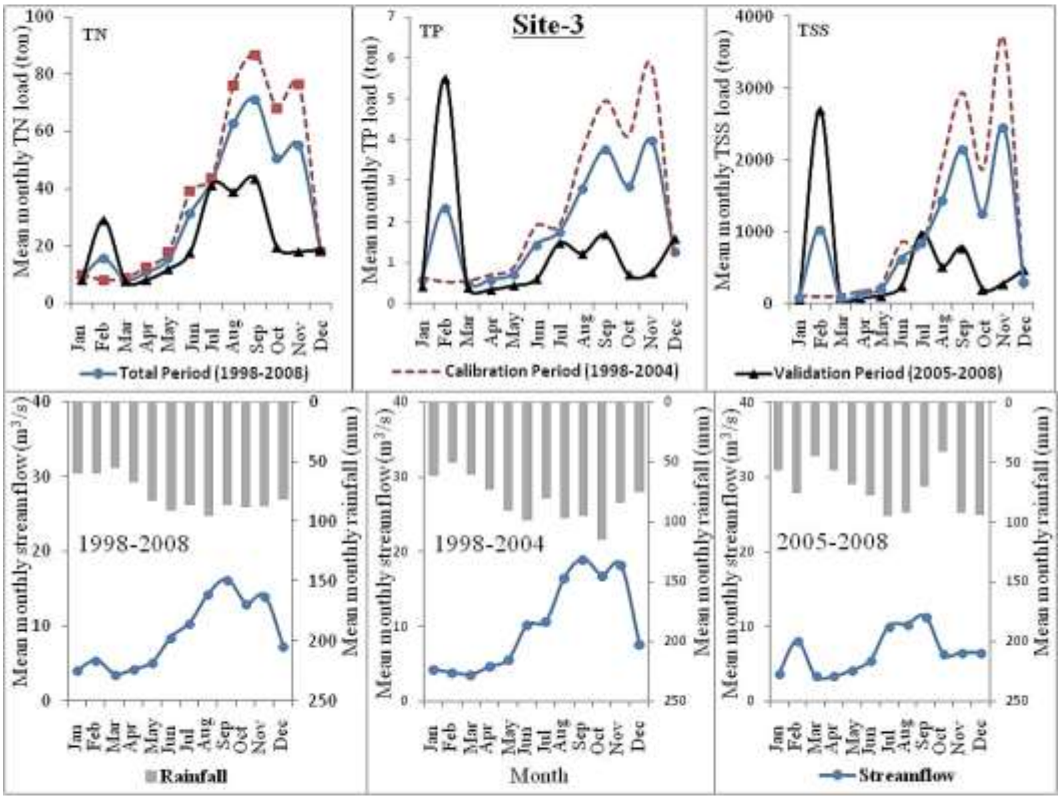


Figure 3.31 Mean monthly TN, TP and TSS loads with streamflow and rainfall at site-3 in the MYC

Table 3.15 Extreme rainfall events at the data sites

	Calibration period (1998-2004)				Validation period (2005-2008)			
	Site-1	Site-2	Site-3	Date	Site-1	Site-2	Site-3	Date
Top three extreme daily rainfall event (mm)	57.1	72.9	52.4	24-04-2004	113.0	129.5	118.9	03-02-2005
	52.5	56.7	49.4	24-07-2003	49.3	64.8	54.4	28-06-2007
	52.3	54.6	43.9	27-12-1998	46.1	56.9	44.6	22-12-2007
Mean daily rainfall (mm)	2.85	3.11	2.70		2.49	2.77	2.36	

3.4. SUMMARY

The Yarra River catchment located in Victoria (Australia) is a valuable asset to all Melbourne residents. The water resources from this catchment are important in terms of a wide range of water uses as well as downstream user requirements and environmental flows. However over the years, due to increases in population, recent land use development in the catchment and inappropriate application of farming chemicals, the river water quality had degraded mainly from non-point sources. This degradation has prompted a need to assess fate and transport of pollutants in the catchment for development of appropriate management strategies to improve water quality.

The study area Middle Yarra Catchment (MYC) is located in the middle segment of the Yarra River catchment. There are several gorges in this area which restrict the flow of the river, in particular Yering Gorge. Majority of the land in the MYC are used for agricultural purposes. The extensive clearing of land in this area has resulted in high runoff during storms with the consequences of erosion on stream banks and increases in sediment loading, causing major non-point source pollution in terms of high nutrient runoff.

All data for the MYWQM were collected from local organizations except DEM. Many data were spatially very coarse especially crop and land management data. Soil and land use digital maps for the MYC were prepared using the ArcGIS tool. Soil data were available only for two layers, and land use data was static type. Climate data were prepared at daily time step for 1980-2008 periods. Stremflow data were processed for 1990-2008 periods, and water quality data was available for 1998-2008 periods. A longer period for streamflow was chosen compared to the water quality constituents so that the model can capture all possible variations in stremflow pattern (wet and dry years).

Baseflow and surface runoff were also calibrated along with the streamflow to represent surface and subsurface hydrological processes accurately in the MYC. Baseflow was separated from mean daily streamflow using automated baseflow separation software "Baseflow Filter Program". In the MYC, baseflow contributes to about 75% of the streamflow. Water quality grab samples were available on a monthly basis without any storm event data. The LOADEST modelling tool was used to estimate TN, TP and TSS loads from these monthly grab samples for calibration purposes of the MYWQM. The LOADEST models performed well for estimating the constituent loads ($R^2 \geq 0.85$). In general, streamflow pattern is consistent with rainfall, and water quality load generation is consistent with streamflow and rainfall in the MYC. From 1997 onwards, the climate is very dry which affected the streamflow and pollutant load generation processes.

The data were collected and/or estimated, and analyzed for three specific purposes in this thesis:

1. To understand the hydrology and water quality processes in the MYC
2. To develop the Middle Yarra Water Quality Model (MYWQM) (Chapter 4)
3. To develop a water quality management plan for the MYC (Chapter 5)

4. DEVELOPMENT OF THE SWAT BASED MIDDLE YARRA WATER QUALITY MODEL

4.1. INTRODUCTION

In Chapter 3, data sources and processing of the data required for developing the Middle Yarra Water Quality Model (MYWQM) were discussed. The next steps of developing the model are assembling of the input data of the study catchment and validating the model. Once developed, reliable physics-based water quality models, such as the MYWQM, are very useful analysis tools because of their ability to perform long-term simulation of catchment management activities on water quality and water quantity (Muttiah and Wurbs, 2002; Moriasi et al, 2007). However, developing reliable catchment simulation models and validating them on real-world catchments with measured data are also challenging. In order to use model outputs for tasks ranging from regulation to research, models should be scientifically sound, robust, and defensible (U.S. EPA, 2002). In this regard, model sensitivity analysis, calibration and validation, and uncertainty analysis help to evaluate the ability of the model to sufficiently predict streamflow and water quality constituent yields for specific applications (White and Chaubey, 2005).

In this chapter, the assembly of the MYWQM and its performance evaluations are described. The chapter begins with a description of the assembly of the MYWQM in Section 4.2, followed by sensitivity analysis, calibration and validation, and uncertainty analysis in Sections 4.3 to 4.5 respectively. Finally, a summary is presented at the end of the chapter.

4.2. ASSEMBLY OF THE MYWQM

Spatial datasets (DEM, land use and soil digital maps) and database input files are assembled together to develop the SWAT based MYWQM. First, the DEM is used to analyze the drainage patterns of the catchment and to delineate it into a number of sub-catchments. The catchment delineation process includes five major steps - DEM set-up, stream definition, outlet and inlet definition, catchment outlets selection and definition, and calculation of sub-catchment parameters. Each sub-catchment is assumed homogeneous with parameters representative of the entire sub-catchment. However, the size of a sub-catchment affects the homogeneity assumption because larger sub-catchments are more likely to have variable conditions. During delineation process, an increase in the number of sub-catchments increases the input data preparation effort and the subsequent computational evaluation. Similarly, a decrease in the number of sub-catchments could affect the simulation results. The impact of sub-catchment scaling upon a catchment simulation is directly related to the sources of heterogeneity, which include the channel network, sub-catchment topography, soils, land use, and climate inputs.

Further discretization of the sub-catchments is made using areas with the same land use, soil types and slope to create the SWAT based MYWQM model computational units that are assumed to be homogeneous in hydrologic response, which are called Hydrologic Response Units (HRUs). This discretization enables the model to reflect difference in evapotranspiration and other hydrologic conditions for different land covers/crops and soils. Hydrologic and water quality components are computed for each HRU and routed to obtain the total for the catchment. This increases the accuracy of load predictions and provides a much better physical description of the water balance. The threshold levels set for multiple HRUs are a function of the project goal and the amount of detail desired by the modeler. The default setting for land use threshold is 20%, soil threshold is 10% and slope threshold is 20%. For most applications, these threshold values are adequate (Winchell et al, 2009). This means, each land use representing 20% or over of the sub-catchment area is included in the model; Similarly, each soil class representing 10% or more of that land use area and each land slope representing 20% or more of that soil area are considered. Land uses, soils or slope that cover a percentage less than the threshold level are eliminated. After the elimination processes the area of the land use, soil or slope is reallocated so that 100 percent of the land area, soil or slope in the sub-catchment is included in the simulation.

Streamflow, sediment, and nutrient yield computations of a catchment model can be affected by the size and the number of sub-catchments and HRUs. Many authors investigated the influence of the size and the number of sub-catchments and HRUs on streamflow, sediment, nutrients, and BMPs. Most studies found minimal effects on streamflow or runoff (Bingner et al, 1997; FitzHugh and Mackay, 2000; Jha et al, 2004;

Tripathi et al, 2005) except Mamillapalli et al (1996). However, Jha et al (2004) found significant effects on sediment, nitrate, and inorganic P and suggested the optimal threshold sub-catchment sizes around 3, 2, and 5 percent of total catchment respectively. Arabi et al (2006) also recommended the average sub-catchment area corresponding to approximately 4 percent of total catchment area to represent the influence of BMPs.

Once the model's catchment delineation and HRU definition is completed, other database input files such as weather and climate data, crop management operation schedule are added to the model at different steps. Finally the main methods to be used in modelling the hydrologic processes in the model are selected before running the model.

The catchment delineation and HRU definition is further discussed in Section 4.2.2 giving details of each of sub-catchments used in the MYWQM including the number of HRUs used in each sub-catchment.

4.2.1. SPATIAL DATASETS AND DATABASE INPUT FILES FOR THE MYWQM

The Geographic Information System (GIS) platform was used in assembling the MYWQM. The spatial datasets (DEM, land use and soil digital maps) and database input files for the MYWQM were organized following the guidelines of Winchell et al (2009) and Neitsch et al (2004; 2005). The GIS linked ArcSWAT interface for SWAT2005 software was used to assemble and develop the MYWQM.

GIS data layers used to build the model included Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) 30m Global Digital Elevation Model (GDEM) (Figure 3.7), soil dataset from Australian Soil Resource Information System (ASRIS) (Figure 3.10 and Table 3.3) and 50m grid raster land use/cover dataset from Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (Figure 3.13). Two other key sets of inputs required for developing the MYWQM were climate data and land management data. Details of these data preparation were discussed in Chapter 3. The following Database Tables and Text Files were prepared in addition to the three GIS data layers (DEM, Soil and Land use digital map).

1. Sub-catchment outlet location table
2. Catchment inlet and data tables
3. Land use and soil look up tables

4. Weather and precipitation station locations and data tables
5. Reservoir location and outflow data table
6. Crop management operation tables

The “sub-catchment outlet location table” was used to force the model to generate sub-catchment outlet points at the data/monitoring sites for calibration purposes. As discussed in Section 3.3.2.1(D), the MYC for this project is the middle part of the Yarra River catchment. So it receives streamflow and water quality contaminant loads from the upstream part of the Yarra River catchment. This is shown by the modelling feature “Inland” in Figure 3.14. The upstream streamflow and water quality contaminant loads (sediment and nutrients) were added like point source loads at the “upstream inlet point” in the MYWQM through the “catchment inlet and data tables”. The “land use and soil look up tables” were used to link land use and soil maps with their database. The “weather and precipitation station locations and data tables” were used to add weather data and station location. Also precipitation data were added with their locations (Figure 3.14).

The “reservoir location and outflow data table” was used to add reservoir location and its outflow in the MYWQM. Data on reservoir outflow and physical characteristics (surface area, total available capacity) were collected from Melbourne Water Corporation. Three reservoirs are situated in the MYC (Figure 3.6). As discussed in Section 3.3.1, only Maroondah reservoir receives natural streamflow within the study area, while Sugarloaf and Silvan are off stream storage reservoirs, filled by diverting water from other reservoirs and river. Therefore, as per SWAT criteria, Maroondah is added as a reservoir, and Sugarloaf and Silvan are added as ponds in the MYWQM (this is the reason in Figure 3.14 only Maroondah was shown as a reservoir). Ponds are assumed to be located off the main channel in a sub-catchment, and do not receive water from upstream sub-catchments. The outflow from Maroondah to Sugarloaf is added as consumptive use which means water used out of the MYC. Since, water from these reservoirs is transferred to most parts of Melbourne’s metropolitan area through different service reservoirs, there is no outflow from these reservoirs to the MYC except minor amount from Maroondah reservoir. Hence these reservoirs have very minor influence on the MYC hydrology.

Finally the crop management operations are scheduled in the MYWQM through the “crop management operation tables”.

4.2.2. CATCHMENT DELINEATION AND HRU DEFINITION IN THE MYWQM

During the delineation process in the MYWQM, a predefined optional digital stream network layer (collected from Geoscience Australia) was imported and superimposed onto the DEM to accurately delineate the location of the streams in the MYC. For the stream definition, the threshold-based stream definition option in SWAT was used to define the minimum size of a sub-catchment and hence the number of sub-catchments. The ArcSWAT interface allows the user to fix the number of sub-catchments by deciding the initial threshold area. The threshold area defines the minimum drainage area required to form the origin of a stream. In the MYWQM, the MYC was subdivided into a total of 51 sub-catchments as shown in Figure 4.1. Among the 51 sub-catchments, areas of 42 sub-catchments were below 3 percent of total catchment area, and only 7 sub-catchments had areas above 4 percent of the total catchment area. These percentages of the sub-catchment areas are reasonably close to the recommended values of Jha et al (2004) and Arabi et al (2006) studies as discussed in Section 4.2. Details of the sub-catchments in the MYC are shown in Table 4.1.

During HRU definition, a sub-catchment is further discretized into a number of HRUs based on the threshold levels of the land use, soil and slope classes on that sub-catchment. Two slope classes ≤10% and >10% were considered in the MYWQM. The slope class ≤10% covers about 43% of the catchment area as shown in the Figure 3.8. In each sub-catchment, each land use representing 5% or over of the sub-catchment area was included in the model. Then each soil representing 10% or more of that land use area and each land slope representing 15% or more of that soil area were considered. Accordingly, the MYC was subdivided into 431 HRUs in the MYWQM as shown in Table 4.1.

Moreover, initial values for baseflow alpha factor (ALPHA_BF) were taken from when baseflow was separated from total streamflow by the “Baseflow Filter Program” (Section 3.3.2.2(A)). Also initial Manning’s n value was taken from Ladson et al (2003) and LWA (2009). The main methods used in modelling the hydrologic processes were the curve number (CN) method for runoff estimating, the Penman-Monteith method for Potential Evapotranspiration (PET) and the Muskingum method for channel routing (channel dimensions remain constant). Moreover, in-stream nutrient transformations were modelled using the QUAL2E equation embedded in SWAT2005 modelling software.

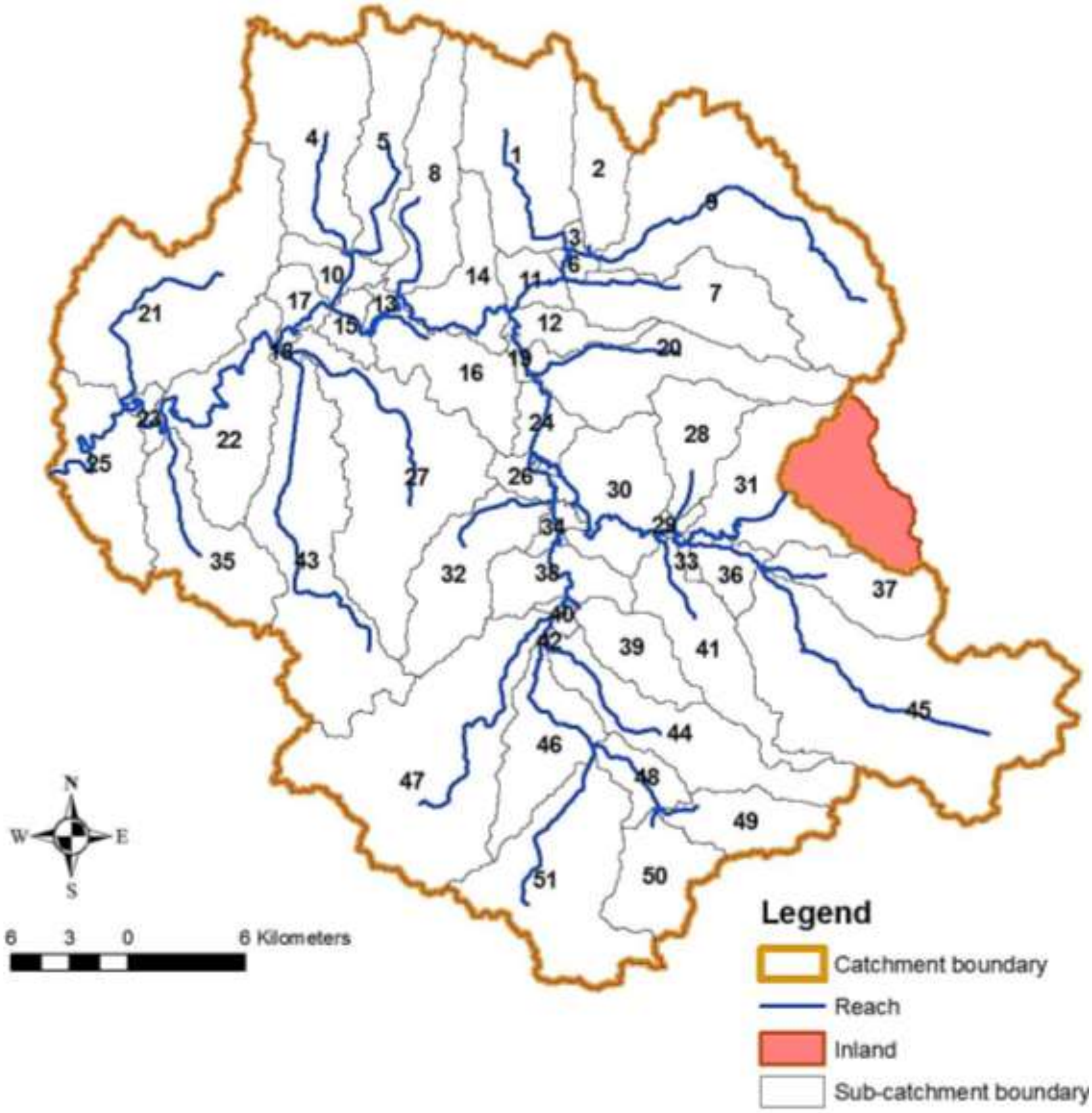


Figure 4.1 Sub-catchment delineation in the MYC

Table 4.1 Details of sub-catchments in the MYC used in the MYWQM									
Sub-catchment (SC)				Major Land use		Major Soil		Major Slope	
No.	Area(km^2)	% of MYC	No. of HRU	Type	% of SC	Type	% of SC	Type	% of SC
1	52.69	3.49	14	FRST	76.41	DERMOSOL	46.25	>10%	71.62
2	19.46	1.29	3	FRSD	87.47	DERMOSOL	94.51	>10%	85.84
3	1.59	0.10	6	FRSD	92.68	SODOSOL	91.39	>10%	64.71
4	51.34	3.40	14	FRSD	36.10	SODOSOL	51.90	>10%	69.35
5	34.88	2.31	13	PAST	32.22	SODOSOL	44.41	>10%	54.38
6	2.68	0.18	8	URBN	60.96	SODOSOL	88.55	≤10%	68.42
7	37.16	2.46	8	FRSD	79.51	DERMOSOL	59.28	>10%	80.00
8	33.31	2.20	7	FRST	54.47	SODOSOL	48.91	>10%	55.54
9	104.85	6.94	4	FRSD	85.88	DERMOSOL	72.36	>10%	84.16
10	9.74	0.64	8	PAST	63.70	SODOSOL	100.00	≤10%	66.47
11	9.12	0.60	14	URBN	40.97	SODOSOL	59.37	≤10%	62.21
12	10.85	0.72	11	PAST	48.63	SODOSOL	66.69	≤10%	72.78
13	2.77	0.18	2	PAST	100.00	SODOSOL	100.00	≤10%	75.46
14	23.63	1.56	12	PAST	55.30	SODOSOL	57.18	≤10%	61.56
15	7.07	0.47	2	PAST	100.00	SODOSOL	100.00	≤10%	72.87
16	27.71	1.83	3	PAST	94.87	SODOSOL	88.16	≤10%	75.96
17	8.80	0.58	6	PAST	66.52	SODOSOL	100.00	≤10%	66.78
18	0.07	0.00	1	PAST	100.00	SODOSOL	100.00	≤10%	100.00
19	1.90	0.13	6	PAST	71.25	SODOSOL	52.84	≤10%	56.78
20	43.40	2.87	11	FRSD	52.40	DERMOSOL	51.42	>10%	72.67
21	82.48	5.46	10	PAST	46.53	SODOSOL	88.02	>10%	62.90
22	42.18	2.79	12	PAST	75.88	SODOSOL	48.02	≤10%	60.11
23	4.00	0.27	8	URBN	38.64	SODOSOL	100.00	>10%	55.01
24	9.82	0.65	2	PAST	100.00	SODOSOL	97.92	≤10%	69.89
25	35.57	2.35	8	URBN	47.45	SODOSOL	91.32	≤10%	51.29
26	6.13	0.41	3	PAST	52.37	SODOSOL	100.00	≤10%	59.20
27	78.09	5.17	8	PAST	63.70	SODOSOL	84.30	≤10%	69.35
28	23.14	1.53	7	FRST	69.19	DERMOSOL	64.04	>10%	64.04
29	0.81	0.05	2	PAST	90.83	SODOSOL	100.00	≤10%	89.23
30	35.12	2.32	7	PAST	55.97	SODOSOL	69.94	≤10%	51.54
31	35.54	2.35	9	FRST	41.95	SODOSOL	52.47	>10%	60.32
32	35.08	2.32	16	PAST	44.28	SODOSOL	53.63	≤10%	64.25
33	2.86	0.19	5	URBN	59.40	SODOSOL	100.00	≤10%	74.70
34	4.27	0.28	2	PAST	100.00	SODOSOL	100.00	≤10%	78.64
35	37.12	2.46	11	URHD	52.18	SODOSOL	73.22	≤10%	77.96
36	9.54	0.63	6	URBN	42.53	SODOSOL	100.00	≤10%	62.09
37	25.30	1.67	4	FRST	89.61	DERMOSOL	89.39	>10%	83.76
38	18.75	1.24	8	PAST	68.01	SODOSOL	99.29	≤10%	71.84
39	19.05	1.26	14	PAST	48.75	SODOSOL	87.53	≤10%	58.64
40	2.56	0.17	3	PAST	67.51	SODOSOL	100.00	≤10%	82.47
41	34.68	2.30	20	FRST	61.00	SODOSOL	54.53	>10%	59.97
42	0.23	0.02	1	PAST	100.00	SODOSOL	100.00	≤10%	95.30
43	75.50	5.00	18	PAST	28.91	SODOSOL	45.88	>10%	51.20
44	44.30	2.93	10	FRST	51.12	DERMOSOL	54.73	>10%	59.29
45	119.79	7.93	4	FRST	82.83	DERMOSOL	91.39	>10%	77.41
46	30.53	2.02	10	PAST	57.29	SODOSOL	81.03	≤10%	73.97
47	96.43	6.38	26	PAST	32.73	SODOSOL	40.07	>10%	52.67
48	11.68	0.77	8	FRST	56.20	SODOSOL	72.83	≤10%	52.52
49	21.10	1.40	2	FRST	80.36	DERMOSOL	83.23	>10%	55.90
50	24.18	1.60	10	FRST	44.54	DERMOSOL	71.43	>10%	58.01
51	62.02	4.10	24	PAST	43.02	SODOSOL	33.97	>10%	56.98

PAST – Pasture, FRST – Forest - Mixed, FRSD – Forest - Deciduous, URBN – Urban, URHD – Urban - High Density.

4.3. SENSITIVITY ANALYSIS OF THE MYWQM

As discussed in Section 2.5.1, complexity in the calibration process increases with the physics-based distributed parameter catchment models such as the MYWQM due to large number of model parameters. Sensitivity analysis methods reducing the number of parameters to be adjusted during calibration are important for simplifying the use of these models. Sensitivity analysis methods identify parameters that do or do not have a significant influence on the model simulations of output variables.

The most sensitive parameters for the MYWQM were identified using the SWAT model inbuilt Latin-Hypercube and One-factor-At-a-Time (LH-OAT) sensitivity analysis method. The LH-OAT sensitivity analysis ranked the parameters based on their effect on the model performance. The model performance was considered by error functions (the sum of the squared errors) of the simulated and observed monthly time series of streamflow (Q), Total Suspended Solid (TSS), Total Nitrogen (TN) and Total Phosphorus (TP) at the 3 calibration sites in the MYC (Section 3.3.2.2). The parameter producing the highest average percentage change in the error function value is ranked as the most sensitive. Details about LH-OAT were discussed in Section 2.5.1.4(A).

The SWAT based MYWQM has a total of 41 parameters which are the default choice in SWAT for sensitivity analysis. Among the 41 parameters, 26 parameters are related to streamflow, 6 parameters are related to sediment, and 9 parameters are related to nutrients. Table 4.2 shows these parameters with their default minimum and maximum values and the processes they involved with.

Two types of sensitivity analysis were performed to justify correlations between a parameter and multiple predicted output variables in the MYWQM. Sensitivity analysis type-I considers all output variables (Q, TSS, TN and TP) and all parameters in Table 4.2 simultaneously to rank the parameter sensitivity globally in the MYWQM. Sensitivity analysis type-II considers only one output variable (e.g. Q) at a time and its related parameters from Table 4.2 to rank the parameter sensitivity for each output variable. The term “globally” means to rank a parameter considering all the three calibration sites for all output variables (analysis type-I) or for a particular variable (analysis type-II). In the analysis type-I for all variables, the simulation period considered was 1998-2004. In the analysis type-II for an individual variable, the simulation period considered for Q was 1990-2002, and for TSS, TN and TP was 1998 to 2004. The simulation periods were chosen based on the availability of observed data. Ten years warm up period preceded these simulation periods.

Table 4.2 Default parameters for sensitivity analysis in SWAT2005

	Name	Min	Max	Description	Process
1	ALPHA_BF	0	1	Baseflow alpha factor [days]	Groundwater
1	BIOMIX	0	1	Biological mixing efficiency	Soil
1	BLAI	0.5	10	Maximum potential leaf area index	Crop
1	CANMX	0	100	Maximum canopy storage [mm]	Runoff
2	CH_COV	-0.001	1	Channel cover factor	Erosion
2	CH_EROD	-0.05	0.6	Channel erodibility factor	Erosion
1	CH_K2	-0.01	500	Channel effective hydraulic conductivity [mm/hr]	Channel
1	CH_N2	-0.01	0.3	Manning's n value for main channel	Channel
1	CN2	35	98	Initial SCS CN II value	Runoff
1	EPCO	0	1	Plant uptake compensation factor	Evaporation
1	ESCO	0	1	Soil evaporation compensation factor	Evaporation
1	GW_DELAY	0	500	Groundwater delay [days]	Groundwater
1	GW_REVAP	0.02	0.2	Groundwater "revap" coefficient	Groundwater
1	GWQMN	0	5000	Threshold water depth in the shallow aquifer for flow [mm]	Groundwater
3	NPERCO	0	1	Nitrogen percolation coefficient	Soil
3	PHOSKD	100	200	Phosphorus soil partitioning coefficient	Soil
3	PPERCO	10	17.5	Phosphorus percolation coefficient	Soil
3	RCHRG_DP	0	1	Deep aquifer percolation fraction	Groundwater
1	REVAPMN	0	500	Threshold water depth in the shallow aquifer for "revap" [mm]	Groundwater
1	SFTMP	-5	5	Snowfall temperature [ºC]	Snow
3	SHALLST_N	0	1000	Concentration of nitrate in groundwater contribution [mg N/l]	Groundwater
1	SLOPE	0	0.6	Average slope steepness [m/m]	Geomorphology
1	SLSUBBSN	10	150	Average slope length [m]	Geomorphology
1	SMFMN	0	10	Melt factor for snow on December 21 [mm H2O/ºC-day]	Snow
1	SMFMX	0	10	Melt factor for snow on June 21 [mm H2O/ºC-day]	Snow
1	SMTMP	-5	5	Snow melt base temperature [ºC]	Snow
1	SOL_ALB	0	0.25	Moist soil albedo	Evaporation
1	SOL_AWC	0	1	Available water capacity [mm H20/mm soil]	Soil
1	SOL_K	0	2000	Saturated hydraulic conductivity [mm/hr]	Soil
3	SOL_LABP	0	100	Initial labile P concentration [mg/kg]	Soil
3	SOL_NO3	0	100	Initial $N0_3$ concentration [mg/kg]	Soil
3	SOL_ORGN	0	100	Initial organic N concentration [mg/kg]	Soil
3	SOL_ORGP	0	100	Initial organic P concentration [mg/kg]	Soil
1	SOL_Z	0	3500	Soil depth [mm]	Soil
2	SPCON	0.0001	0.01	Lin. re-entrainment parameter for channel sediment routing	Channel
2	SPEXP	1	1.5	Exp. re-entrainment parameter for channel sediment routing	Channel
1	SURLAG	1	24	Surface runoff lag time [days]	Runoff
1	TIMP	0	1	Snow pack temperature lag factor	Snow
1	TLAPS	0	50	Temperature lapse rate [°C/km]	Geomorphology
2	USLE_C	0.001	0.5	Minimum USLE cover factor	Crop
2	USLE_P	0	1	USLE support practice factor	Erosion

1: Streamflow parameters, 2: Sediment parameters and 3: Nutrients parameters

4.3.1. SENSITIVITY ANALYSIS TYPE-I

The global sensitivity ranks of all parameters considering all output variables (Q, TSS, TN and TP) simultaneously are shown in Table 4.3. The last column in Table 4.3 shows the global rank, and is used to assess global parameter sensitivity. The highest sensitivity rank (lowest numerical value) owned by a particular parameter among the variables at any site was considered as the global rank for that parameter (van Griensven et al, 2006). For example, SPCON got the highest sensitivity rank of 1 for TSS at Site-1. So its global rank was considered as 1 as shown in Table 4.3, although SPCON got sensitivity rank of 42 for other variables at all the sites.

Table 4.3 Sensitivity results for the parameters in the MYWQM for Q, TSS, TN and TP at the three calibration sites in the MYC

Parameter	Q			TSS			TN			TP			Global
	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Rank
CH_N2	1	1	1	2	1	1	2	1	1	3	1	1	1
RCHRG_DP	2	4	7	5	6	3	1	3	2	16	22	16	1
SURLAG	16	16	15	15	23	24	3	9	10	1	6	9	1
SPCON	42	42	42	1	3	4	42	42	42	42	42	42	1
CH_K2	14	2	10	12	2	9	16	2	15	10	2	8	2
CN2	5	3	3	7	8	5	6	6	3	4	4	2	2
CANMX	10	6	9	11	10	15	5	17	24	2	14	11	2
CH_COV	42	42	42	23	4	2	42	42	42	42	42	42	2
GWQMN	6	10	2	13	16	11	8	8	4	23	23	17	2
ESCO	4	9	6	3	18	12	4	7	17	11	5	15	3
GW_REVAP	3	14	12	8	9	22	9	15	20	24	42	25	3
SOL_AWC	7	12	4	19	17	13	12	4	8	12	3	18	3
USLE_P	42	18	17	17	19	8	17	12	5	7	8	3	3
SLOPE	12	7	5	22	12	7	18	16	6	15	10	4	4
SPEXP	42	42	42	4	5	10	42	42	42	42	42	42	4
ALPHA_BF	8	5	14	6	7	6	10	5	11	5	7	5	5
BIOMIX	21	42	42	21	21	20	13	23	7	8	12	6	6
SOL_Z	9	15	11	9	13	18	7	13	13	6	11	13	6
SLSUBBSN	22	42	42	25	25	21	19	20	9	17	16	7	7
GW_DELAY	15	8	42	14	22	25	21	22	23	26	24	26	8
SOL_K	11	13	8	10	11	16	22	14	16	20	17	20	8
BLAI	13	11	13	20	14	19	11	10	22	9	9	14	9
SOL_ORGP	42	42	42	42	42	42	27	21	25	19	15	10	10
NPERCO	8	20	16	18	15	17	14	11	12	14	13	19	11
SOL_LABP	42	42	42	42	42	42	25	42	14	18	19	12	12
SOL_ORGN	19	42	18	16	20	24	15	19	18	13	18	22	13
REVAPMN	17	42	42	26	42	42	20	42	42	28	42	42	17
SOL_ALB	23	17	42	24	42	26	26	25	26	25	42	21	17
PPERCO	42	42	42	42	42	42	28	18	19	27	21	23	18
EPCO	20	19	19	27	24	23	23	26	27	21	26	27	19
PHOSKD	42	42	42	42	42	42	24	24	21	22	20	24	20
USLE_C	42	42	42	42	26	42	42	42	42	42	25	42	25
CH_EROD	42	42	42	42	42	42	42	42	42	42	42	42	42
SFTMP	42	42	42	42	42	42	42	42	42	42	42	42	42
SHALLST_N	42	42	42	42	42	42	42	42	42	42	42	42	42
SMFMN	42	42	42	42	42	42	42	42	42	42	42	42	42
SMFMX	42	42	42	42	42	42	42	42	42	42	42	42	42
SMTMP	42	42	42	42	42	42	42	42	42	42	42	42	42
SOL_NO3	42	42	42	42	42	42	42	42	42	42	42	42	42
TIMP	42	42	42	42	42	42	42	42	42	42	42	42	42
TLAPS	42	42	42	42	42	42	42	42	42	42	42	42	42

Streamflow parameters, Sediment parameters and Nutrients parameters

Q - Streamflow, TSS - Sediment, TN - Total Nitrogen and TP - Total Phosphorus

Parameters with no appearance of sensitivity get rank 42

Global rank 1 was categorized as 'very important', rank 2–8 as 'important', rank 9–25 as 'slightly important' and rank 42 as 'not important' following the ranking categorization by Van Griensven et al (2006). The results identified 4 very important parameters (global sensitivity rank of 1) that cover channel, runoff and groundwater processes, and thus involve the hydrology of the system. In addition, there were 17 important parameters (global sensitivity >1 and <9) that cover all remaining processes listed in Table 4.2, except crop processes. Also, there were 11 'slightly important' parameters (global sensitivity 9-25) and nine parameters did not cause any change to model output at all (rank of 42). Table 4.3 shows that ranking of the parameters scattered among the variables at different sites.

The scattered appearance of the higher ranked parameters shows that the ranking depends on the variable and the location. However, some generalizations can be made such as the overall importance of channel processes (CH_N2, SPCON, and CH_K2), groundwater processes (RCHRG_DP) and runoff processes (SURLAG, CN2 and CANMX) in the MYC. This indicates the in-stream process (channel processes) has significant impact on water quality along with upland processes in the MYC. Therefore in-stream processes should be considered in developing the MYWQM.

These results also show that the hydrologic parameters dominate the highest parameter ranks. Some hydrologic parameters, like SURLAG, appeared almost only on the pollutant list (SURLAG got highest global sensitivity rank 1 for TP at site-1 as shown in Table 4.3) while being relatively unimportant for streamflow (highest rank 15). This means that water quality variable are potentially capable of contributing to the identification of streamflow parameters within SWAT, and a single parameter is correlated to multiple variables (SURLAG is a streamflow parameter but also highly correlated to TN and TP based on the sensitivity). Moreover, there are clear differences in ranking of a parameter among the three sites in the catchment. This result illustrates how parameter importance depends on land use, topography and soil types, meaning that a generalization within a catchment is limited. This justifies the importance of multi-site parameterization.

4.3.2. SENSITIVITY ANALYSIS TYPE-II

In the analysis type-II, streamflow related parameters for streamflow (Q), and sediment related parameters for sediment (TSS) were considered. However, all nutrient parameters (both TN and TP related) were considered for TN. Similarly, all nutrient parameters were also considered for TP. The global sensitivity results for individual variable with their related parameters are shown in Tables 4.4 and 4.5.

In general, Tables 4.4 and 4.5 show that the parameter ranks in sensitivity analysis type-I are consistent with the parameter ranks in sensitivity analysis type-II. However, there were some exceptions. For example, ALFA_BF got higher rank and SURLAG got lower rank for streamflow in sensitivity analysis type-II compared to the analysis type-I. For TN and TP variables, NPERCO and SOL_ORGN parameters received higher ranks in sensitivity analysis type-II compared to the analysis type-I. Also nitrogen related parameters among all nutrient parameters received higher rank in case of TP sensitivity analysis (Table 4.5) which means nitrogen and phosphorus parameters are closely correlated.

Table 4.4 Sensitivity results for the parameters in the MYWQM for Q and TSS individually at the three calibration sites in the MYC

Q Parameters	Q Site-1	Q Site-2	Q Site-3	Global Rank	TSS Parameters	TSS Site-1	TSS Site-2	TSS Site-3	Global Rank
CH_N2	1	1	1	1	SPCON	1	1	1	1
ALPHA_BF	2	2	2	2	CH_COV	2	2	2	2
CH_K2	6	3	3	3	USLE_P	4	3	4	3
ESCO	3	5	7	3	SPEXP	5	4	3	3
CN2	10	4	6	4	CH_EROD	3	7	7	3
SOL_AWC	4	12	11	4	USLE_C	6	7	5	5
BLAI	12	6	4	4					
SOL_Z	5	14	8	5					
CANMX	11	13	5	5					
GWQMN	7	9	13	7					
SOL_K	14	7	12	7					
SLOPE	16	8	9	8					
GW_REVAP	8	27	27	8					
GW_DELAY	9	10	10	9					
SURLAG	13	11	14	11					
BIOMIX	17	17	15	15					
REVAPMN	19	15	18	15					
EPCO	15	16	16	15					
TIMP	27	27	17	17					
SOL_ALB	18	27	19	18					
SLSUBBSN	27	18	27	18					
SFTMP	27	27	27	27					
SMFMN	27	27	27	27					
SMFMX	27	27	27	27					
SMTMP	27	27	27	27					
TLAPS	27	27	27	27					

Q – Streamflow and TSS – Sediment; Q and TSS Parameters with no appearance of sensitivity get rank 27 and 7 respectively

Table 4.5 Sensitivity results for the parameters in the MYWQM for TN and TP individually at the three calibration sites in the MYC

TN and TP Parameters	TN			Global Rank	TN and TP Parameters	TP			Global Rank
	Site-1	Site-2	Site-3			Site-1	Site-2	Site-3	
RCHRG_DP	1	1	1	1	NPERCO	2	2	1	1
NPERCO	2	2	2	2	SOL_ORGN	1	6	2	1
SOL_ORGN	3	3	3	3	RCHRG_DP	3	1	4	1
PHOSKD	5	4	4	4	SOL_ORGP	5	3	3	3
SOL_NO3	4	10	10	4	SOL_LABP	7	4	5	4
PPERCO	6	5	5	5	SOL_NO3	4	10	10	4
SOL_LABP	7	6	7	6	PHOSKD	6	5	6	5
SOL_ORGP	8	7	6	6	PPERCO	8	7	7	7
SHALLST_N	10	10	10	10	SHALLST_N	10	10	10	10

TN - Total Nitrogen and TP - Total Phosphorus ; Parameters with no appearance of sensitivity get rank 10

4.3.3. MOST SENSITIVE PARAMETERS IN THE MYWQM

The most sensitive parameters in the MYWQM were selected based on the two types of sensitivity analysis. In general, very important and important parameters were selected from Tables 4.3, 4.4 and 4.5 for Q, TSS, TN and TP as shown in Table 4.6. However, there were few exceptions. For example, BIOMIX and SLSUBBSN were not considered for Q. Because these parameters received lower rank in the analysis type-II (Table 4.4), and also these parameters were ranked as important in the analysis type-I mainly for TN or TP variable, not for Q (Table 4.3). Streamflow parameters from Table 4.6 were used for streamflow autocalibration in the MYWQM at the three sites simultaneously. Similarly TSS, TN and TP parameters from Table 4.6 were used for TSS, TN and TP autocalibration at the three sites simultaneously.

Table 4.6 Parameters selected for autocalibration in the MYWQM

Q Parameters	TSS, TN and TP Parameters
ALPHA_BF	CH_COV
CANMX	CH_EROD
CH_K2	NPERCO
CH_N2	PHOSKD
CN2	PPERCO
EPCO	RCHRG_DP
ESCO	SOL_LABP
GW_DELAY	SOL_NO3
GW_REVAP	SOL_ORGN
GWQMN	SOL_ORGP
SLOPE	SPCON
SOL_AWC	SPEXP
SOL_K	USLE_P
SOL_Z	
SURLAG	

4.4. CALIBRATION AND VALIDATION OF THE MYWQM

As discussed in Section 2.5.1, calibration and validation are essential for physically-based distributed models to get reliable outputs from these models. Traditionally calibration is performed manually. Manual calibration of physics-based distributed catchment models like SWAT is difficult because of large number of parameters and almost infeasible in many large-scale applications. However, manual calibration forces the user to better understand the model, the important processes in the catchment and parameter sensitivity. On the other hand, autocalibration is powerful and labor saving that can be used to substantially reduce the frustration and subjectivity that often characterize manual calibrations (Van Liew et al, 2005). If it is used in combination with a manual approach, the autocalibration tool shows promising results in providing initial estimates for model parameters. Van Liew et al (2005) suggested that autocalibration be attempted first, followed by manual calibration, to ensure that average annual means and the general balances are correct. Another approach as suggested by Jeong et al (2010) is to perform manual calibration first on the average annual hydrologic balance and average annual loads (minimizing percent bias).

Calibration and validation are typically performed by splitting the available observed data into two datasets: one for calibration, and another for validation. Data are most frequently split by time periods, carefully ensuring that wet, moderate, and dry years occur in both periods (Gan et al, 1997). This is often not feasible due to limitations in the length of monitoring data available for calibration and validation. A contrasting view from Reckhow (1994) contends that validation conditions should be different in the sense that the important processes and forcing functions or responses differ from the calibrated conditions, as the purpose of validation is to provide an independent assessment of model performance. If a longer time period is available for hydrology than water quality data, it is important to use all the hydrology data available for calibration and validation to capture long-term trends (Arnold et al, 2012). In addition, because of greater uncertainty, sediment and nutrients are calibrated at a monthly and annual scale only.

As discussed in Section 2.5.1, in most catchment modelling studies streamflow, sediment and nutrients are calibrated at one monitoring site, usually at the catchment outlet, which does not consider how well the model predicts catchment response at all other locations within the catchment. Also when water quality models include multi-variable (streamflow, sediment and nutrients), correlations between one parameter and multiple output variables often complicate the multi-variable calibration process. In this case, a step-by-step calibration in a logical order is performed (Madsen, 2003). However, in each of the steps in the step-by-step calibration process, only part of the available information is being used. In addition, this approach also incorporates the risk of accumulation of the errors (model errors, and errors on the input and output variables) to the end step. A multi-site and multi-objective calibration, using all the output variables simultaneously (multi-variable) during the calibration process, allows the use of all the available information that can contribute to the identification of the parameters reducing complexity in the calibration process (van Griensven et al, 2002).

Initially, the MYWQM was calibrated manually at the three sites following the steps provided by Santhi et al (2001a) as shown in the flow diagram of Figure 2.8 in Section 2.5.1. Only the basic parameters related to hydrology, erosion and water quality as shown in Figure 2.8 and the in-stream process parameters from Table 4.7 were adjusted manually to get the simulated outputs reasonably close to the observed values (minimizing percent bias). Also runoff and baseflow components were adjusted during this step. Finally autocalibration was completed at the 3 sites at a time considering all the sensitive parameters from Table 4.6. After autocalibration, additional fine-tuning was done manually for some parameters.

Table 4.7 Parameters mainly related to in-stream water quality in SWAT2005

Name	Min	Max	Description	Process
AI0	10	100	Ratio of chlorophyll-a to algal biomass	In-stream
AI1	0.07	0.09	Fraction of algal biomass that is nitrogen	In-stream
AI2	0.01	0.02	Fraction of algal biomass that is phosphorus	In-stream
BC1	0.1	1	Rate const. for bio. oxidation of NH4 to NO2 at 20°C [1/day]	In-stream
BC2	0.2	2	Rate const. for bio. oxidation of NO2 to NO3 at 20°C [1/day]	In-stream
BC3	0.2	0.4	Rate const. for hydro. of organic N to NH4 at 20°C [1/day]	In-stream
BC4	0.01	0.7	Rate const. for minerali. of organic P to diss. P at 20°C [1/day]	In-stream
RCN	0	15	Concentration of nitrogen in rainfall [mg N/l]	Nutrient cycling
RS1	0.15	1.82	Local algal settling rate in the reach at 20°C [m/day]	In-stream
RS2	0.001	0.10	Benthic (Sedi.) source rate for diss. Phosph.at 20°C [mg/m^{2}day]	In-stream
RS3	0	1	Benthic (Sedi.) source rate for NH4-N at 20°C [mg/m^{2}day]	In-stream
RS4	0.001	0.10	Rate coefficient for organic N settling at 20°C [1/day]	In-stream
RS5	0.001	0.10	Organic phosphorus settling rate in the reach at 20°C [1/day]	In-stream
RSDCO	0.02	0.10	Residue decomposition coefficient	Nutrient cycling

Streamflow (Q) was calibrated from 1990 to 2002 and validated from 2003 to 2008 at the three sites in the MYC. Similarly, sediment (TSS) and nutrients (TN, TP) were calibrated from 1998 to 2004 and validated from 2005 to 2008. A longer calibration period for streamflow was considered, because a longer data series was available for streamflow which can be used to capture all possible variations in stremflow pattern (wet, moderate and dry years). Also the streamflow, sediment and nutrient data sets were split for calibration and validation periods in such a way that the conditions at each period are different. The ParaSol (SCE-UA) tool embedded in SWAT2005 was used for multi-site (3 sites), multi-variable (Q, TSS, TN and TP) and multi-objective (one objective for each variable) autocalibration and uncertainty analysis in the MYWQM. Details of ParaSol were discussed in Section 2.5.1.4(B). Since the calibration periods for streamflow, and sediment and nutrients were different, first streamflow was calibrated at the three sites simultaneously. Then sediment and nutrients were calibrated at three sites simultaneously.

The performance of a model is evaluated using graphical and statistical techniques to determine the quality and reliability of the predictions when compared to observed values. Moriasi et al (2007) thoroughly reviewed the water quality model evaluation statistics in detail, and recommended three quantitative statistics (i.e. Nash-Sutcliffe efficiency (E_{NS}^2), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR)), in addition to the graphical techniques, be used in model evaluation. The optimal value of RSR and PBIAS is 0; and positive and negative values of PBIAS indicate model underestimation and overestimation bias respectively. As per Moriasi et al (2007), in general model simulation can be judged as satisfactory if $E_{NS}^2 > 0.50$ and RSR ≤ 0.70, and if PBIAS $< \pm 25\%$ for streamflow, PBIAS $< \pm 55\%$ for sediment (TSS), and PBIAS $< \pm 70\%$ for nutrients (TN and TP) for a monthly time step (and that appropriate relaxing and tightening of the standard be performed for daily and annual time step evaluations respectively). In addition to these three evaluation statistics, the coefficient of determination (R^2) was also considered in the MYWQM. Details about these objective functions were discussed in Section 2.5.3.

4.4.1. STREAMFLOW (Q)

As discussed in Section 3.3.2.2(A), the streamflow calibration period 1990-2002 includes both wet and dry years. However, the validation period 2003-2008 is mainly dry. Ten years of warm-up period was considered before calibration and validation periods. As per the SWAT manual (Neitsch et al, 2004), the use of the warm-up period becomes more important as the simulation periods of interest shortens. For 30 year simulations, a warm-up period is optional (Neitsch et al, 2004). For a simulation covering 5 years or less, a warm-up period is recommended. A reasonable warm-up period is essential to get the hydrologic cycle fully operational based on the catchment topography and climate. However, longer warm-up period increases the simulation time during autocalibration.

Runoff and baseflow were also calibrated manually since an incorrect representation of the baseflow and surface runoff can cause wrong estimates of sediment and pollutant loads in the MYC. As per Grayson et al (1999b), accurate estimation of catchment water balance is a vital prerequisite for water quality modelling. As discussed in Section 3.3.2.2(A), the “Baseflow Filter Program” software was used to separate observed total streamflow into surface runoff and baseflow. To keep consistency, the simulated streamflow was also separated into surface runoff and baseflow component using the “Baseflow Filter Program” software, and compared with observed data (Santhi et al, 2006). Baseflow contributes on average 75% of observed total streamflow in the MYC whereas in the MYWQM, it is 77%.

4.4.1.1. CALIBRATION

The calibrated values of the parameters governing streamflow which were finally used in the MYWQM are shown in Table 4.8. Values of some parameters vary among the sub-catchments and HRUs which are changed multiplying by a number during calibration process (instead of replacing it) as shown by the word “Varied” in Table 4.8.

Table 4.8 Calibrated parameters governing streamflow in the MYWQM

Q Parameters	Default value	Changed value after calibration		
		Site-1	Site-2	Site-3
ALPHA_BF	0.048	0.913	0.186	0.45
CANMX	0	3.345	8	8
CH_K2	0	94.515	50	50
CH_N2	0.043	0.01	0.031	0.031
CN2	Varied	Varied*0.68	Varied*0.763	Varied*0.7644
EPCO	1	0.49	0.30	0.85
ESCO	0.95	0.001	0.91	0.10
GW_DELAY	31	21	21	21
GW_REVAP	0.02	0.144	0.20	0.20
GWQMN	0	3000	4700	4950
SLOPE	Varied	Varied*0.345	Varied*0.46	Varied*0.4955
SOL_AWC	Varied	Varied*0.433	Varied*0.462	Varied*0.3742
SOL_K	Varied	Varied*0.343	Varied*0.457	Varied*0.2273
SOL_Z	Varied	Varied*1.174	Varied*0.95	Varied*0.95
SURLAG	4	2.466	2.466	2.466

“Varied” means value of the parameter varies among the sub-catchments and HRUs in the catchment.

The daily, monthly and annual calibration statistics for streamflow at the 3 sites are shown in Tables 4.9 to 4.11 respectively. The results are also presented graphically in Figures 4.2 to 4.19. In general, the calibration results showed good agreement between observed and simulated flows (total streamflow, baseflow and runoff) without any unsatisfactory ratings as can be seen in Tables 4.9 to 4.11 based on the Moriasi et al (2007) guidelines (shown on the same page along with Tables 4.9 to 4.11). Moreover, the model underestimated flows in wet years but overestimated in dry years. Details are discussed in the following sections.

(A) SITE-1

As per the Moriasi et al (2007) guidelines on model performance ratings, the MYWQM performance was very good for monthly and annual total streamflow ($E_{NS}^2 > 0.75$, $R^2 > 0.75$, RSR < 0.50, and PBIAS ≤ 10% as shown in Tables 4.9 to 4.11), and satisfactory for daily total streamflow ($E_{NS}^2 > 0.50$, $R^2 > 0.60$, RSR < 0.70, and PBIAS ≤ 10% as shown in Tables 4.9 to 4.11). Similarly daily, monthly and annual baseflow and runoff calibrations were satisfactory at site-1. Daily runoff calibration was considered satisfactory, although E_{NS}^2 value was 0.49 < 0.50, and RSR value was 0.72 > 0.70. Since the Moriasi et al (2007) guidelines were for monthly time step, some relaxing on the guideline was considered for the daily step as suggested by Arnold et al (2012).

In general, the MYWQM underestimated flows in wet years (1990-1996) and overestimated flows in dry years (1997-2002) as shown in Figures 4.2, 4.4 and 4.6 with some exceptions (e.g. total streamflow and baseflow in the years of 1995 and 1996 as shown in Figures 4.4 and 4.6) which is consistent with other SWAT studies. The scatter plots of the flows (as shown in Figures 4.3, 4.5 and 4.7) show that the model overall underestimated daily, monthly and annual total streamflow, baseflow and runoff in the calibration period at site-1. This can also be seen in Tables 4.9 to 4.11 where PBIAS values are positive which means underestimation. Also the runoff underestimation was higher than the baseflow as can be seen in Figures 4.3, 4.5 and 4.7, and in Tables 4.9 to 4.11 where runoff PBIAS values are higher. Moreover, the recession limbs’ bottom out at site-1 as shown in Figures 4.2 and 4.4 for baseflow means that the Woori Yallock creek is an intermittent creek i.e. it may cease flowing during dry periods.

Table 4.9 Daily streamflow calibration statistics for period 1990-2002

Calibration	Total streamflow				Baseflow				Runoff			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.62	0.61	10	0.62	0.76	0.55	5	0.67	0.51	**0.49**	20	**0.72**
Site-2	0.86	0.85	6	0.38	0.92	0.92	1	0.29	0.67	0.66	21	0.58
Site-3	0.78	0.77	10	0.48	0.90	0.87	6	0.36	0.50	**0.42**	23	**0.76**

Table 4.10 Monthly streamflow calibration statistics for period 1990-2002

Calibration	Total streamflow				Baseflow				Runoff			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.81	0.79	10	0.45	0.83	0.60	6	0.63	0.66	0.59	20	0.64
Site-2	0.94	0.93	6	0.27	0.93	0.93	2	0.26	0.91	0.84	21	0.40
Site-3	0.93	0.89	10	0.34	0.93	0.89	6	0.33	0.84	0.80	23	0.45

Table 4.11 Annual streamflow calibration statistics for period 1990-2002

Calibration	Total streamflow				Baseflow				Runoff			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.85	0.79	10	0.46	0.86	0.64	6	0.60	0.84	0.63	20	0.60
Site-2	0.96	0.92	6	0.28	0.95	0.94	2	0.25	0.98	0.79	21	0.46
Site-3	0.96	0.87	10	0.36	0.95	0.88	6	0.35	0.97	0.76	23	0.49

R^2 = Coefficient of determination
E_{NS}^2 = Nash-Sutcliffe efficiency
PBIAS = Percent bias
RSR = ratio of the root mean square error (RMSE) to the standard deviation of observed data

The **bold** numbers in the tables do not satisfy the Moriasi et al (2007) satisfactory criteria.

General performance ratings for recommended statistics for monthly time step (Moriasi et al, 2007)

Performance	RSR	E_{NS}^2	PBIAS (%)		
Rating			Q	TSS	TN and TP
Very good	$0.00 \leq RSR \leq 0.50$	$0.75 < E_{NS}^2 \leq 1.00$	PBIAS $< \pm10$	PBIAS $< \pm15$	PBIAS$< \pm25$
Good	$0.50 < RSR \leq 0.60$	$0.65 < E_{NS}^2 \leq 0.75$	$\pm10 \leq$ PBIAS $< \pm15$	$\pm15 \leq$ PBIAS $< \pm30$	$\pm25 \leq$ PBIAS $< \pm40$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < E_{NS}^2 \leq 0.65$	$\pm15 \leq$ PBIAS $< \pm25$	$\pm30 \leq$ PBIAS $< \pm55$	$\pm40 \leq$ PBIAS $< \pm70$
Unsatisfactory	$RSR > 0.70$	$E_{NS}^2 \leq 0.50$	PBIAS $\geq \pm25$	PBIAS $\geq \pm55$	PBIAS $\geq \pm70$

Some of the overestimation in dry periods could be due to the underestimation of the extraction of water by irrigators, since the timing of the extraction is difficult to assess due to the use of storage tanks. The irrigators could also be using groundwater, which was not considered in the MYWQM. Also the SWAT model diverts threshold daily maximum irrigation water from a reach when streamflow exceeds threshold minimum flow in the reach. This means there is more possibility of maximum irrigation water diversion in the model during wet periods when reaches run full (i.e. underestimation in SWAT streamflow), but in reality maximum irrigation is applied in dry periods (i.e. less water diversion in SWAT, hence overestimation).

Moreover, the transmission losses are often dynamic (Dunkerley and Brown, 1999; Lange, 2005) with large losses occurring during low flows and small floods, and much lower losses occurring during large floods (only in the floodplain). In addition, during the flood recession, transmission losses might actually be negative as water might be added to the river from floodplain storage (Rassam et al, 2006). In SWAT the routing and reach file parameters in the model are however static and apply for the whole periods of study (Vervoort, 2007). Other reasons may be due to the uncertainties in rainfall spatial distributions and also use of static land uses in the MYWQM.

The simulation results of the MYWQM were consistent with other SWAT studies. Green and Van Griensven (2008) found that SWAT overestimates runoff in the dry periods and underestimates in the wet periods. Similarly, Kirsch et al (2002) found that SWAT underestimates runoff during extremely wet years. Vervoort (2007) applied SWAT2000 for modelling hydrology in the Mooki catchment in NSW (Australia), and found that the model in general underestimates the peak runoff and over predicts many of the lower flows and some of the smaller peaks. Watson et al (2003) evaluated SWAT for modelling the water balance of the Woady Yaloak River catchment in Victoria (Australia), and found that SWAT overestimates the low flows. Bouraoui et al (2002b) also found similar results in the Yorkshire Ouse catchment, UK.

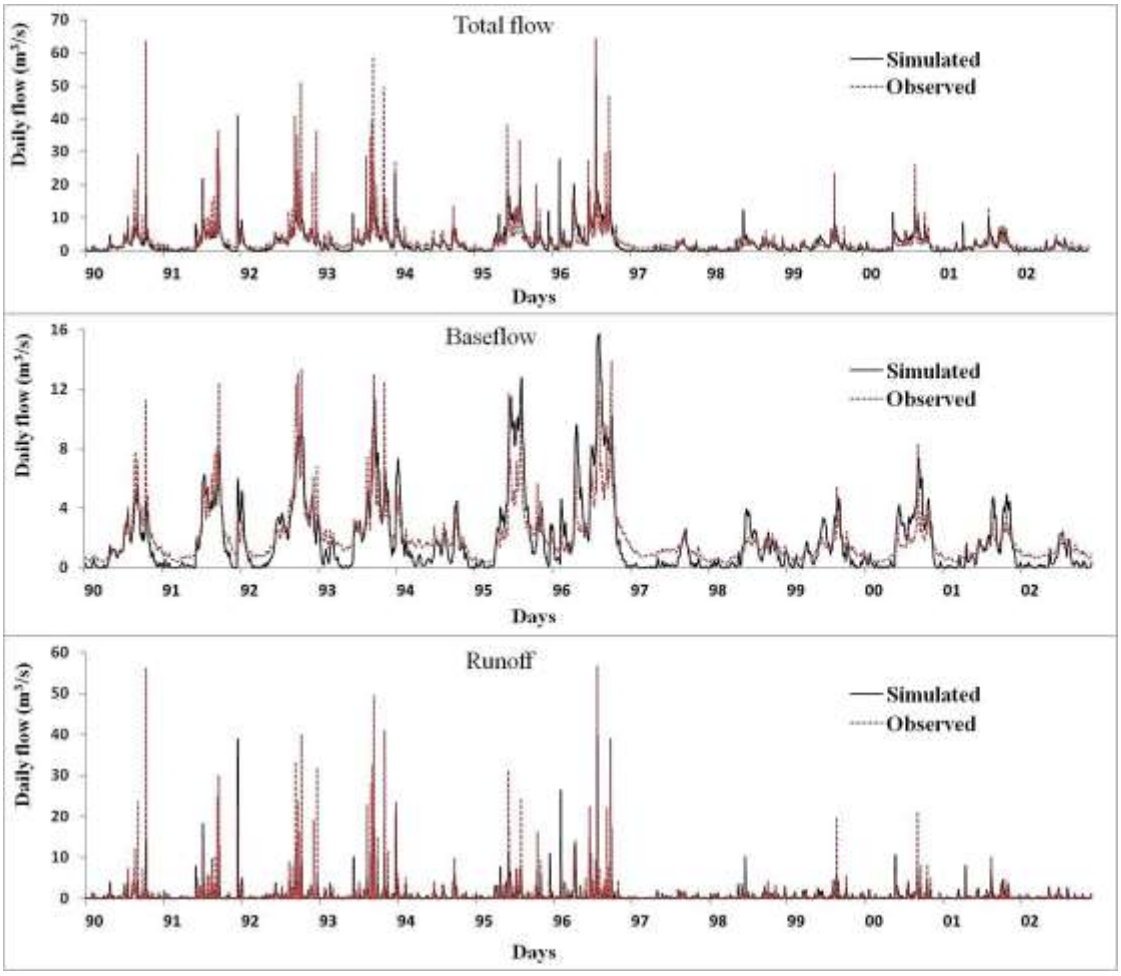


Figure 4.2 Calibration of daily flows at site-1

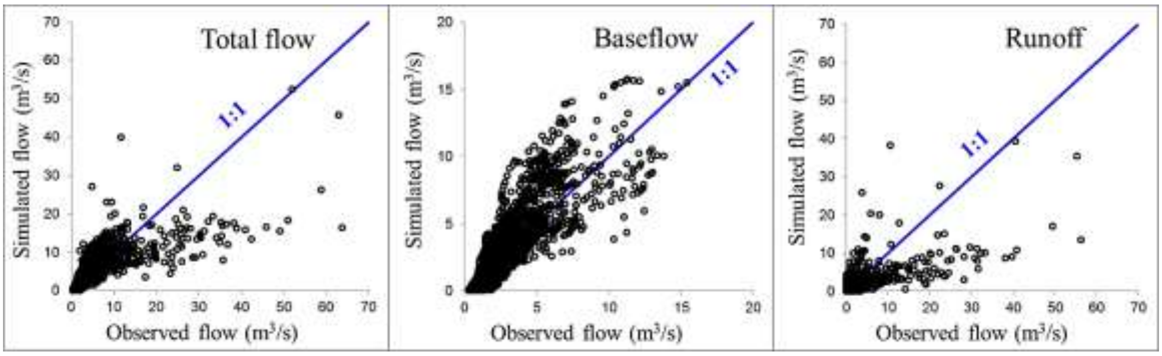


Figure 4.3 Scatterplot of daily flows for calibration at site-1

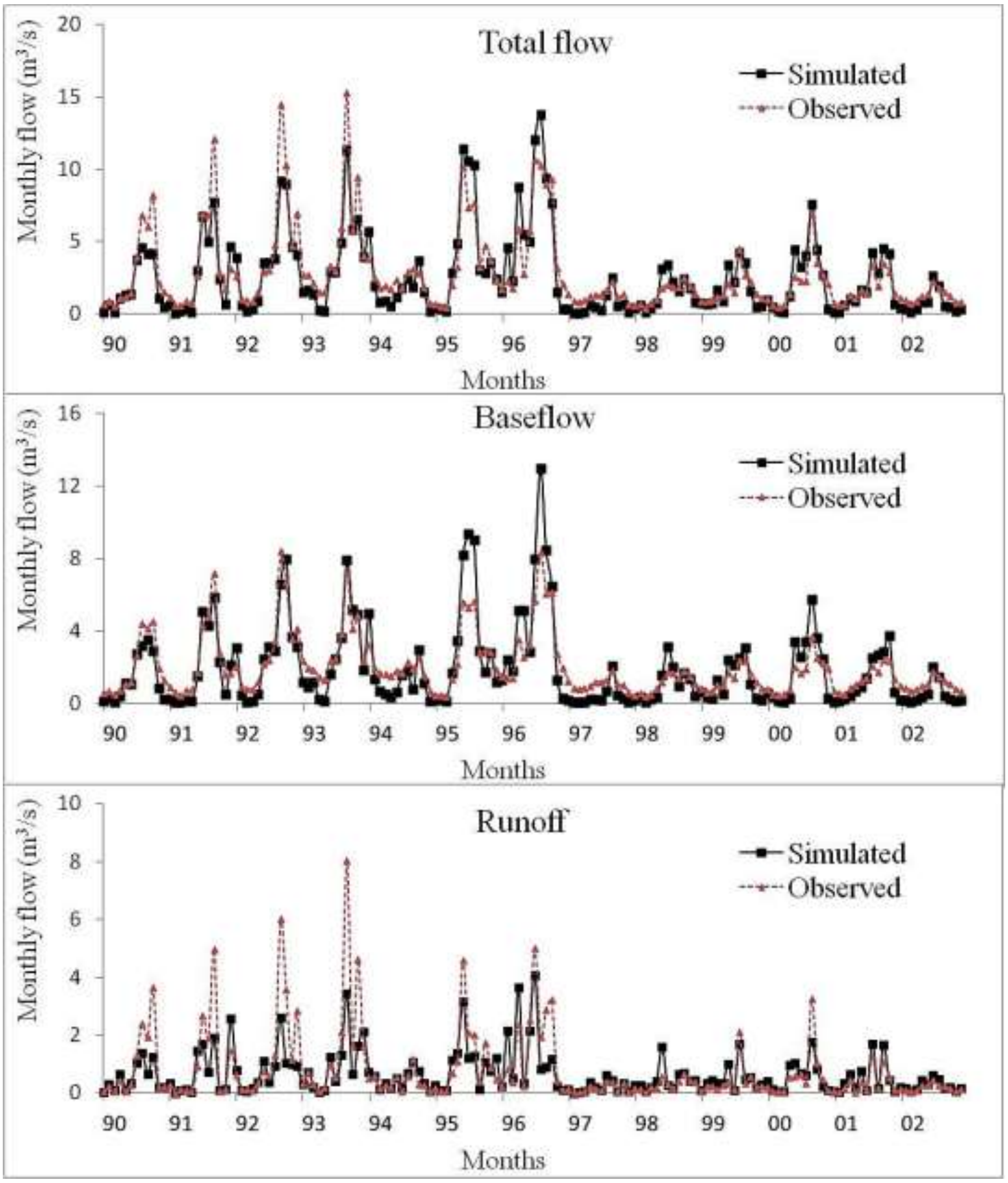


Figure 4.4 Calibration of monthly flows at site-1

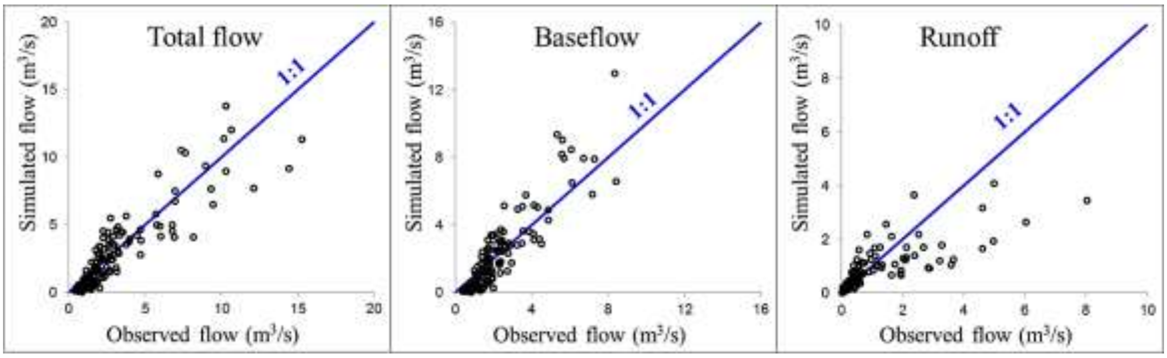


Figure 4.5 Scatterplot of monthly flows for calibration at site-1

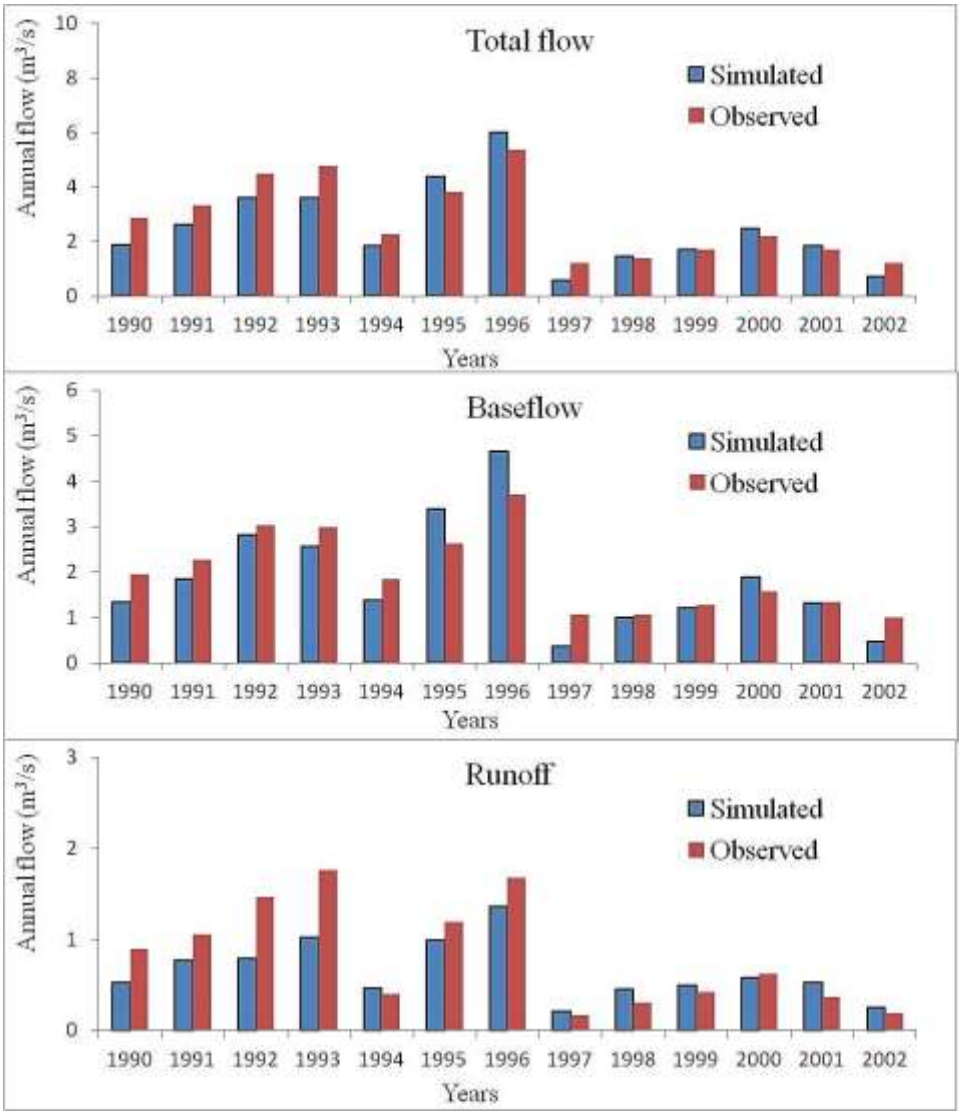


Figure 4.6 Calibration of annual flows at site-1

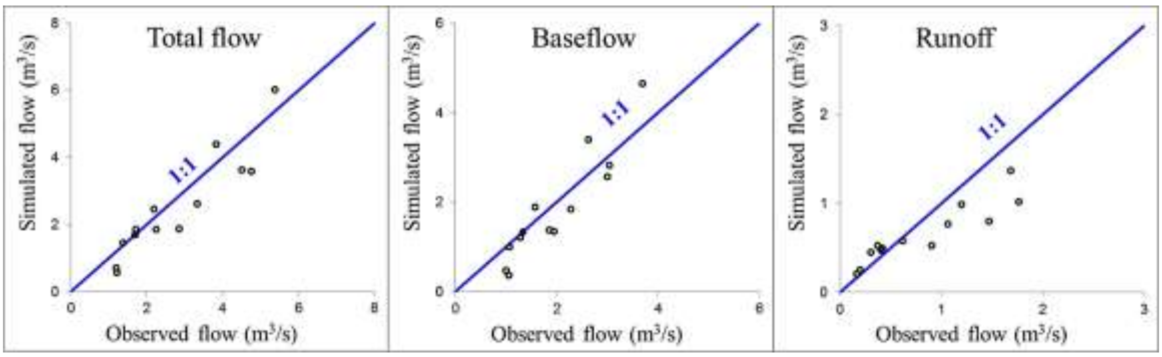


Figure 4.7 Scatterplot of annual flows for calibration at site-1

(B) SITE-2

The MYWQM performance was very good for daily, monthly and annual total streamflow and baseflow at site-2 ($E_{NS}^2 > 0.75$, $R^2 > 0.75$, RSR < 0.50, and PBIAS ≤ 10% as shown in Tables 4.9 to 4.11). Similarly daily, monthly and annual runoff calibrations were considered as satisfactory at site-2 ($E_{NS}^2 > 0.65$, $R^2 > 0.65$, RSR < 0.60, but PBIAS <25% as shown in Tables 4.9 to 4.11) because PBIAS was below the good performance rating.

Similar like at site-1, the MYWQM underestimated flows in wet years (1990-1996) and overestimated flows in dry years (1997-2002) as shown in Figures 4.8, 4.10 and 4.12 at site-2. The scatter plots of the flows (as shown in Figures 4.9, 4.11 and 4.13) show that the model overall underestimated daily, monthly and annual total streamflow, baseflow and runoff in calibration at site-2. This can also be seen in Tables 4.9 to 4.11 where PBIAS values are positive which means underestimation. However, the underestimation rate was lower at site-2 than at site-1. Also the runoff underestimation was much higher than the baseflow as can be seen in Figures 4.9, 4.11 and 4.13, and in Tables 4.9 to 4.11 where runoff PBIAS values are much higher. Some possible reasons for underestimation and overestimation patterns of the MYWQM were discussed in the section of site-1 along other similar SWAT studies.

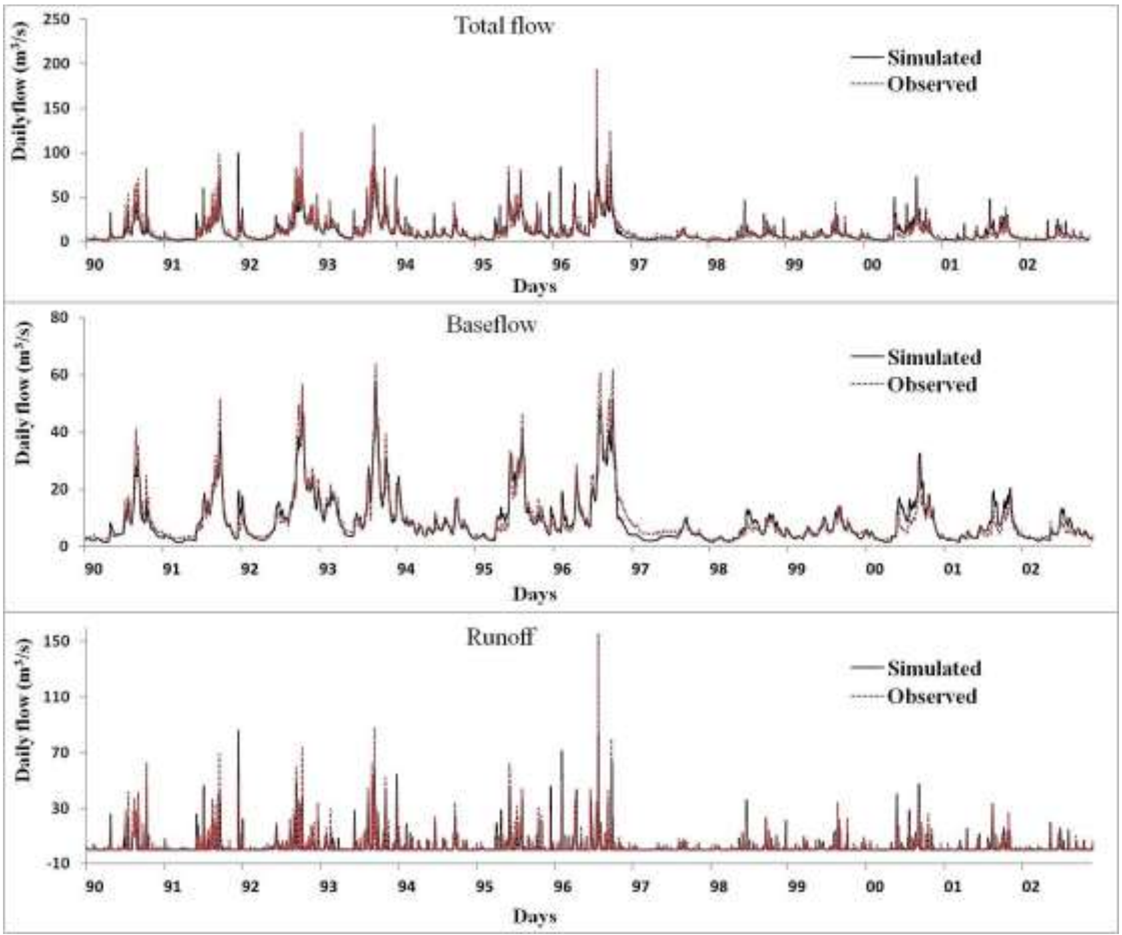


Figure 4.8 Calibration of daily flows at site-2

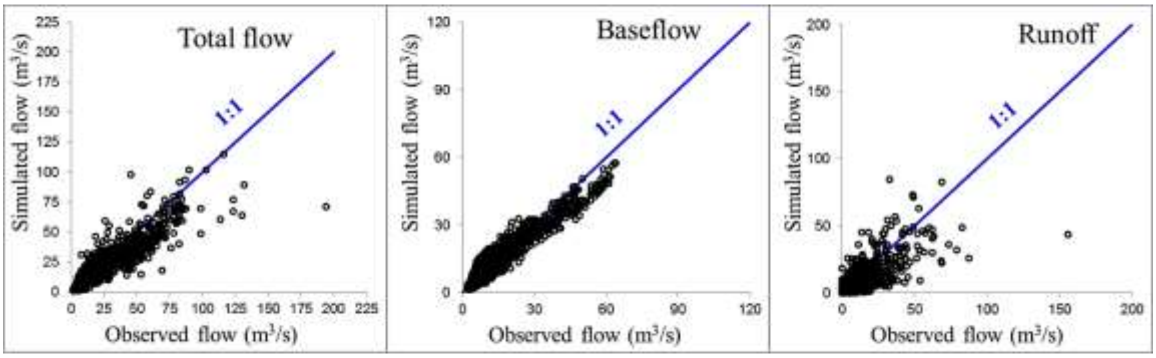


Figure 4.9 Scatterplot of daily flows for calibration at site-2

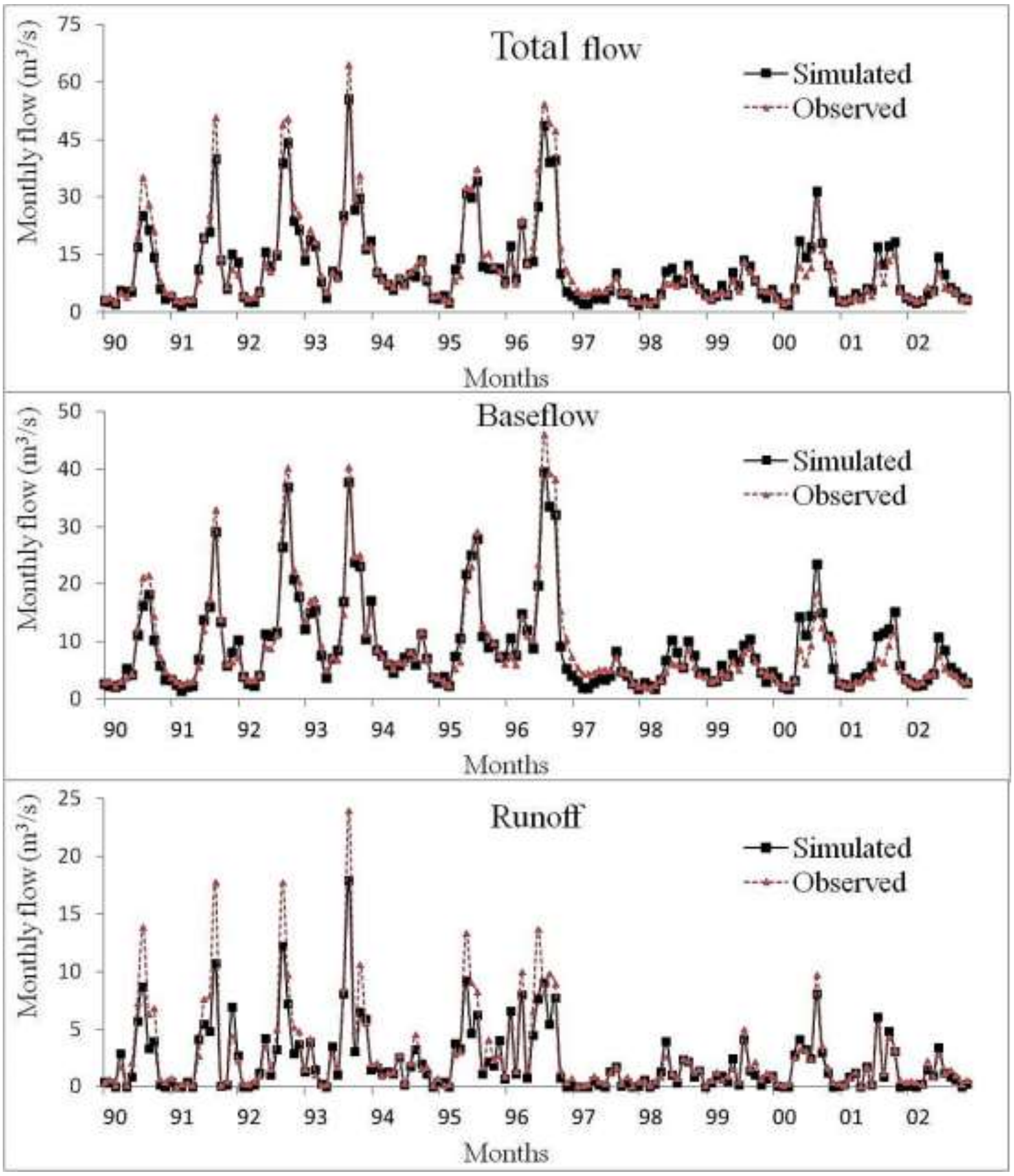


Figure 4.10 Calibration of monthly flows at site-2

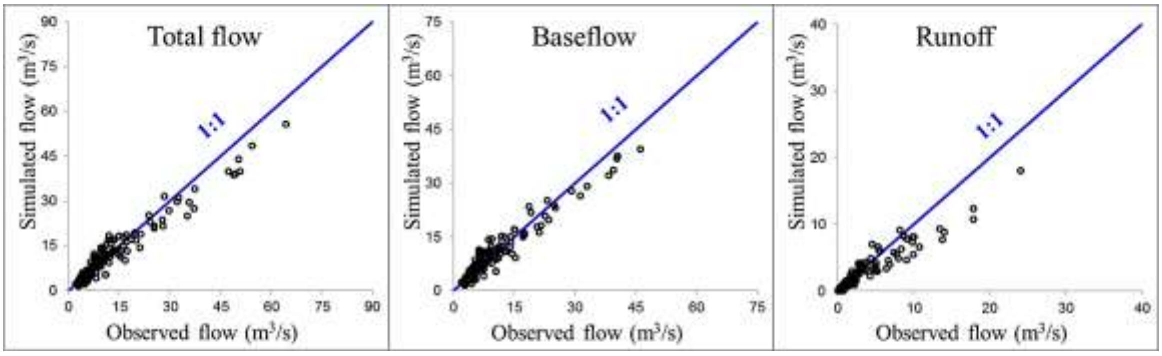


Figure 4.11 Scatterplot of monthly flows for calibration at site-2

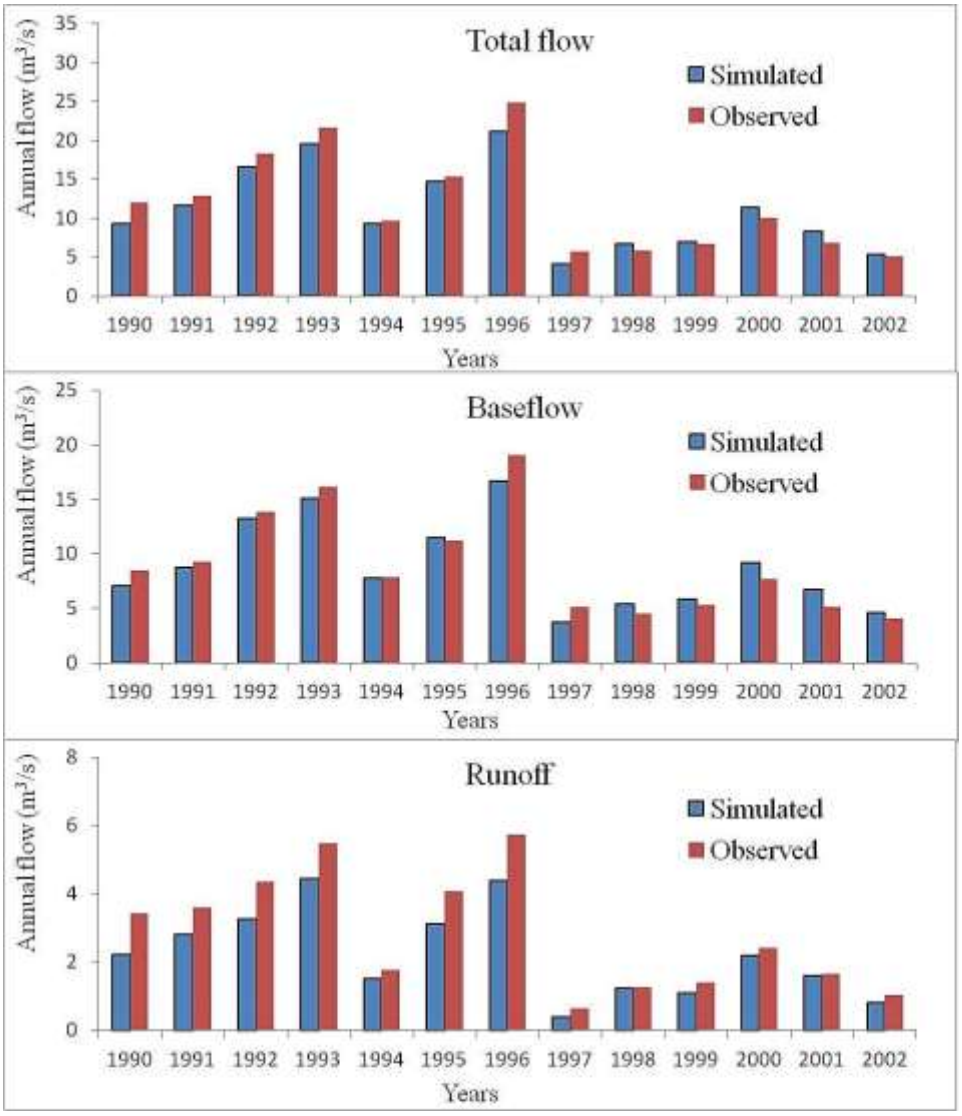


Figure 4.12 Calibration of annual flows at site-2

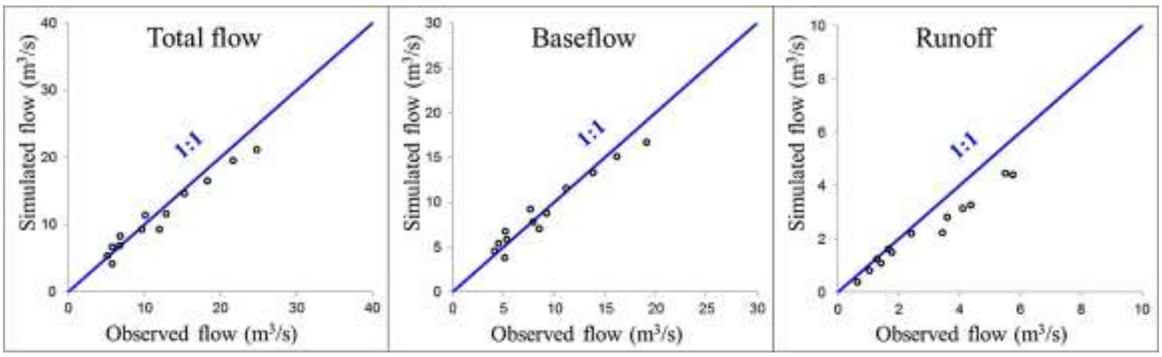


Figure 4.13 Scatterplot of annual flows for calibration at site-2

(C) SITE-3

The MYWQM performance was very good for daily, monthly and annual total streamflow and baseflow (E_{NS}^2 > 0.75, R^2 > 0.75, RSR < 0.50, and PBIAS ≤ 10% as shown in Tables 4.9 to 4.11). Similarly daily, monthly and annual runoff calibrations were satisfactory at site-3. Daily runoff calibration was considered satisfactory although E_{NS}^2 value was 0.42 < 0.50, and RSR value was 0.76 > 0.70. Since the Moriasi et al (2007) guidelines were for monthly time step, some relaxing on the guideline was considered for the daily step.

Similar like at site-1 and site-2, the MYWQM underestimated flows in wet periods (1990-1996) and overestimated flows in dry periods (1997-2002) as shown in Figures 4.14, 4.16 and 4.18 at site-3 except annual runoff at Figure 4.18. The scatter plots of the flows (as shown in Figures 4.15, 4.17 and 4.19) show that the model overall underestimated daily, monthly and annual total streamflow, baseflow and runoff in the calibration period at site-2. This can also be seen in Tables 4.9 to 4.11 where PBIAS values are positive which means underestimation. Also the runoff underestimation was much higher than the baseflow as can be seen in Tables 4.9 to 4.11 where runoff PBIAS values are much higher. Some possible reasons for underestimation and overestimation patterns of the MYWQM were discussed in the section of site-1 along other similar SWAT studies.

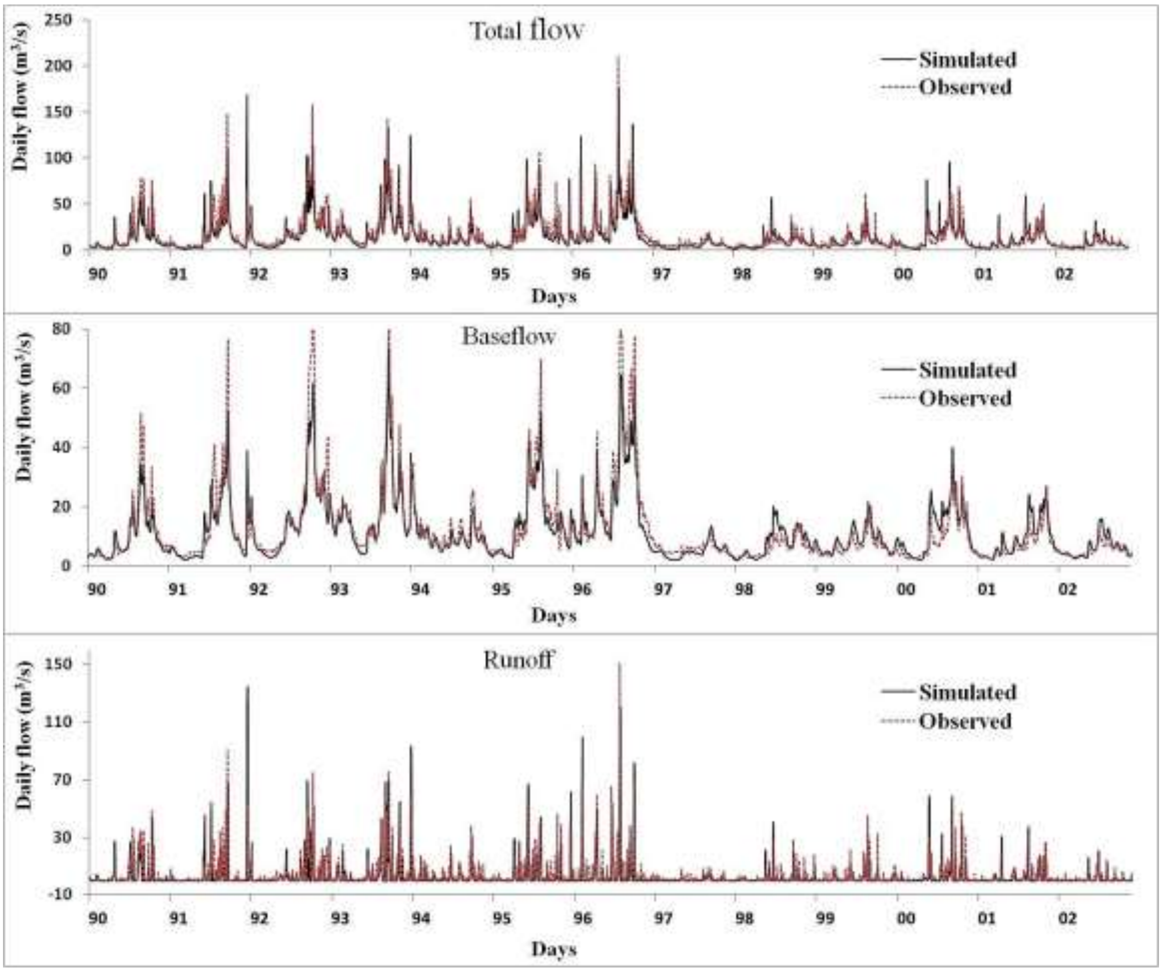


Figure 4.14 Calibration of daily flows at site-3

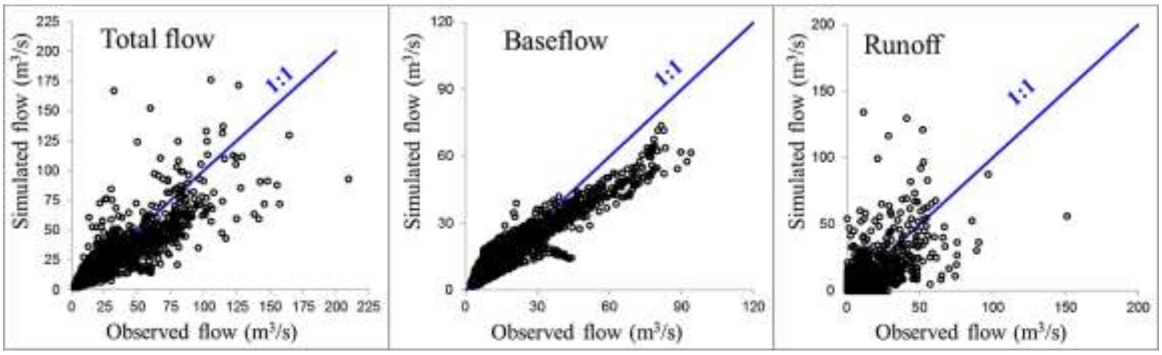


Figure 4.15 Scatterplot of daily flows for calibration at site-3

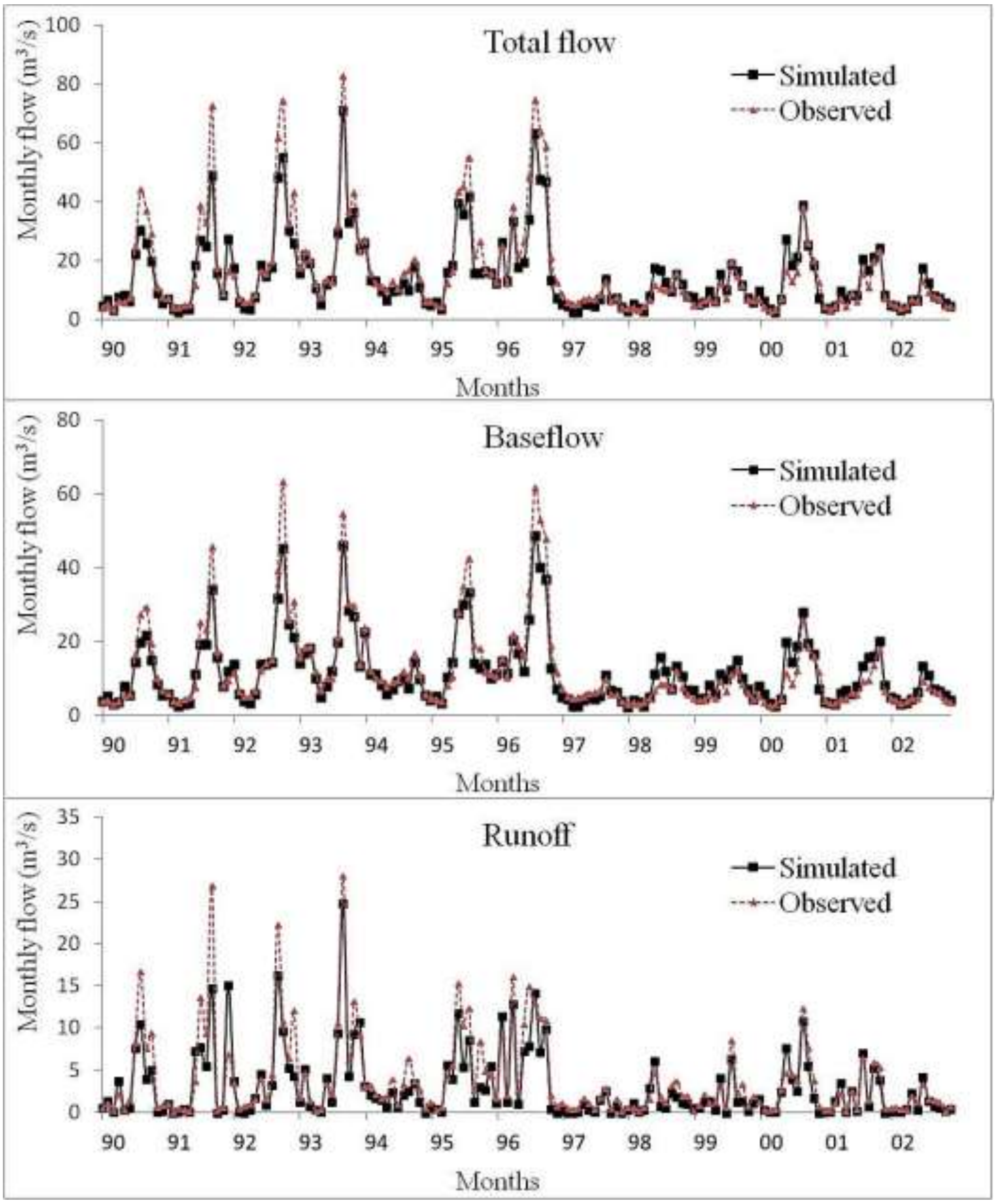


Figure 4.16 Calibration of monthly flows at site-3

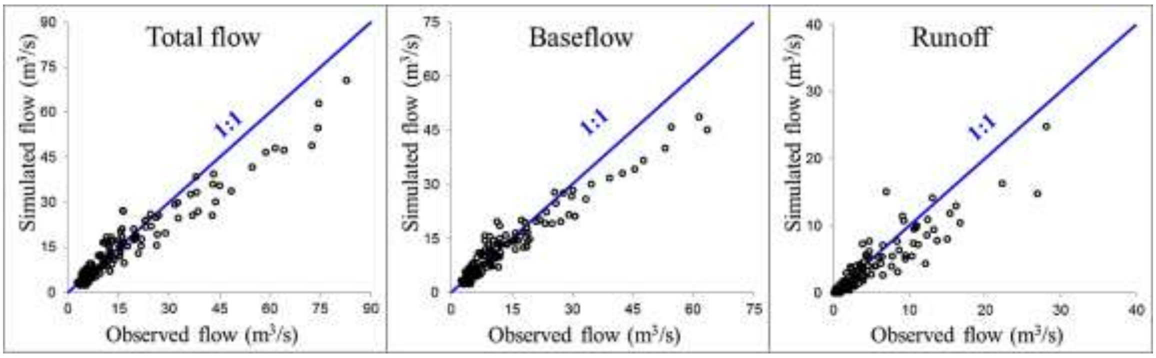


Figure 4.17 Scatterplot of monthly flows for calibration at site-3

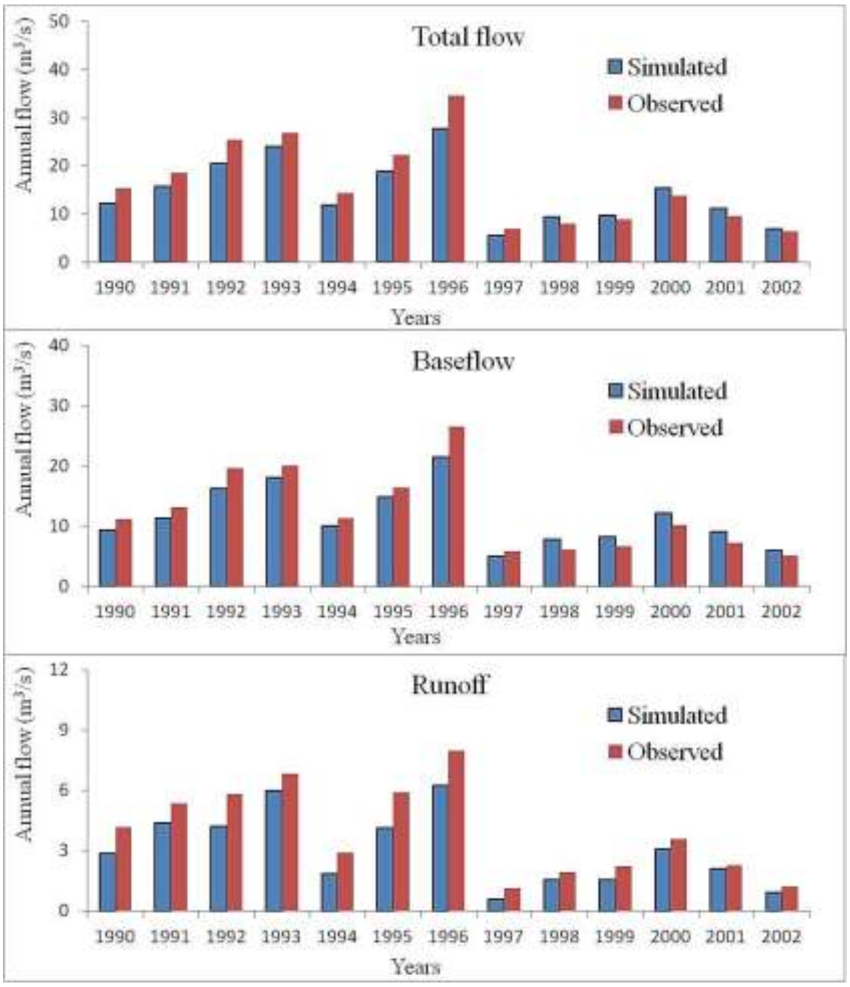


Figure 4.18 Calibration of annual flows at site-3

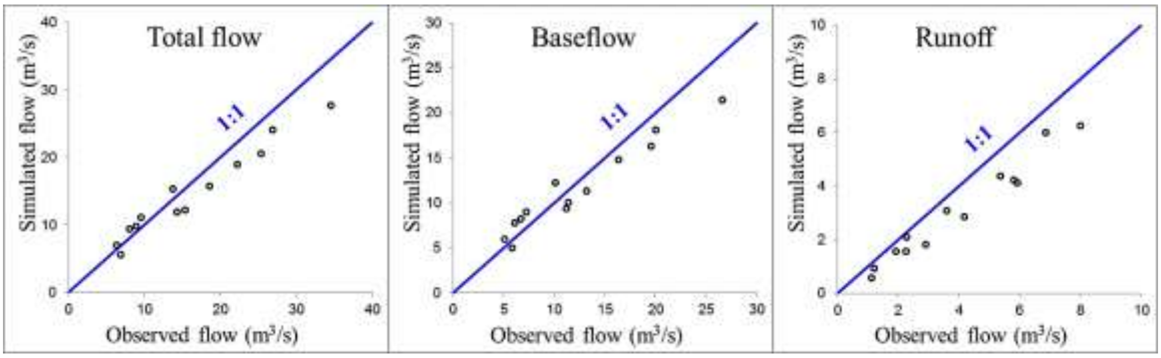


Figure 4.19 Scatterplot of annual flows for calibration at site-3

4.4.1.2. VALIDATION

The daily, monthly and annual validation statistics for streamflow at the three sites are shown in Tables 4.12 to 4.14 respectively. The results are also presented graphically in Figures 4.20 to 4.37. In general, the validation results showed good to satisfactory agreement between observed and simulated flows with some exceptions (at site-1) as can be seen in Tables 4.12 to 4.14 based on the Moriasi et al (2007) guidelines (shown on the same page along with Tables 4.12 to 4.14).). Moreover, the model underestimated flows in wet years but overestimated in dry years. Details are discussed in the following sections.

(A) SITE-1

As per the Moriasi et al (2007) guidelines on model performance ratings, the MYWQM performance was satisfactory for daily and monthly total streamflow (E_{NS}^2 > 0.70, R^2 > 0.70, RSR < 0.60, and PBIAS < 25% as shown in Tables 4.12 to 4.14), but unsatisfactory for annual total streamflow (E_{NS}^2 < 0.50 and RSR > 0.70 as shown in Tables 4.12 to 4.14). Also daily, monthly and annual baseflow validation was unsatisfactory (mainly because of higher PBIAS > 25% value). However, the validation results for daily, monthly and annual runoff was good compared to other flows at this site (E_{NS}^2 > 0.65, R^2 > 0.70, RSR < 0.60, and PBIAS < 15% as shown in Tables 4.12 to 4.14).

Within the validation period (2003-2008), 2006-2008 is drier compared to 2003-2005. So like the calibration, in general the model underestimated flows in wet years (2003-2005) and overestimated flows in dry years (2006-2008) as shown in Figures 4.20, 4.22 and 4.24 with the exceptions for total streamflow and baseflow in 2006. The scatter plots of the flows (as shown in Figures 4.21, 4.23 and 4.25) show that the model overall underestimated daily, monthly and annual total streamflow, baseflow and runoff in validation period. This underestimation rate is much higher (mainly because of baseflow as can be seen in Tables 4.12 to 4.14 with higher positive PBIAS values compared to the values in Tables 4.9 to 4.11) compared to the calibration period, although validation period is much drier than the calibration period. This is because of the intermittent nature of the Woori Yallock creek at site-1 as shown in Figures 4.20 and 4.22. This means the recession limbs' bottom out is more in the validation period. Hence the model under predicted the baseflow more compared to the calibration periods.

Table 4.12 Daily streamflow validation statistics for period 2003-2008

Calibration	Total streamflow				Baseflow				Runoff			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.73	0.70	21	0.55	0.65	0.51	**26**	0.70	0.74	0.71	11	0.54
Site-2	0.75	0.75	1	0.50	0.81	0.80	-6	0.44	0.64	0.62	20	0.61
Site-3	0.74	0.72	-3	0.53	0.79	0.77	-11	0.48	0.67	0.53	19	0.69

Table 4.13 Monthly streamflow validation statistics for period 2003-2008

Calibration	Total streamflow				Baseflow				Runoff			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.80	0.76	22	0.49	0.71	0.56	**26**	0.66	0.85	0.77	11	0.47
Site-2	0.88	0.88	1	0.35	0.83	0.83	-6	0.41	0.87	0.85	19	0.39
Site-3	0.82	0.82	-3	0.43	0.81	0.79	-11	0.46	0.82	0.79	19	0.46

Table 4.14 Annual streamflow validation statistics for period 2003-2008

Calibration	Total streamflow				Baseflow				Runoff			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.77	**0.49**	20	**0.72**	0.67	**0.22**	**26**	**0.89**	0.82	0.65	11	0.59
Site-2	0.94	0.85	1	0.38	0.90	0.77	-6	0.48	0.98	0.77	19	0.47
Site-3	0.87	0.81	-3	0.43	0.84	0.71	-11	0.54	0.87	0.70	19	0.55

R^2 = Coefficient of determination
E_{NS}^2 = Nash-Sutcliffe efficiency
PBIAS = Percent bias
RSR = ratio of the root mean square error (RMSE) to the standard deviation of observed data

The **bold** numbers in the tables do not satisfy the Moriasi et al (2007) satisfactory criteria.

General performance ratings for recommended statistics for a monthly time step (Moriasi et al, 2007)

Performance	RSR	E_{NS}^2	PBIAS (%)		
Rating			Q	TSS	TN and TP
Very good	$0.00 \leq RSR \leq 0.50$	$0.75 < E_{NS}^2 \leq 1.00$	PBIAS $< \pm 10$	PBIAS $< \pm 15$	PBIAS$< \pm 25$
Good	$0.50 < RSR \leq 0.60$	$0.65 < E_{NS}^2 \leq 0.75$	$\pm 10 \leq$ PBIAS $< \pm 15$	$\pm 15 \leq$ PBIAS $< \pm 30$	$\pm 25 \leq$ PBIAS $< \pm 40$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < E_{NS}^2 \leq 0.65$	$\pm 15 \leq$ PBIAS $< \pm 25$	$\pm 30 \leq$ PBIAS $< \pm 55$	$\pm 40 \leq$ PBIAS $< \pm 70$
Unsatisfactory	$RSR > 0.70$	$E_{NS}^2 \leq 0.50$	PBIAS $\geq \pm 25$	PBIAS $\geq \pm 55$	PBIAS $\geq \pm 70$

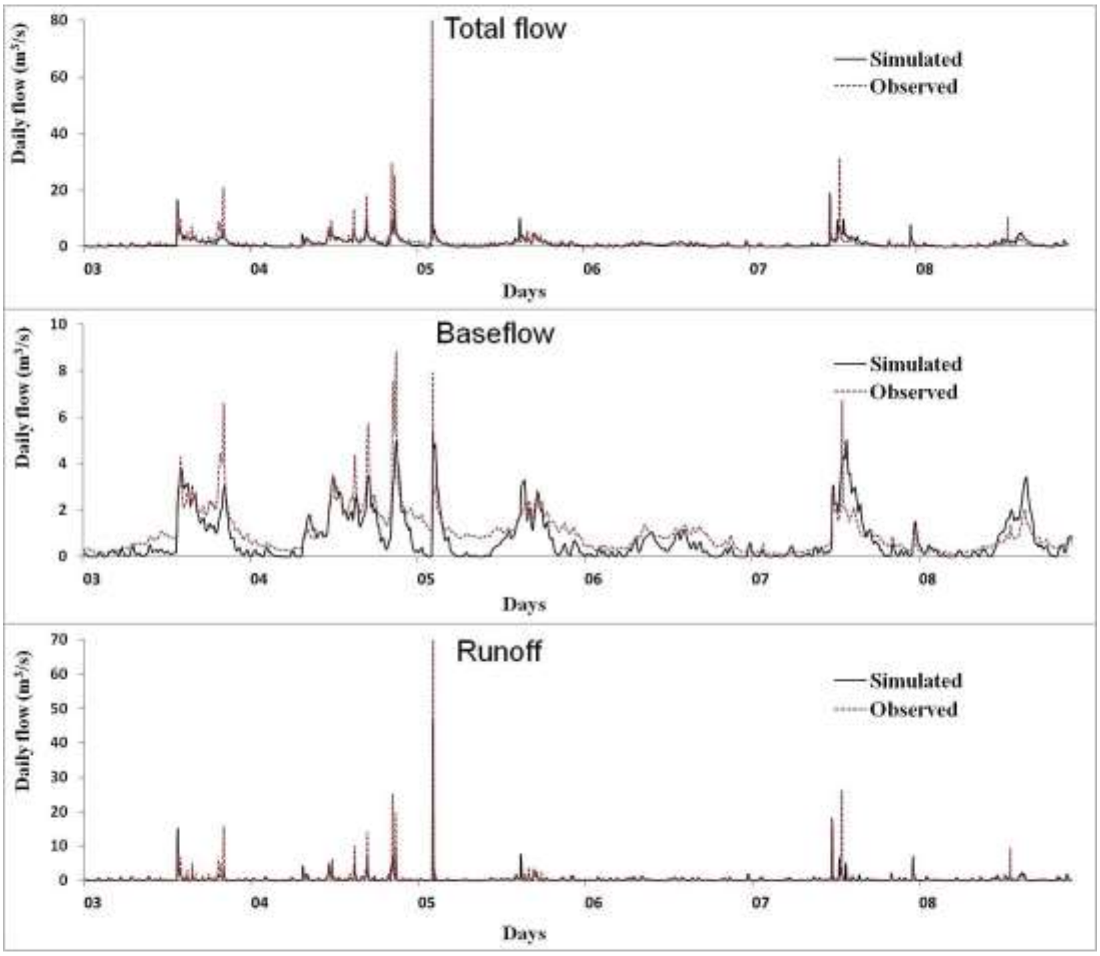


Figure 4.20 Validation of daily flows at site-1

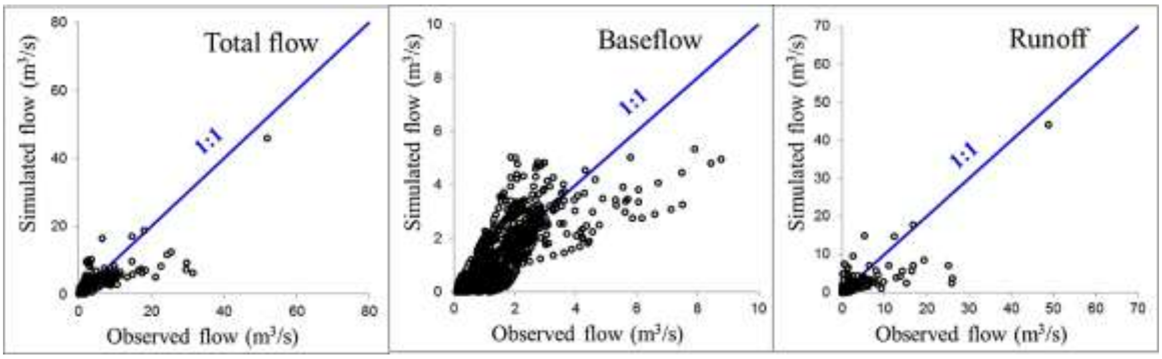


Figure 4.21 Scatterplot of daily flows for validation at site-1

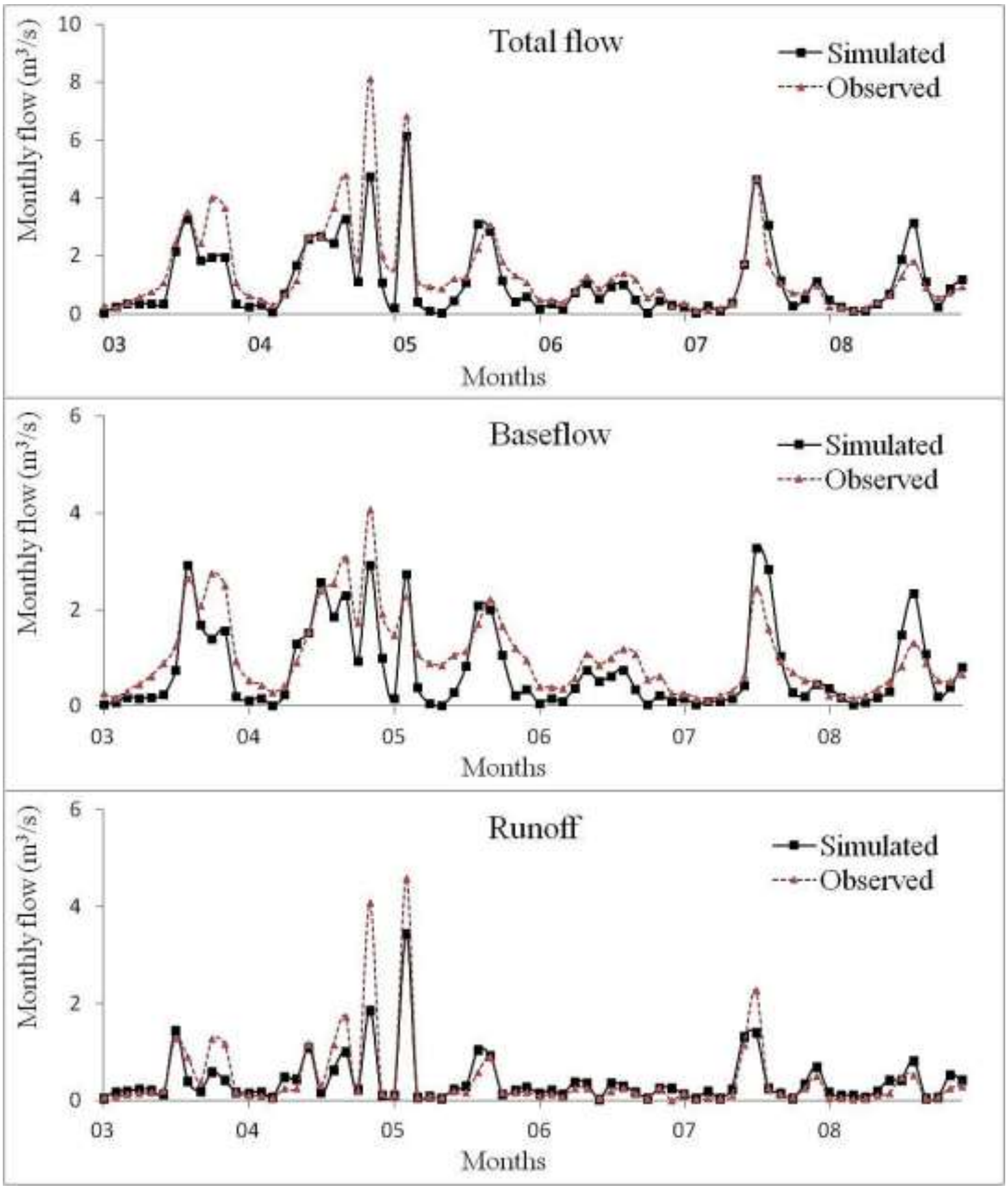


Figure 4.22 Validation of monthly flows at site-1

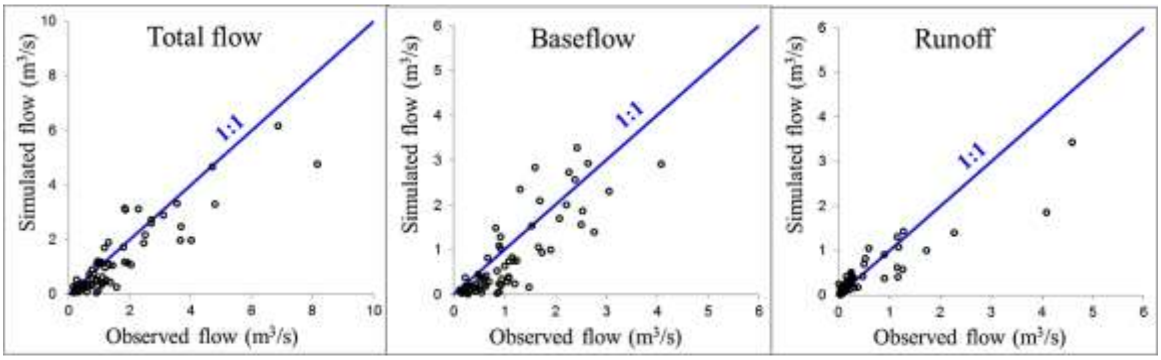


Figure 4.23 Scatterplot of monthly flows for validation at site-1

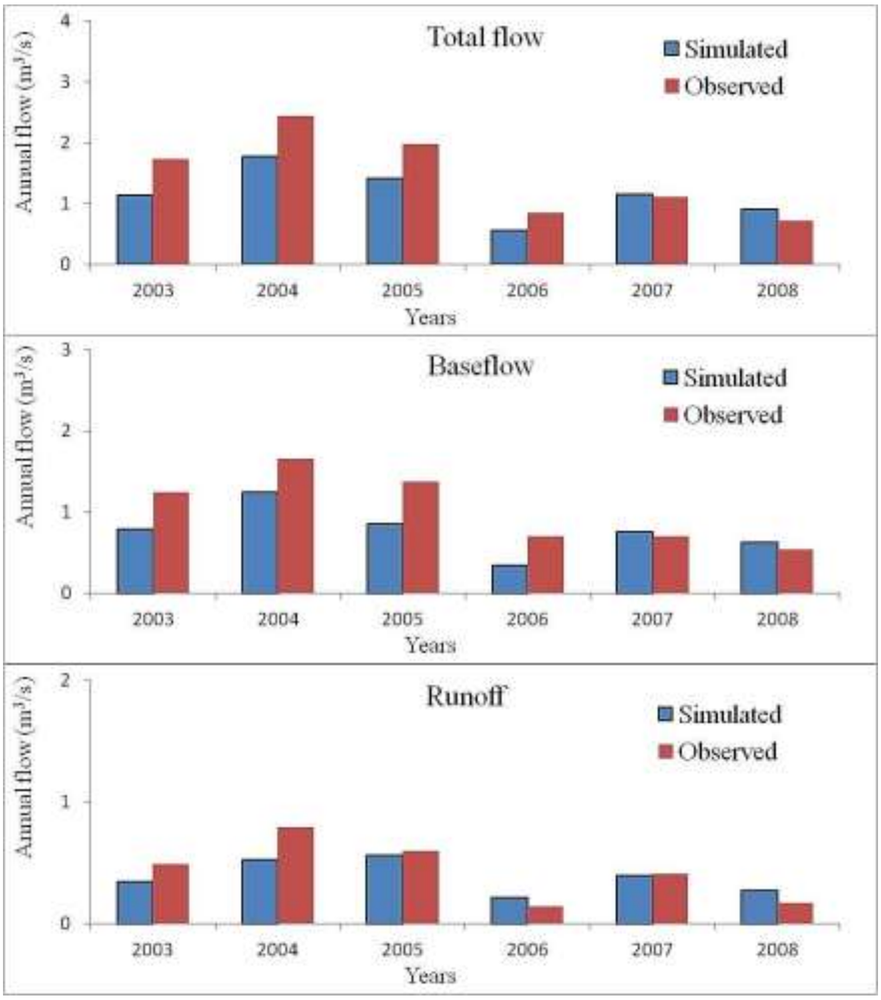


Figure 4.24 Validation of annual flows at site-1

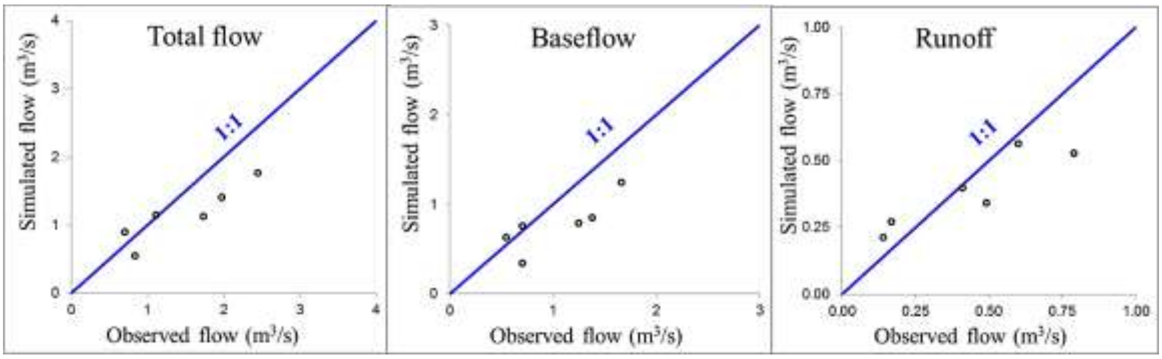


Figure 4.25 Scatterplot of annual flows for validation at site-1

(B) SITE-2

The performance ratings at site-2 was very good for daily, monthly and annual total streamflow and baseflow ($E_{NS}^2 > 0.75$, $R^2 > 0.75$, RSR ≤ 0.50, and PBIAS < ±10% as shown in Tables 4.12 to 4.14). For daily, monthly and annual runoff, it was satisfactory ($E_{NS}^2 > 0.60$, $R^2 > 0.60$, RSR < 0.70, and PBIAS < 25% as shown in Tables 4.12 to 4.14).

Similar to site-1, at site-2 the model underestimated flows in wet years (2003-2005) and overestimated flows in dry years (2006-2008) as shown in Figures 4.26, 4.28 and 4.30 except runoff. The scatter plots of the flows (as shown in Figures 4.27, 4.29 and 4.31) show that the model underestimated daily, monthly and annual total streamflow and runoff, but overestimated baseflow (negative PBIAS values in Tables 4.12 to 4.14 which mean overestimation).

(C) SITE-3

The performance ratings at site-3 was also very good for daily, monthly and annual total streamflow ($E_{NS}^2 > 0.75$, $R^2 > 0.75$, RSR ≤ 0.50, and PBIAS < ±10% as shown in Tables 4.12 to 4.14). However, some relaxing on the guideline was considered for the daily step as suggested by Arnold et al (2012). Moreover, the validation was good and satisfactory for daily, monthly and annual baseflow and runoff respectively based on the Tables 4.12 to 4.14.

Similar to site-1 and site-2, the MYWQM underestimated flows in wet years (2003-2005) and overestimated flows in dry years (2006-2008) as shown in Figures 4.32, 4.34 and 4.36. The scatter plots of the flows (as shown in Figures 4.33, 4.35 and 4.37) show that the model overestimated daily, monthly and annual total streamflow, baseflow, but underestimated runoff. This can also be seen in Tables 4.12 to 4.14 where negative PBIAS values mean overestimation. The overestimation in the validation period was expected as SWAT model overestimates streamflow during dry period, and the validation period was drier than the calibration period.

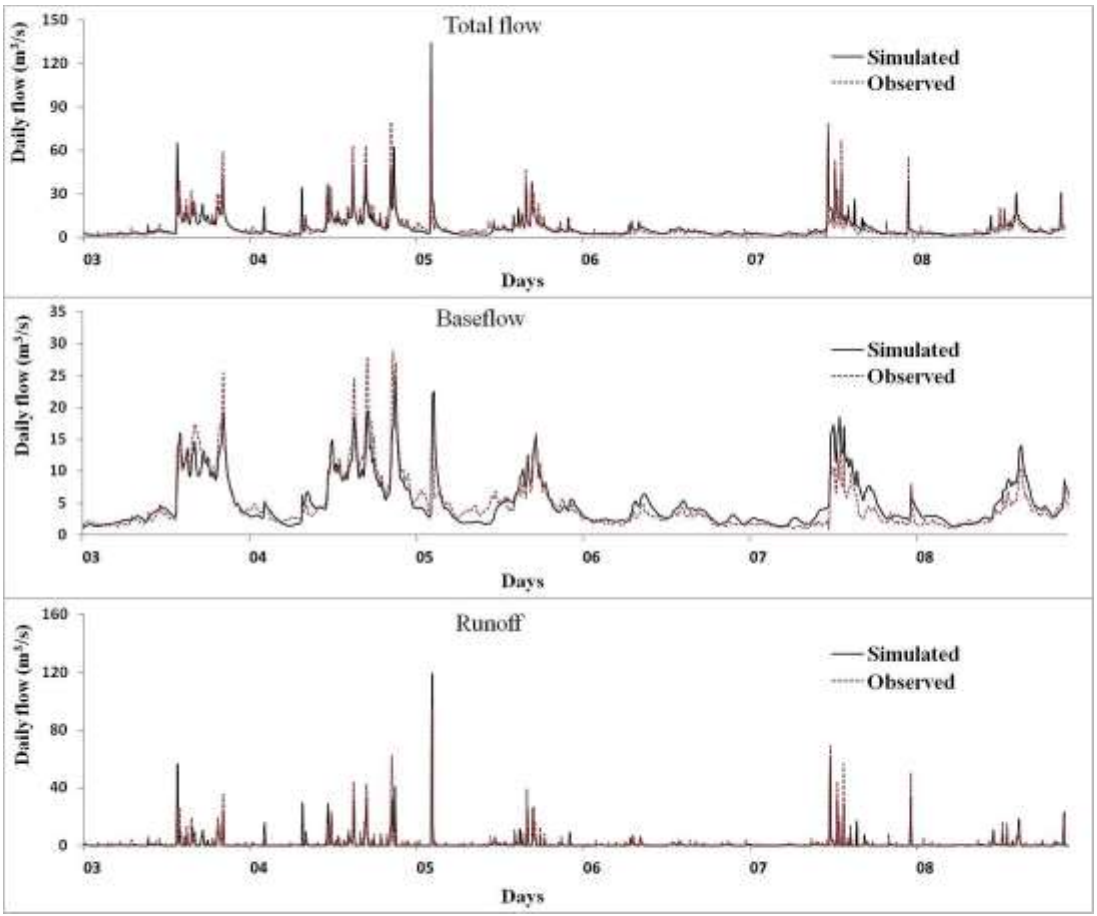


Figure 4.26 Validation of daily flows at site-2

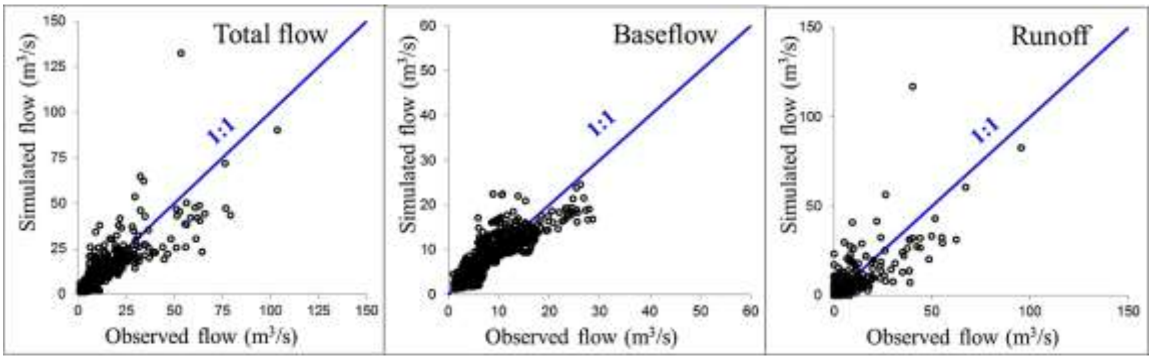


Figure 4.27 Scatterplot of daily flows for validation at site-2

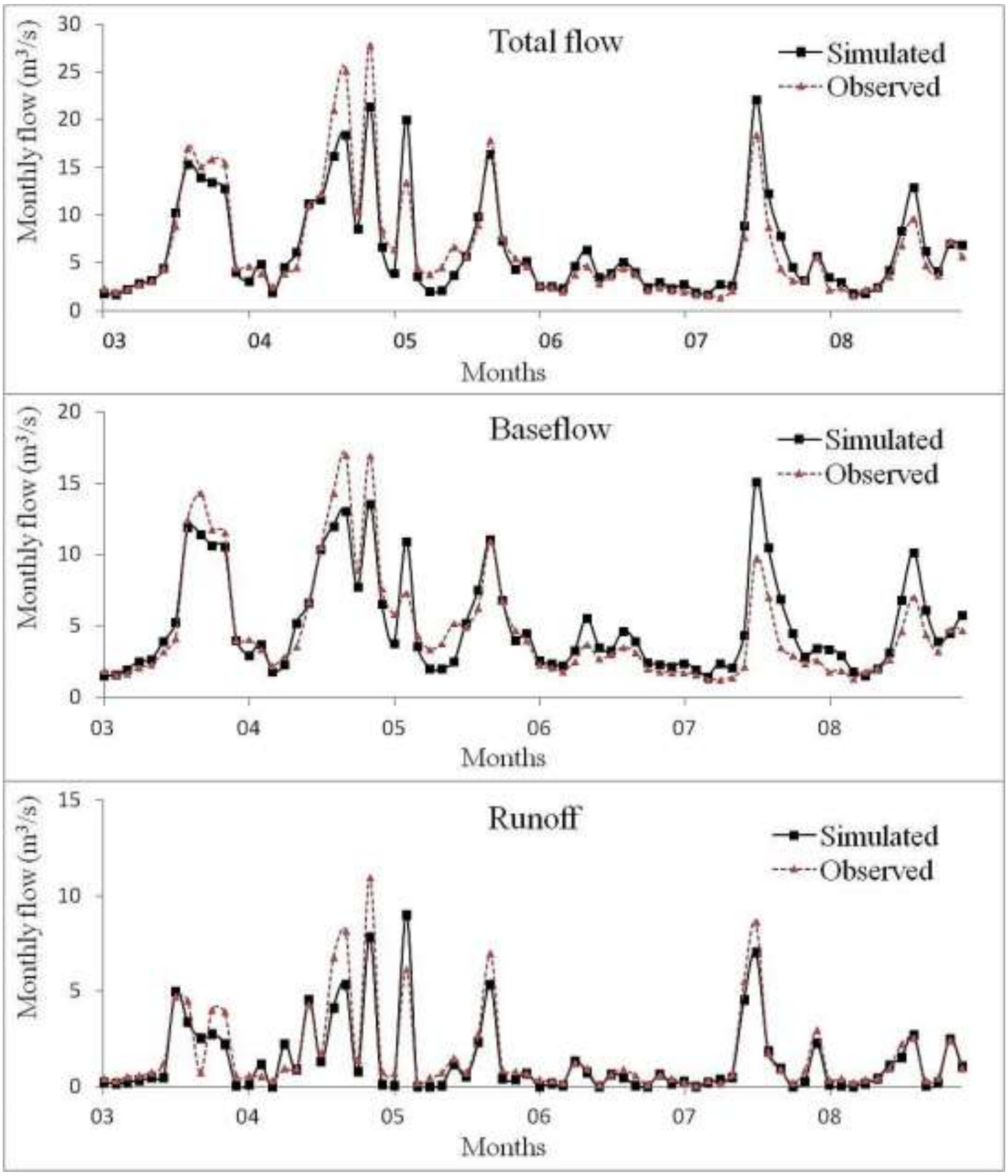


Figure 4.28 Validation of monthly flows at site-2

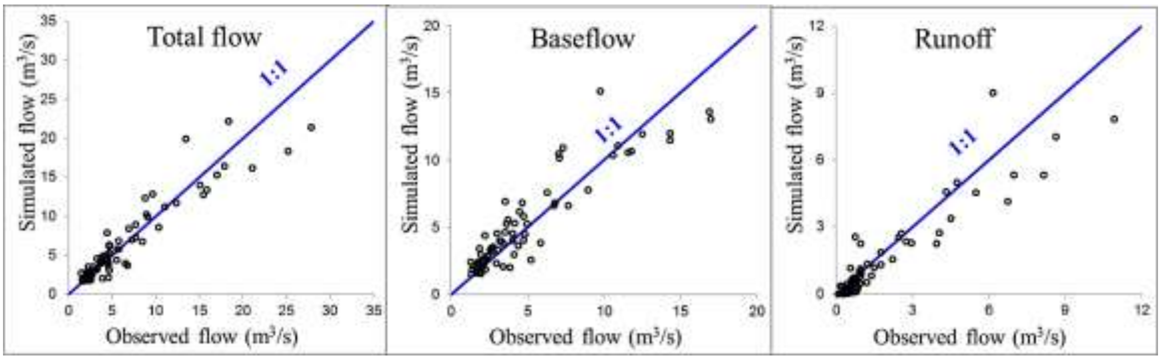


Figure 4.29 Scatterplot of monthly flows for validation at site-2

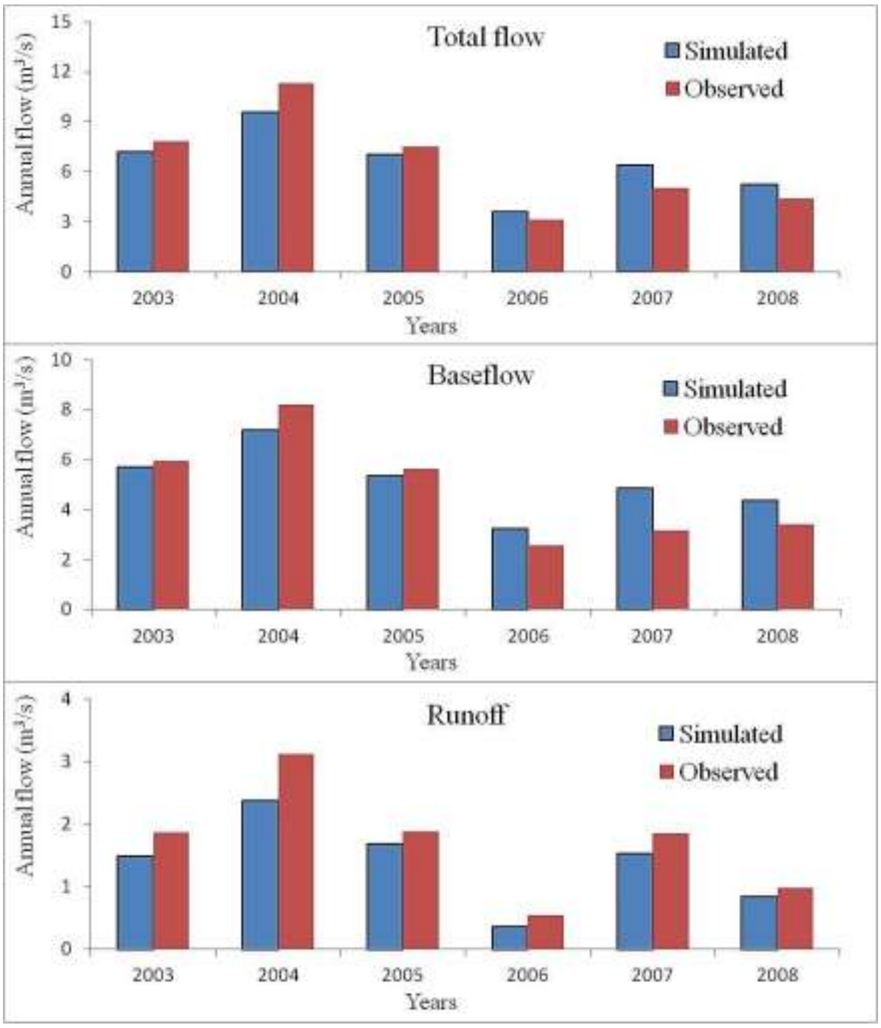


Figure 4.30 Validation of annual flows at site-2

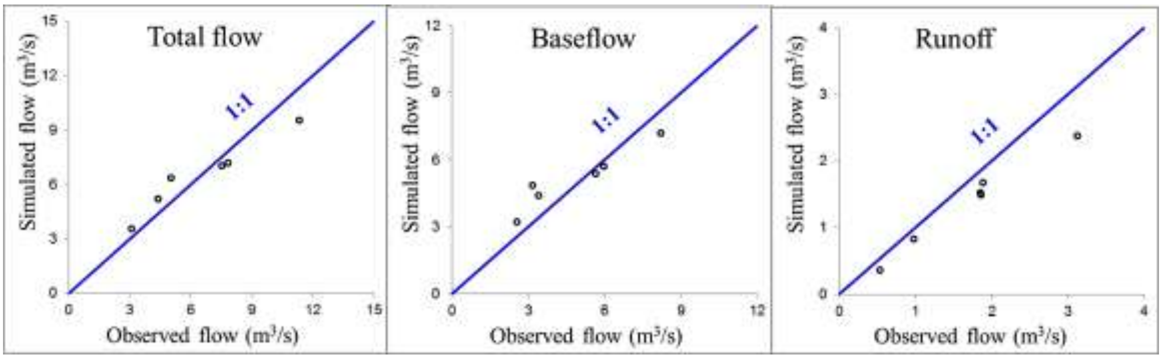


Figure 4.31 Scatterplot of annual flows for validation at site-2

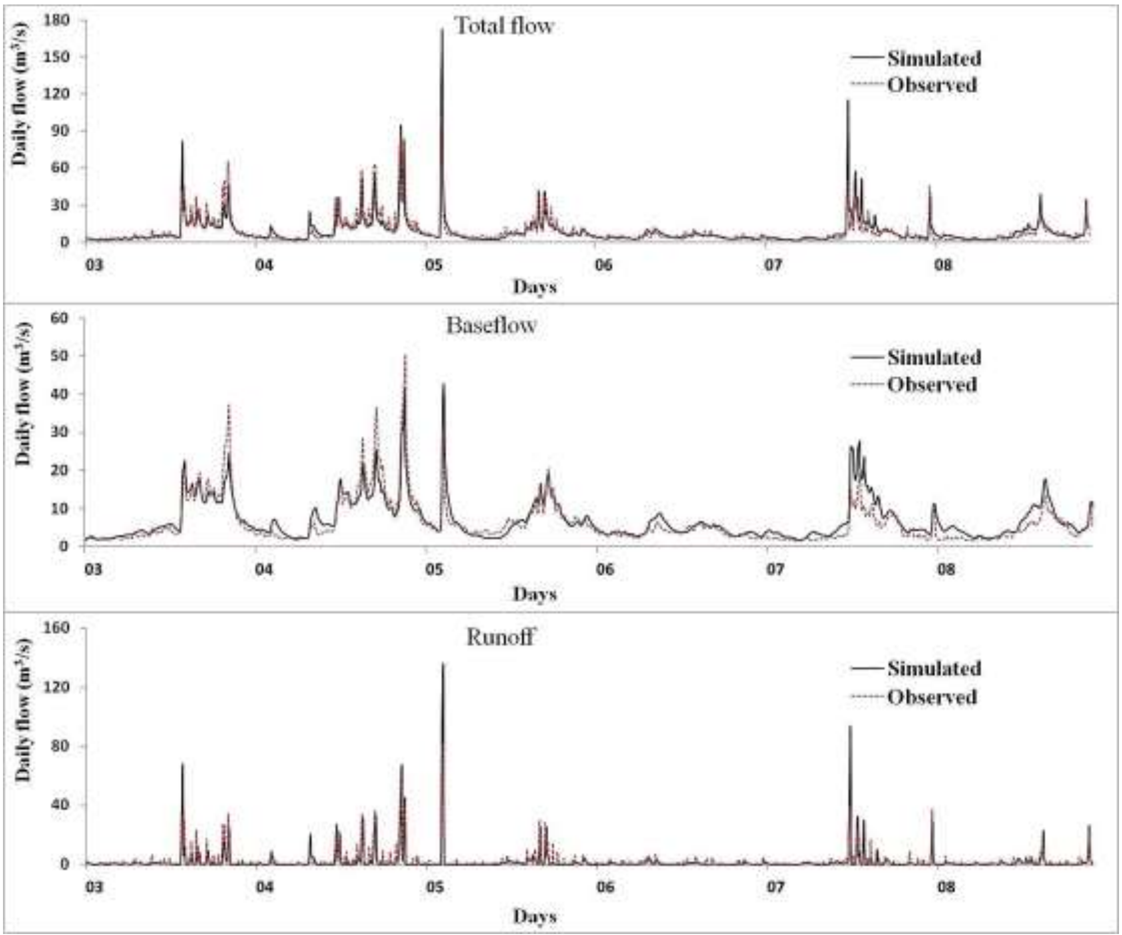


Figure 4.32 Validation of daily flows at site-3

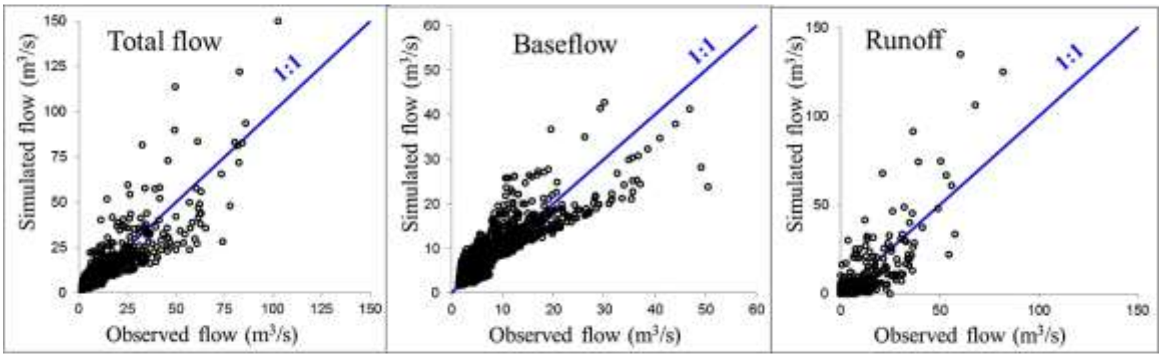


Figure 4.33 Scatterplot of daily flows for validation at site-3

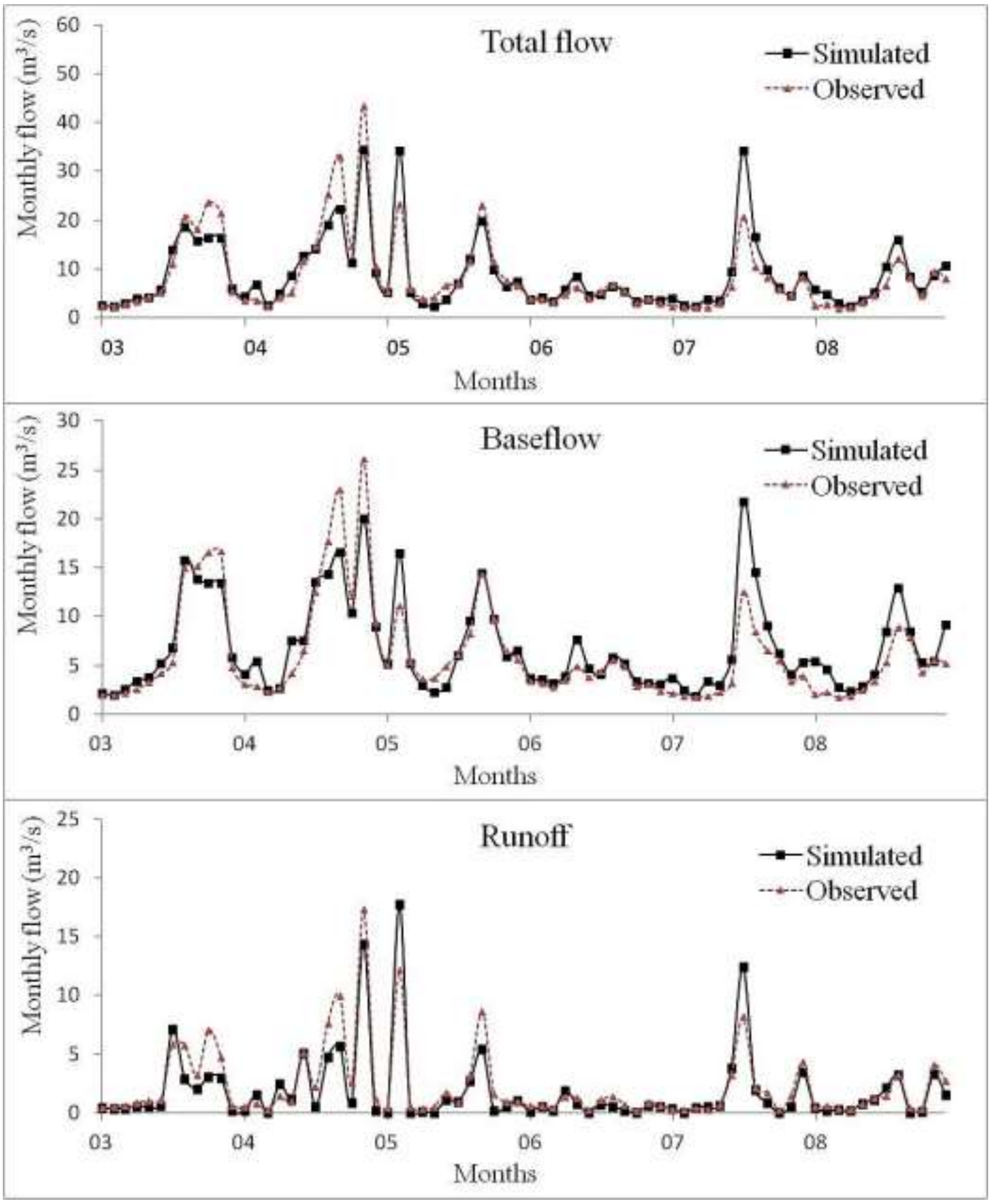


Figure 4.34 Validation of monthly flows at site-3

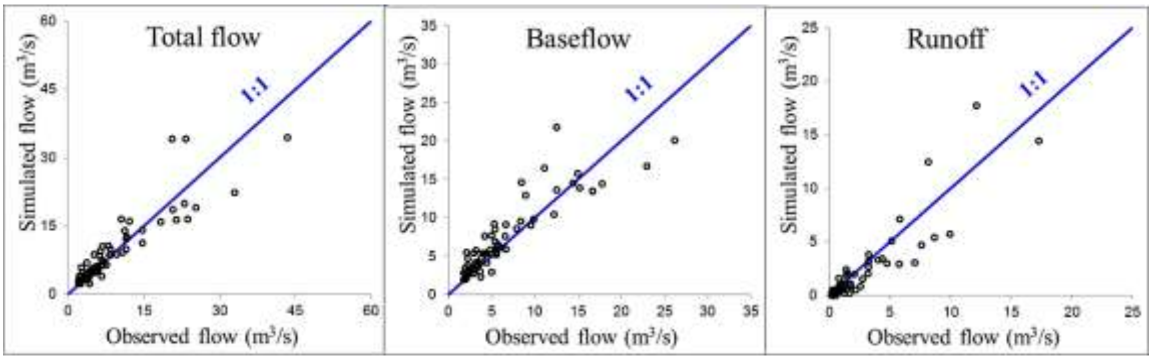


Figure 4.35 Scatterplot of monthly flows for validation at site-3

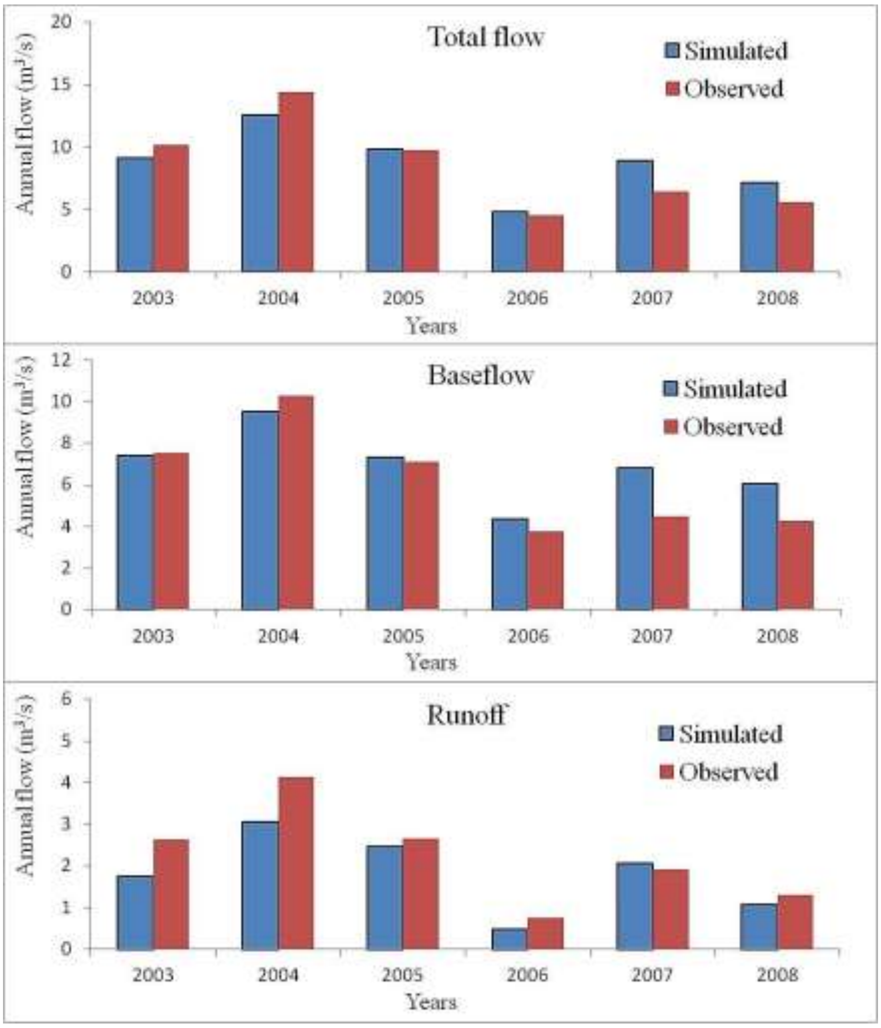


Figure 4.36 Validation of annual flows at site-3

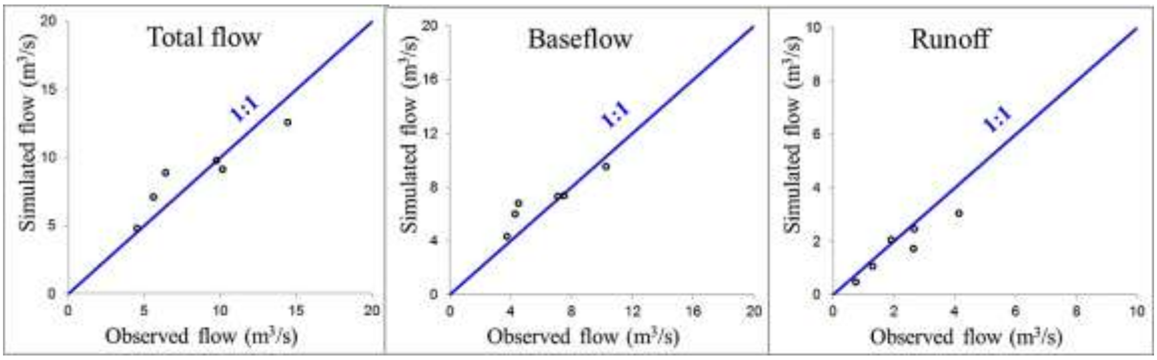


Figure 4.37 Scatterplot of annual flows for validation at site-3

4.4.2. SEDIMENT (TSS) AND NUTRIENTS (TN, TP)

As discussed in Section 3.3.2.2(B), the calibration and validation periods for sediment and nutrients were selected as 1998-2004 and 2005-2008 respectively based on availability of data. Ten years of warm-up period was considered before the calibration and validation periods similar to streamflow as discussed in Section 4.4.1. Sediment and nutrients were calibrated simultaneously at the three sites.

4.4.2.1. CALIBRATION

The calibrated values of the parameters governing sediment and nutrients which were finally used in the MYWQM are shown in Table 4.15.

Table 4.15 Calibrated parameters governing sediment and nutrients in the MYWQM

TSS, TN and TP Parameters	Default value	Changed value after calibration		
		Site-1	Site-2	Site-3
CH_COV	0	0.02	0.05	0.25
CH_EROD	0	0.01	0.25	0.45
NPERCO	0.2	0.12	0.12	0.12
PHOSKD	175	195	195	195
PPERCO	10	10	10	10
RCHRG_DP	0.05	0.05	0.17	0.18
SOL_LABP	0	5	1	0.525
SOL_NO3	0	55	30	65
SOL_ORGN	0	95	75	85
SOL_ORGP	0	63	46	30
SPCON	0.0001	0.0001	0.0001	0.0001
SPEXP	1	1	1	1
USLE_P	1	0.27	0.45	0.7
AI0	50	75	75	75
AI1	0.08	0.09	0.09	0.09
AI2	0.015	0.015	0.015	0.015
BC1	0.55	1	1	1
BC2	1.1	1.98	1.98	1.98
BC3	0.21	0.2	0.2	0.2
BC4	0.35	0.05	0.01	0.01
RCN	1	0.01	0.01	0.01
RS1	1	0.15	0.15	0.15
RS2	0.05	0.001	0.001	0.001
RS3	0.5	0.01	0.01	0.01
RS4	0.05	0.001	0.01	0.001
RS5	0.05	0.1	0.1	0.1
RSDCO	0.05	0.08	0.08	0.08

The monthly and annual calibration statistics for TSS, TN and TP at the three sites are shown in Tables 4.16 and 4.17 respectively. The results are also presented graphically in Figures 4.38 to 4.49. In general, the calibration results showed good agreement between observed and simulated values for TSS, and very good agreement for TN as can be seen in Tables 4.16 and 4.17 based on the Moriasi et al (2007) guidelines (shown on the same page along with Tables 4.16 and 4.17). However, the calibration results were unsatisfactory for TP except at site-3 (MYC outlet). Moreover, the MYWQM underestimated peak monthly loads as can be seen in Figures 4.38, 4.42 and 4.46. Details are discussed in the following sections.

(A) SITE-1

As per the Moriasi et al (2007) guidelines on model performance ratings, the MYWQM performances were good for monthly and annual TSS loads at site-1 ($E_{NS}^2 > 0.65$, $R^2 > 0.65$, RSR < 0.60, and PBIAS < 15% as shown in Tables 4.16 and 4.17). Similarly, monthly and annual TN calibrations were very good ($E_{NS}^2 > 0.75$, $R^2 \geq 0.80$, RSR < 0.50, and PBIAS < ±25% as shown in Tables 4.16 and 4.17). However, the calibration results of TP for both monthly and annual steps were unsatisfactory ($E_{NS}^2 \leq 0.50$, $R^2 < 0.60$, RSR > 0.70).

Figure 4.38 shows that the model underestimated the peak monthly loads especially TSS and TP loads. The scatter plots (as shown in Figures 4.39 and 4.41) and Figure 4.40 also show that the model underestimated TSS and TP loads but overestimated TN loads. This can also be seen in Tables 4.16 and 4.17 where PBIAS values for TSS and TP are positive (which means underestimation), and PBIAS value for TN is negative (which means overestimation).

During the streamflow calibration, surface runoff was underestimated (at all 3 sites) which leads to the underestimation of TSS loads and also TP loads as TP is closely related to TSS. Also, since the simulated and observed baseflow were very close (low PBIAS values in Table 4.9 to 4.11) in the streamflow calibration, this may lead to the overestimation of TN. This can be seen later in Table 5.8 of Section 5.2.3 (Chapter 5) that significant amount of TN load (NO_3 component) was carried by subsurface flows.

Table 4.16 Monthly sediment and nutrients calibration statistics for period 1998-2004

Calibration Sites	Sediment (TSS)				Total Nitrogen (TN)				Total Phosphorus (TP)			
	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.67	0.67	8	0.58	0.80	0.77	-8	0.48	0.47	**0.46**	13	**0.74**
Site-2	0.92	0.89	14	0.32	0.92	0.92	-1	0.28	0.48	**0.45**	18	**0.74**
Site-3	0.77	0.62	2	0.61	0.86	0.79	15	0.46	0.53	0.51	19	0.70

Table 4.17 Annual sediment and nutrients calibration statistics for period 1998-2004

Calibration Sites	Sediment (TSS)				Total Nitrogen (TN)				Total Phosphorus (TP)			
	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.84	0.74	8	0.51	0.93	0.76	-8	0.49	0.58	**0.49**	13	**0.72**
Site-2	0.91	0.80	14	0.45	0.98	0.98	-1	0.15	0.74	**0.50**	18	**0.71**
Site-3	0.91	0.78	2	0.47	0.96	0.79	15	0.46	0.89	0.69	19	0.56

R^2 = Coefficient of determination
E_{NS}^2 = Nash-Sutcliffe efficiency
PBIAS = Percent bias
RSR = ratio of the root mean square error (RMSE) to the standard deviation of observed data

The **bold** numbers in the tables do not satisfy the Moriasi et al (2007) satisfactory criteria.

General performance ratings for recommended statistics for monthly time step (Moriasi et al, 2007)

Performance Rating	RSR	E_{NS}^2	PBIAS (%)		
			Q	TSS	TN and TP
Very good	$0.00 \le RSR \le 0.50$	$0.75 < E_{NS}^2 \le 1.00$	PBIAS $< \pm 10$	PBIAS $< \pm 15$	PBIAS$< \pm 25$
Good	$0.50 < RSR \le 0.60$	$0.65 < E_{NS}^2 \le 0.75$	$\pm 10 \le$ PBIAS $< \pm 15$	$\pm 15 \le$ PBIAS $< \pm 30$	$\pm 25 \le$ PBIAS $< \pm 40$
Satisfactory	$0.60 < RSR \le 0.70$	$0.50 < E_{NS}^2 \le 0.65$	$\pm 15 \le$ PBIAS $< \pm 25$	$\pm 30 \le$ PBIAS $< \pm 55$	$\pm 40 \le$ PBIAS $< \pm 70$
Unsatisfactory	$RSR > 0.70$	$E_{NS}^2 \le 0.50$	PBIAS $\ge \pm 25$	PBIAS $\ge \pm 55$	PBIAS $\ge \pm 70$

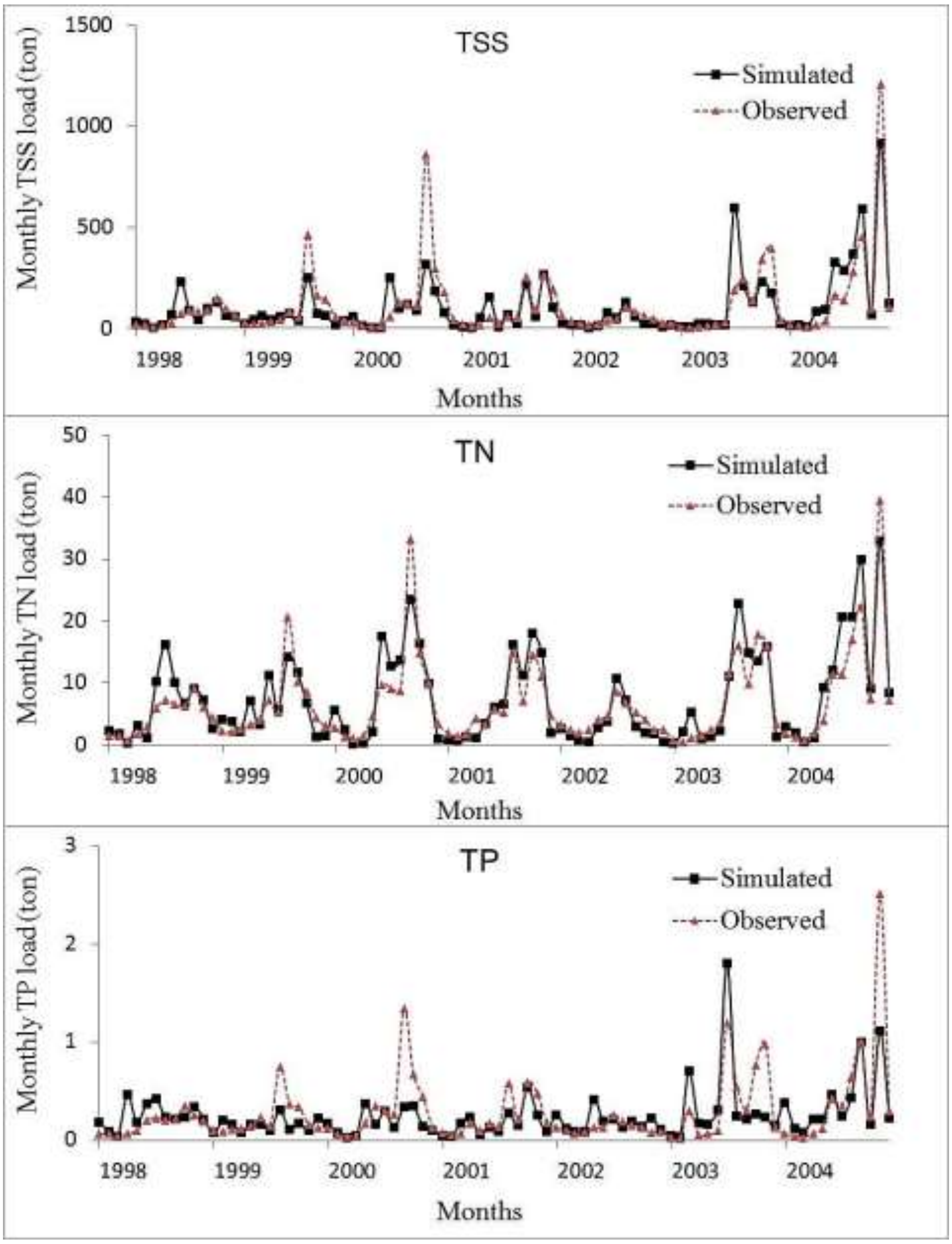


Figure 4.38 Calibration of monthly TSS, TN and TP at site-1

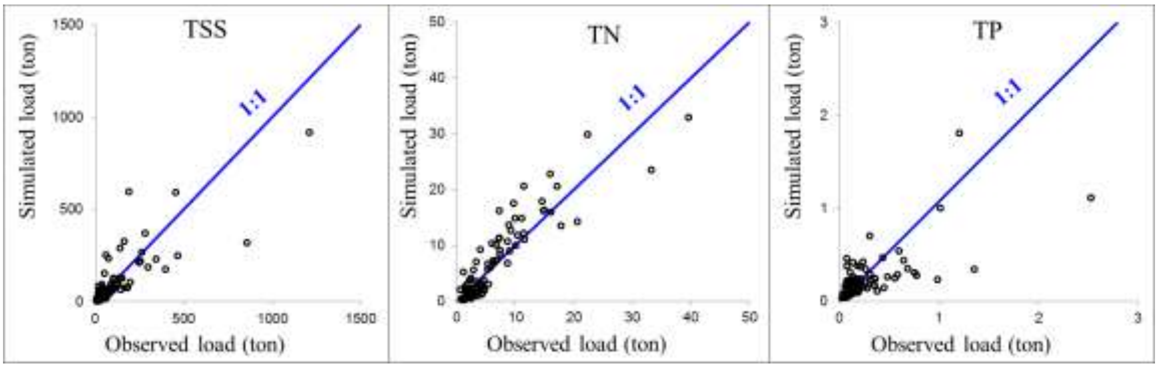


Figure 4.39 Scatterplot of monthly TSS, TN and TP for calibration at site-1

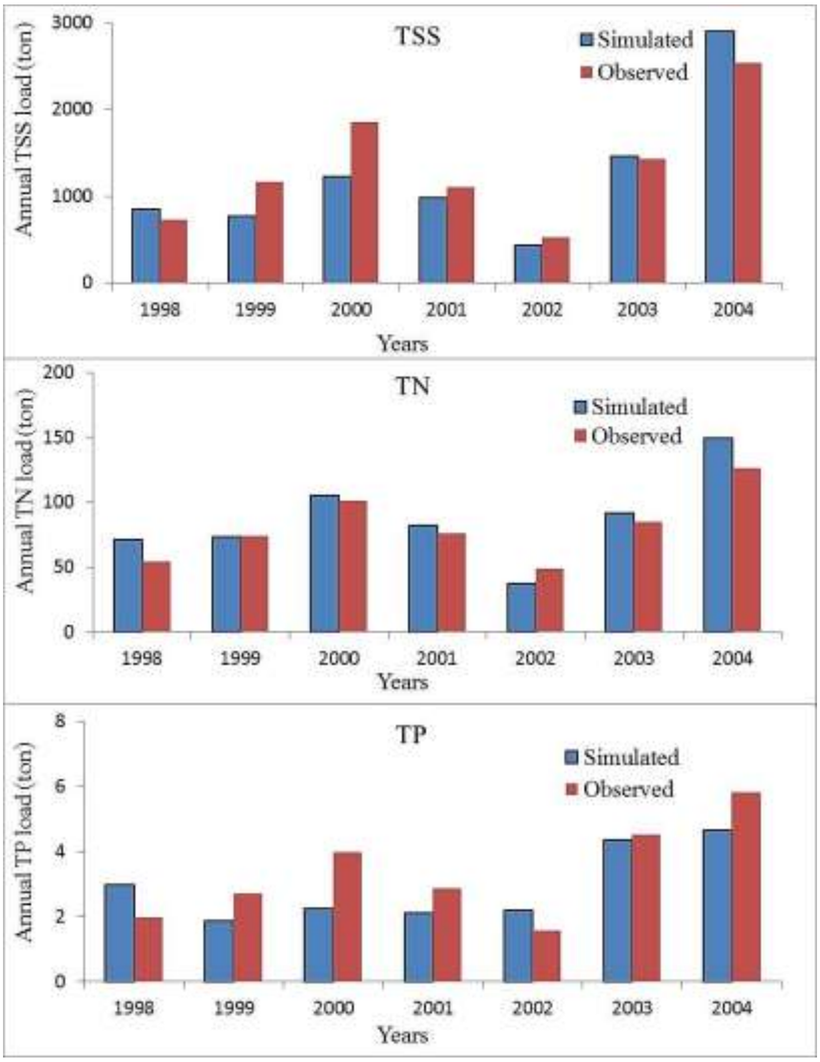


Figure 4.40 Calibration of annual TSS, TN and TP at site-1

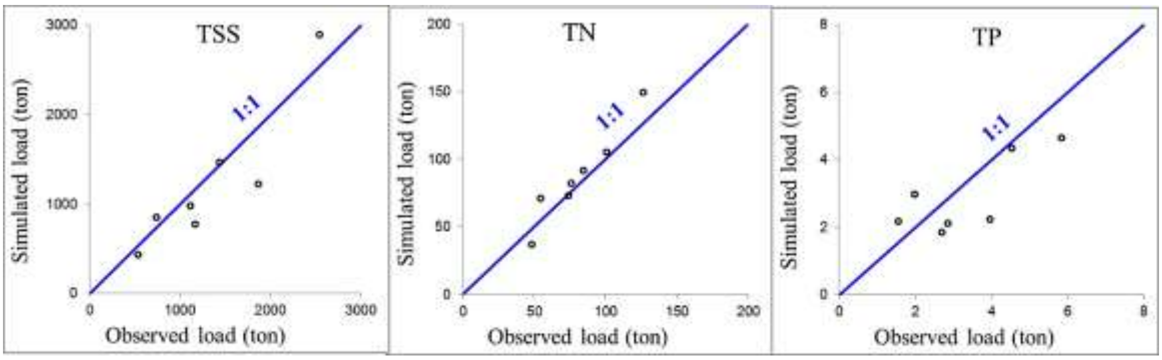


Figure 4.41 Scatterplot of annual TSS, TN and TP for calibration at site-1

(B) SITE-2

At site-2, the MYWQM performances were very good for monthly and annual TSS loads (E_{NS}^2 > 0.75, R^2 > 0.90, RSR < 0.50, and PBIAS < 15% as shown in Tables 4.16 and 4.17). Similarly, monthly and annual TN calibrations were also very good (E_{NS}^2 > 0.75, R^2 > 0.90, RSR < 0.50, and PBIAS < ±25% as shown in Tables 4.16 and 4.17). However, the calibration results of TP for both monthly and annual steps were unsatisfactory (E_{NS}^2 ≤ 0.50, and RSR > 0.70) similar like at site-1.

Similar to site-1, the model underestimated the peak monthly loads especially TSS and TP loads (Figure 4.42). For the same reasons as explained with site-1, the model underestimated TSS and TP loads but overestimated TN loads. This can be seen in the scatter plots (as shown in Figures 4.43 and 4.45) and in Figure 4.44 along with Tables 4.16 and 4.17.

(C) SITE-3

At site-3, the MYWQM performances were satisfactory for monthly TSS loads (E_{NS}^2 > 0.50, R^2 > 0.75, RSR < 0.70 and PBIAS < 15% as shown in Tables 4.16 and 4.17), and very good for annual TSS (E_{NS}^2 > 0.75, R^2 > 0.90, RSR < 0.50 and PBIAS < 15% as shown in Tables 4.16 and 4.17). Similarly to site-1 and site-2, monthly and annual TN calibrations were very good. The calibration results of TP for monthly and annual steps were satisfactory (E_{NS}^2 > 0.50, R^2 > 0.50, RSR ≤ 0.70 and PBIAS < 25% as shown in Tables 4.16 and 4.17) and good respectively (E_{NS}^2 > 0.65, R^2 > 0.85, RSR < 0.70 and PBIAS < 25% as shown in Tables 4.16 and 4.17).

Similar to site-1 and site-2, the model underestimated the peak monthly loads (Figure 4.46). At this site, the model also underestimated TN along with TSS and TP loads. This can be seen in the scatter plots (as shown in Figures 4.47 and 4.49) and in Figure 4.48 along with Tables 4.16 and 4.17.

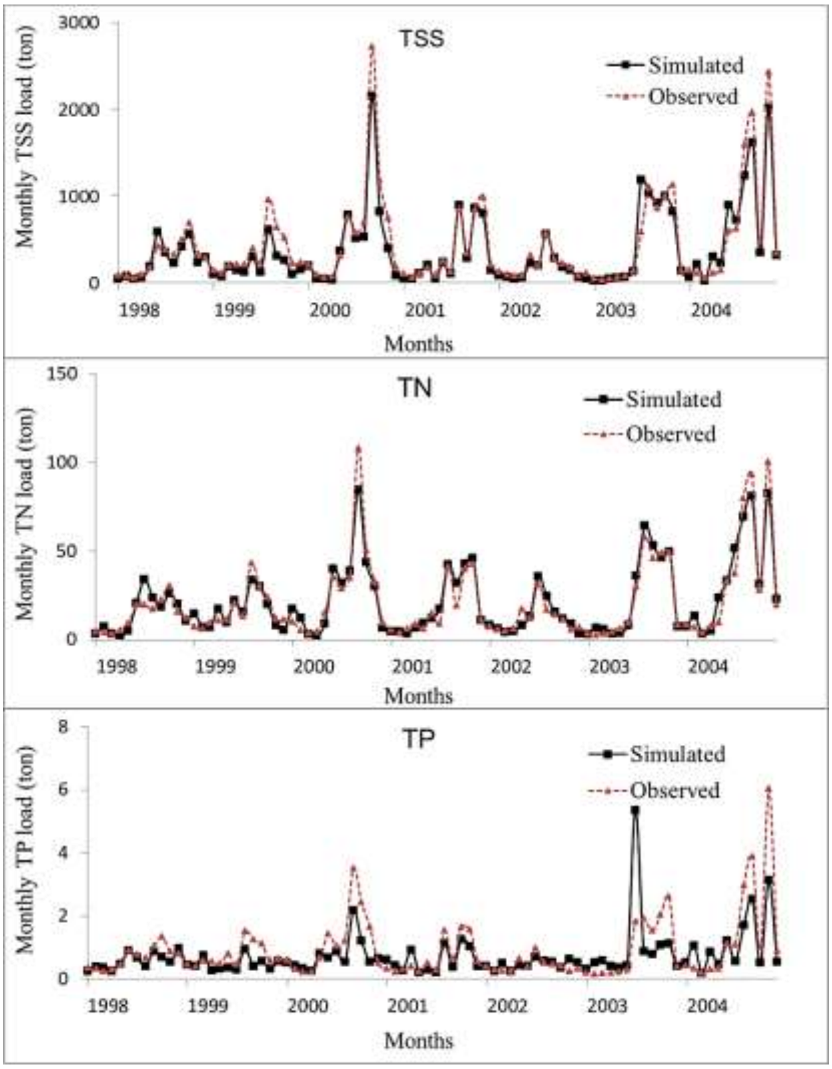


Figure 4.42 Calibration of monthly TSS, TN and TP at site-2

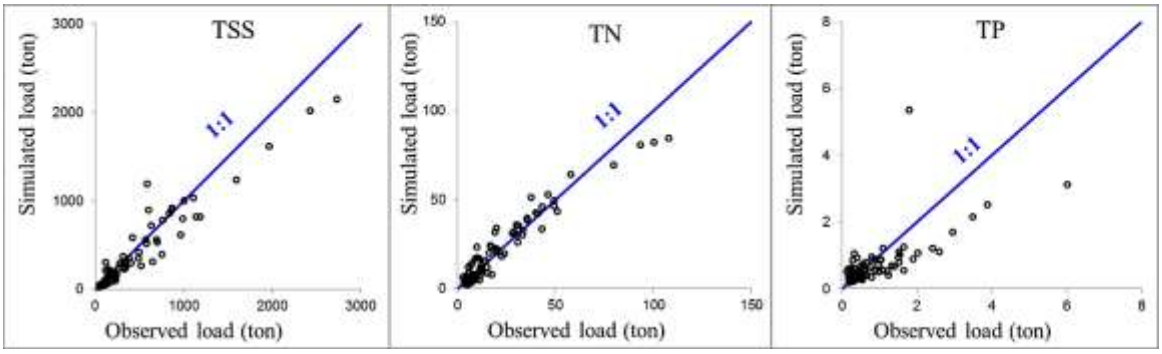


Figure 4.43 Scatterplot of monthly TSS, TN and TP for calibration at site-2

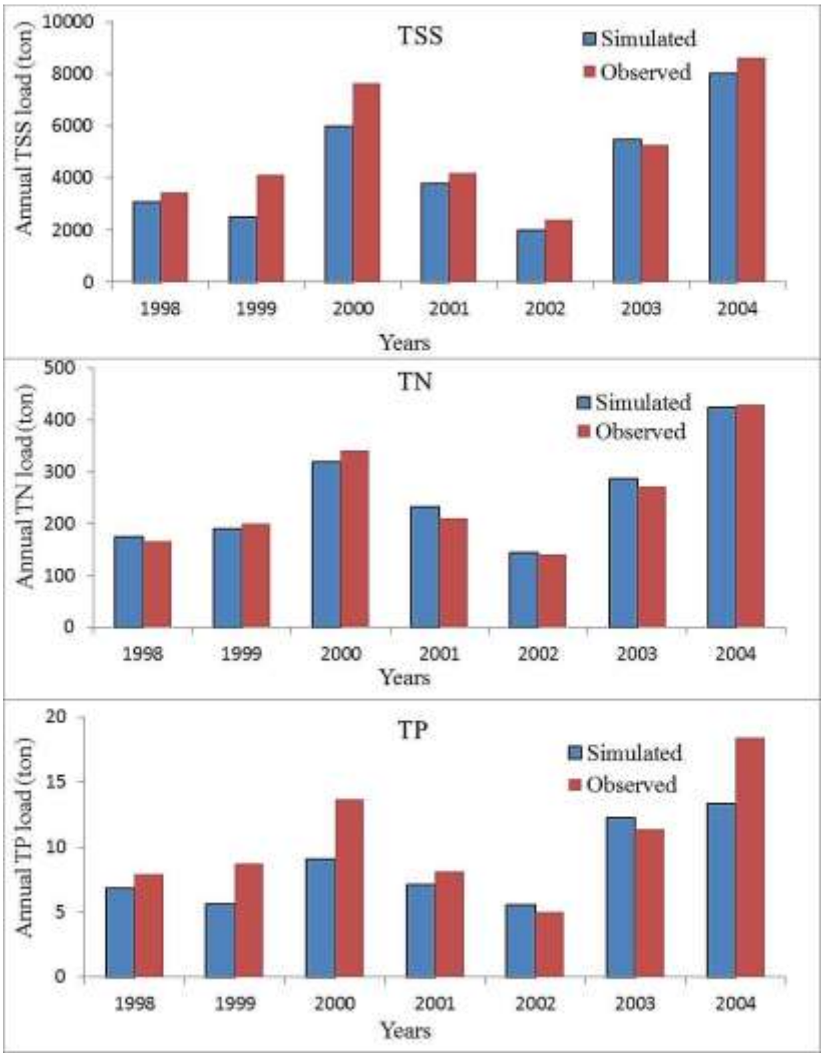


Figure 4.44 Calibration of annual TSS, TN and TP at site-2

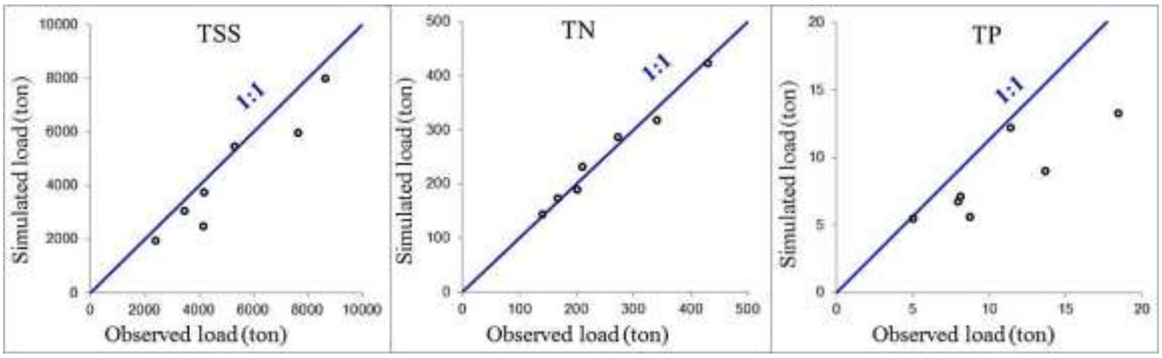


Figure 4.45 Scatterplot of annual TSS, TN and TP for calibration at site-2

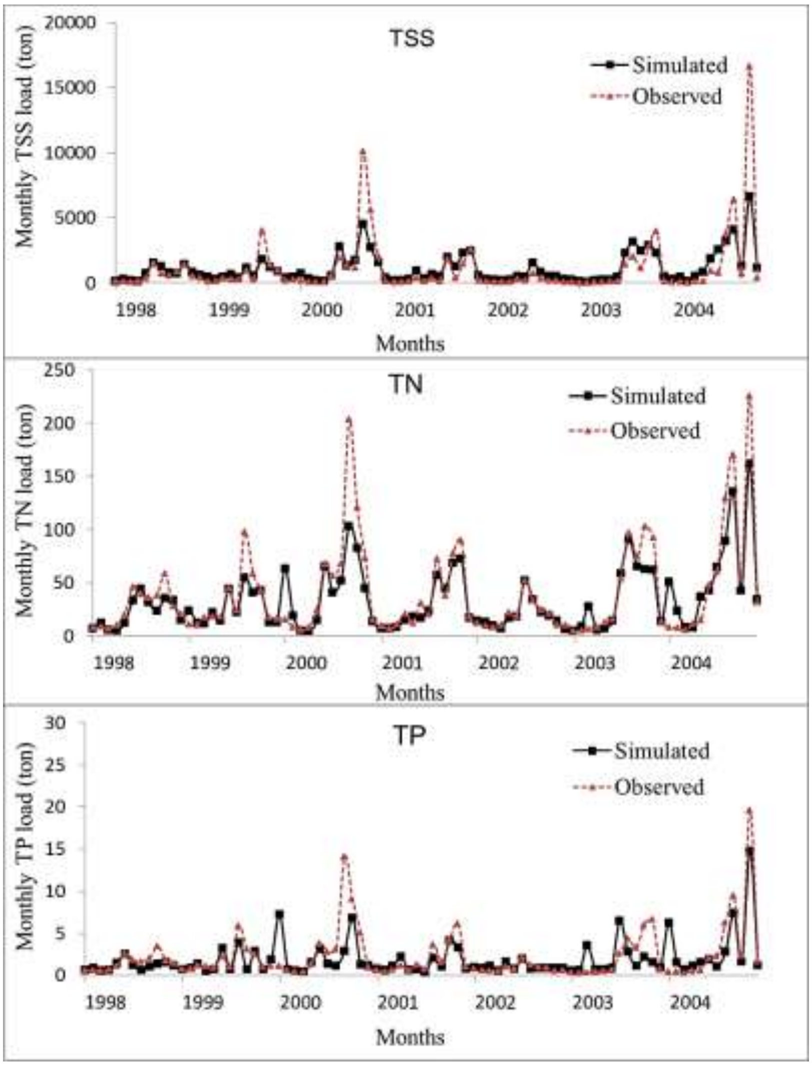


Figure 4.46 Calibration of monthly TSS, TN and TP at site-3

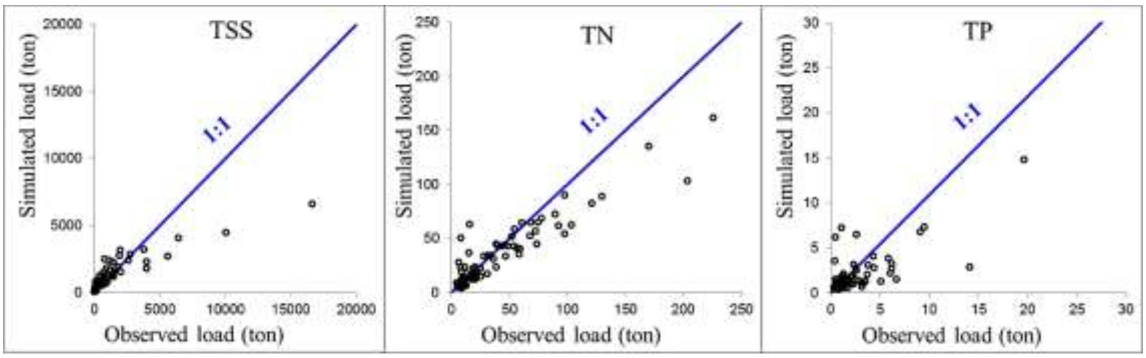


Figure 4.47 Scatterplot of monthly TSS, TN and TP for calibration at site-3

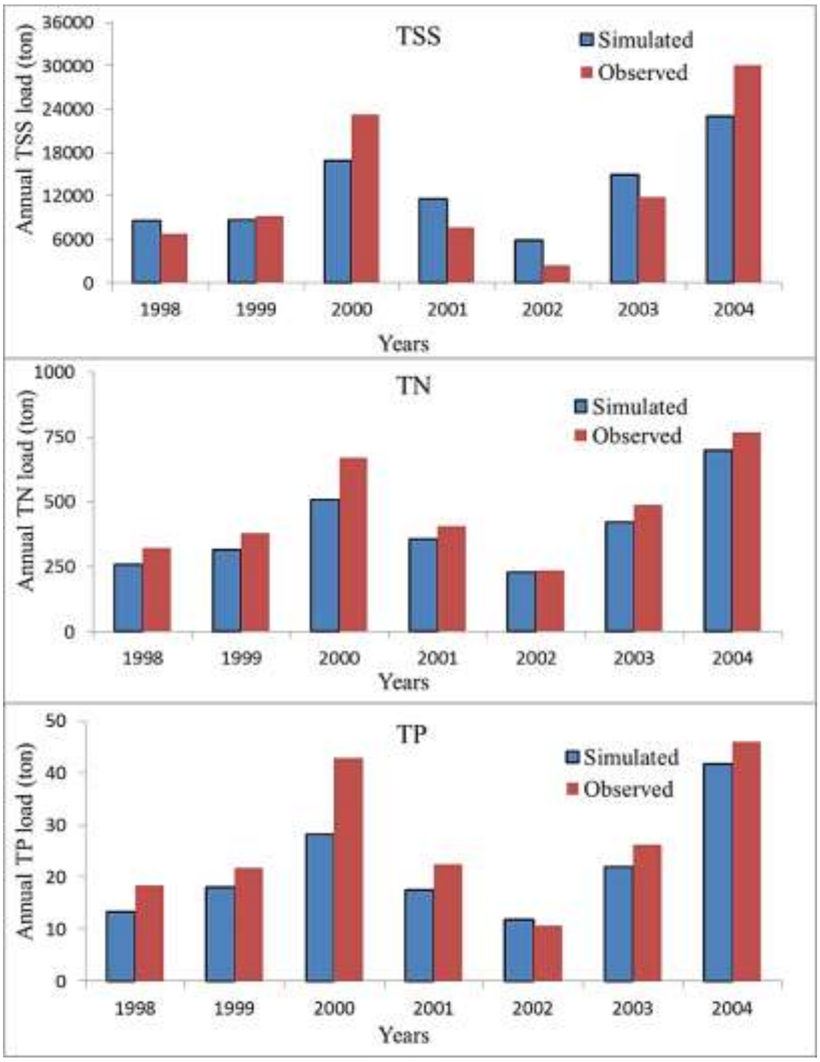


Figure 4.48 Calibration of annual TSS, TN and TP at site-3

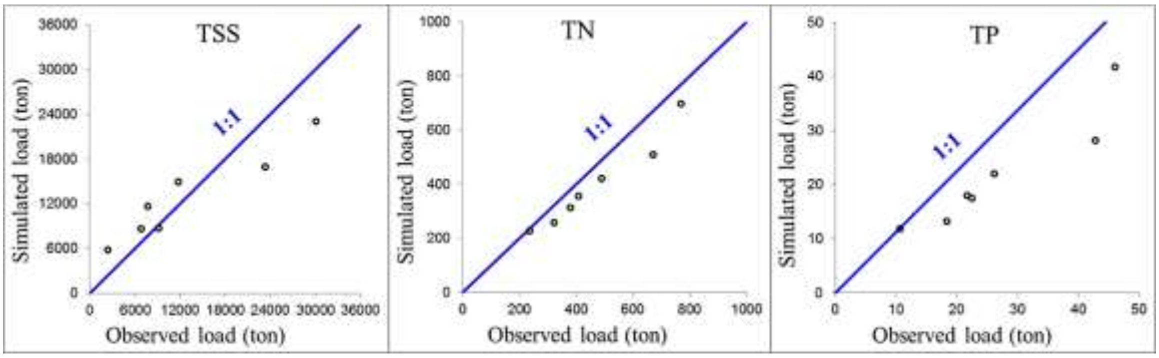


Figure 4.49 Scatterplot of annual TSS, TN and TP for calibration at site-3

4.4.2.2. VALIDATION

The monthly and annual validation statistics at the three sites are shown in Tables 4.18 and 4.19 respectively. The results are also presented graphically in Figures 4.51 to 4.62. In general, the validation results showed good agreement between observed and simulated values for TSS and TN loads with some exceptions especially for TN. However, the performance ratings of TP were unsatisfactory especially for annual steps. These can be seen in Tables 4.18 and 4.19 based on the Moriasi et al (2007) guidelines (shown on the same page along with Tables 4.18 and 4.19). Moreover, the MYWQM overestimated peak monthly loads especially TSS and TP loads (Figures 4.51, 4.55 and 4.59) opposite to the calibration periods. Details are discussed in the following sections.

(A) SITE-1

As per the Moriasi et al (2007) guidelines on model performance ratings, the MYWQM performances were satisfactory for monthly TSS loads (${E_{NS}}^2 > 0.50$, $R^2 > 0.95$, RSR < 0.70, and PBIAS **<** ±55% as shown in Tables 4.18 and 4.19), and good for annual TSS loads (${E_{NS}}^2 > 0.75$, $R^2 > 0.95$, RSR < 0.50, and PBIAS **<** ±30% as shown in Tables 4.18 and 4.19). Also monthly TN loads were satisfactory (${E_{NS}}^2 > 0.50$, $R^2 > 0.65$, RSR < 0.70, and PBIAS **<** ±70% as shown in Tables 4.18 and 4.19), but annual TN loads were unsatisfactory (${E_{NS}}^2 < 0.50$ and RSR > 0.70 as shown in Tables 4.18 and 4.19). The validation results of TP loads for both monthly and annual steps were unsatisfactory (${E_{NS}}^2 < 0.50$, RSR > 0.70 and PBIAS ≥ ±70 as shown in Tables 4.18 and 4.19).

Figure 4.51 shows that the model overestimated the peak monthly loads. The scatter plots (as shown in Figures 4.52 and 4.54) and Figure 4.53 also show that the model overestimated loads. This can also be seen in Tables 4.18 and 4.19 where PBIAS values are negative which means overestimation. The overestimation of TP was much higher than those of TSS and TN.

Several reasons may cause this overestimation in the model. The model underestimated streamflow in wet years but overestimated in dry years mainly for runoff as discussed in Section 4.4.1. Since the validation period of sediment and nutrients (when average annual streamflow was 6.57 m^3/s at the MYC outlet) is drier than their calibration period (when average annual streamflow was 10.16 m^3/s at the MYC outlet), the model simulated higher percentage of runoff in streamflow during the validation period.

Table 4.18 Monthly sediment and nutrients validation statistics for period 2005-2008

Calibration	Sediment (TSS)				Total Nitrogen (TN)				Total Phosphorus (TP)			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.97	0.63	-29	0.61	0.67	0.55	-21	0.67	0.87	0.61	**-81**	0.62
Site-2	0.86	0.66	-17	0.63	0.84	0.83	-8	0.42	0.95	0.62	-53	0.61
Site-3	0.78	0.68	-17	0.56	0.83	0.78	-5	0.47	0.97	0.71	-56	0.54

R^2 = Coefficient of determination
E_{NS}^2 = Nash-Sutcliffe efficiency
PBIAS = Percent bias
RSR = ratio of the root mean square error (RMSE) to the standard deviation of observed data

The **bold** numbers in the tables do not satisfy the Moriasi et al (2007) satisfactory criteria.

Table 4.19 Annual sediment and nutrients validation statistics for period 2005-2008

Calibration	Sediment (TSS)				Total Nitrogen (TN)				Total Phosphorus (TP)			
Sites	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR	R^2	E_{NS}^2	PBIAS (%)	RSR
Site-1	0.99	0.77	-29	0.48	0.72	**0.43**	-21	**0.75**	0.95	**0.05**	**-81**	**0.97**
Site-2	0.85	0.72	-17	0.53	0.99	0.89	-8	0.32	0.94	**0.01**	-53	**1.00**
Site-3	0.85	0.69	-17	0.55	0.98	0.95	-5	0.22	0.97	**0.35**	-56	**0.81**

General performance ratings for recommended statistics for monthly time step (Moriasi et al, 2007)

Performance	RSR	E_{NS}^2	PBIAS (%)		
Rating			Q	TSS	TN and TP
Very good	$0.00 \le RSR \le 0.50$	$0.75 < E_{NS}^2 \le 1.00$	PBIAS $< \pm10$	PBIAS $< \pm15$	PBIAS $< \pm25$
Good	$0.50 < RSR \le 0.60$	$0.65 < E_{NS}^2 \le 0.75$	$\pm10 \le$ PBIAS $< \pm15$	$\pm15 \le$ PBIAS $< \pm30$	$\pm25 \le$ PBIAS $< \pm40$
Satisfactory	$0.60 < RSR \le 0.70$	$0.50 < E_{NS}^2 \le 0.65$	$\pm15 \le$ PBIAS $< \pm25$	$\pm30 \le$ PBIAS $< \pm55$	$\pm40 \le$ PBIAS $< \pm70$
Unsatisfactory	$RSR > 0.70$	$E_{NS}^2 \le 0.50$	PBIAS $\ge \pm25$	PBIAS $\ge \pm55$	PBIAS $\ge \pm70$

SWAT simulates three flow components: direct runoff, lateral flow and groundwater flow of the total streamflow at each sub-catchment level. The MYWQM showed that at site-1, site-2 and site-3 runoff contributed 17, 19 and 30 percent of total streamflow respectively during the calibration period (1998-2004), whereas in the validation period (2005-2008) runoff contributed 36, 40 and 49 percent of total streamflow respectively. These higher percentages of runoff caused over prediction of the loads in the validation period.

As discussed in Section 3.3.2.2(B), observed sediment and nutrient loads were estimated from monthly grab samples by the regression based LOADEST model. These grab samples were collected randomly without targeting any storm events. As was shown in Figure 3.24, there were some samples collected during the runoff of the hydrographs in the calibration period (1998-2004). However, there were no samples collected during the runoff of the hydrographs in the validation period (2005-2008) except one sample in February of 2005 at site-3. This has caused underestimation of the observed TSS, TN and TP loads by the LOADEST model in the validation period. Walling and Webb (1981, 1988) performed a rigorous evaluation of regression methods, and showed that they can produce an underestimation of 23–83% of the actual load. Haggard et al (2003) also recommended from their research that there should be at least 6 storm event samples per year to produce a root mean square error of less than 15%.

Abbaspour et al (2007b) pointed out a common problem in the model prediction of particulates such as sediment and organic phosphorus, which is the ‘‘second-storm’’ effect as shown in Figure 4.50. After a storm, there is less sediment to be moved, and the remaining surface layer is much more difficult to mobilize. Hence, a similar intensity storm, or even a bigger intensity second or third storm could actually result in smaller sediment loads. The SWAT model, however, does not account for this effect as illustrated in Figure 4.50, hence, over predicts the loads.

Correct information on the amount and date of fertilizer or manure or pesticide application does not often exist, while it is expected that such information is crucial for a correct modelling (Neitsch et al, 2002). Moreover, all farmers do not apply fertilizer or manure on the same day and at the same rate. A randomly defined application date may easily coincide with a rainy day leading to overestimation of loads. In reality, farmers do not apply fertilizer or manure on rainy days. A proper calibration then requires some inverse modelling techniques (which mean determining unknown causes or calibration parameters based on observation of their effects (Abbaspour et al, 2004; Abbaspour et al, 2007b)) to tackle this problem (Holvoet et al, 2005) which is also the case for this project (fertilizer and manure application types, rates and dates were adjusted and fixed based on their effects on the simulated nutrient loads during the calibration process). Green and Van Griensven (2008) also pointed out that overestimation may occur due to the rain events that occurred soon after fertilizer or manure had been applied. Holvoet et al (2005) performed a sensitivity analysis on hydrology and pesticide in the Nil basin in Belgium using the SWAT model, and found that the date of application (pesticide) was much more important than errors that may occur in the application rate or rainfall errors. The model may also overestimate nutrient loads in the validation period due to the carryover effects of fertilizer or manure that had been applied in the calibration period (Green and van Griensven, 2008).

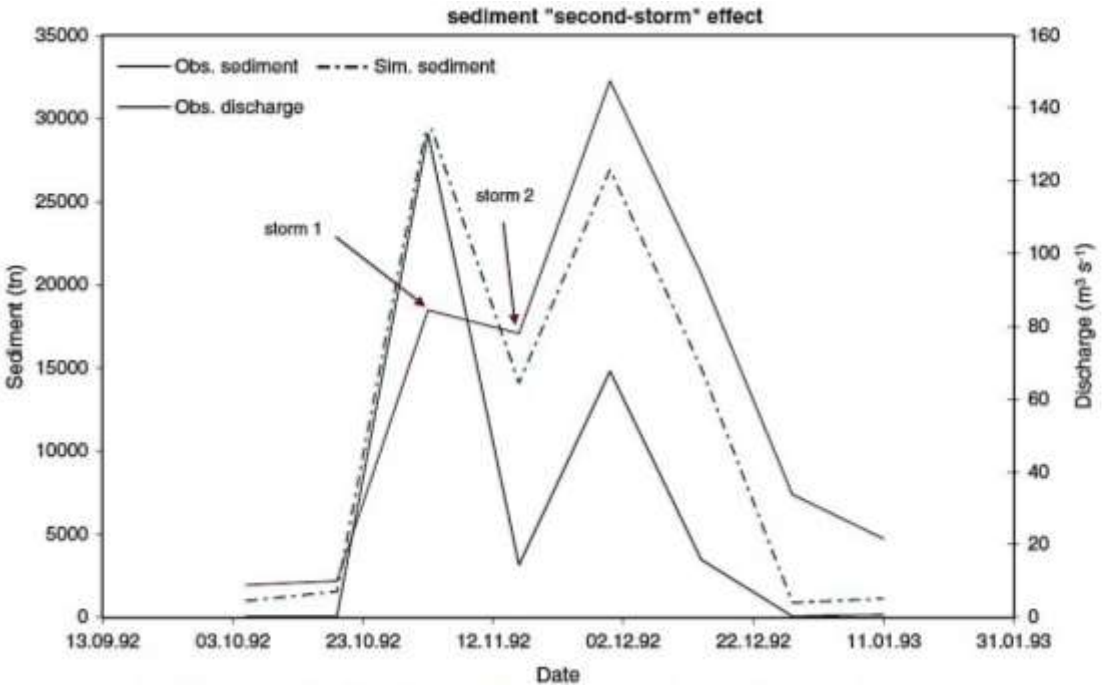


Figure 4.50 ‘‘second-storm’’ effect on sediment (Abbaspour et al, 2007)

Most extreme rainfall events occurred in the validation period as shown in Table 3.15. Longer periods between runoff events and then high intensity events lead to concentrated pollutant runoff in the dry periods (as discussed before in Section 3.2.3.4). This may cause overprediction of peak loads and overall higher sediment and nutrient loads generation in the validation period. Cerro et al (2012) found that during a drought period of some years, there was less flow and fewer nitrates in the river. In that period, applied N accumulated in the aquifer. With a new raining period of some years, more flow was generated and leads to an exponentially increased nitrate concentration for the following years. Nitrate concentration increments were higher when the drought period was longer; thus, the alluvial aquifer acts as storage for nitrates.

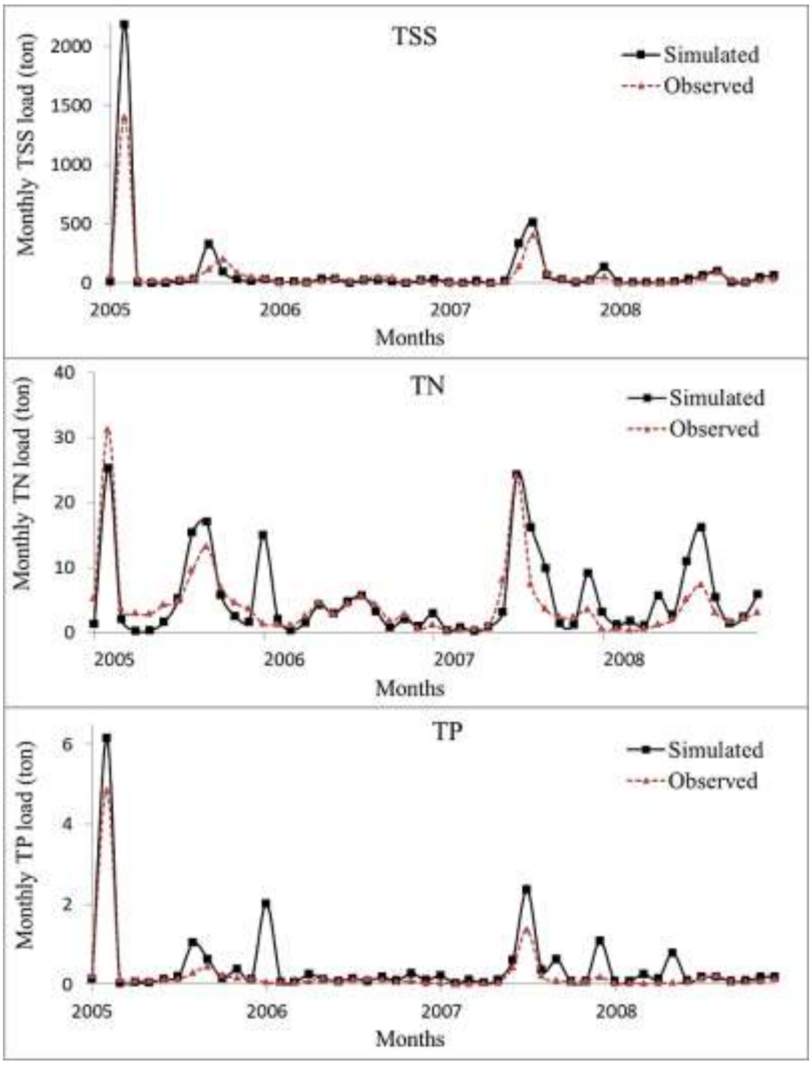


Figure 4.51 Validation of monthly TSS, TN and TP at site-1

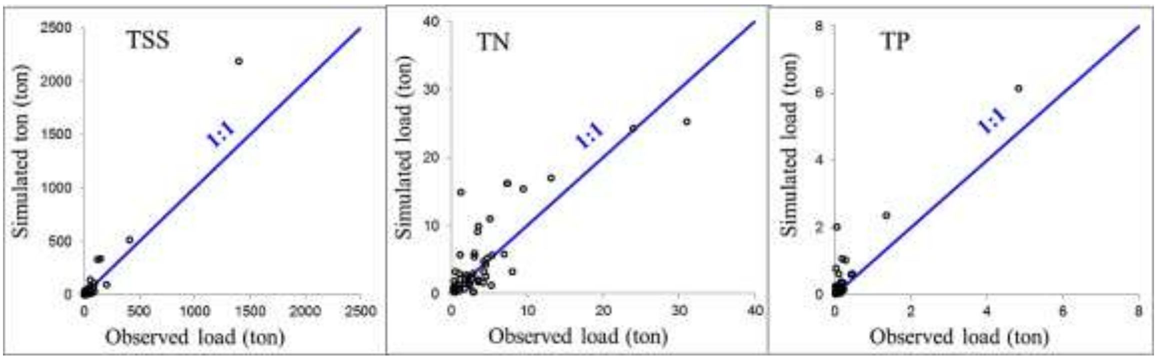


Figure 4.52 Scatterplot of monthly TSS, TN and TP for validation at site-1

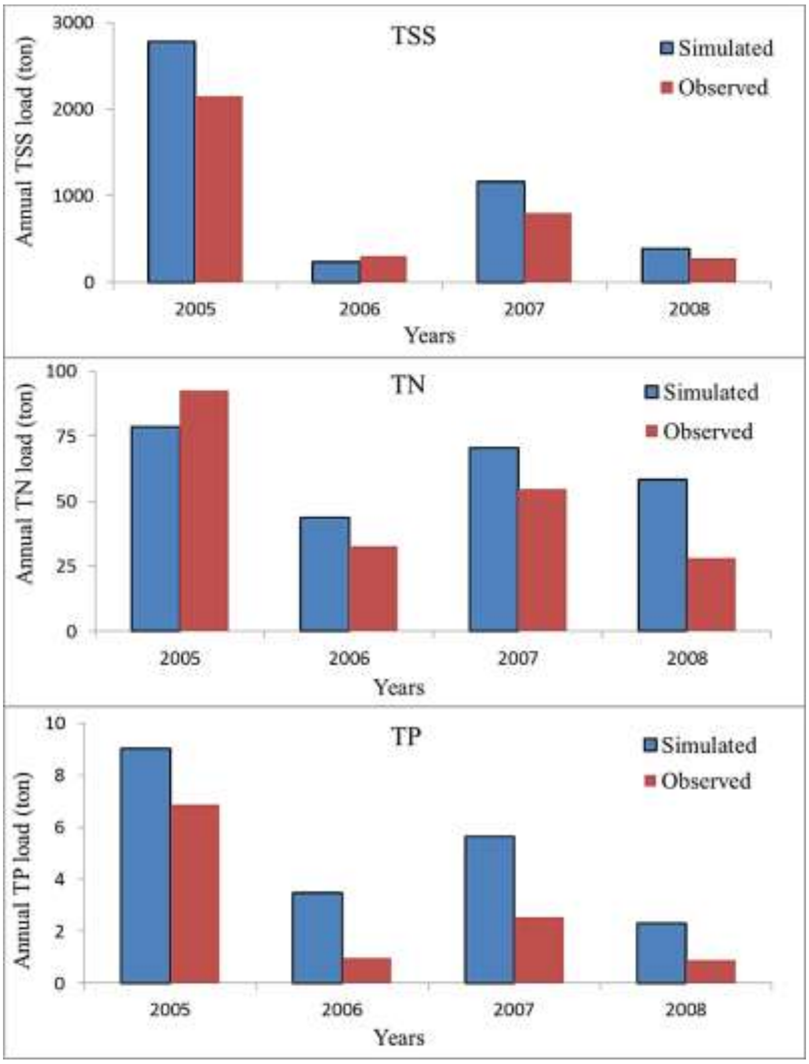


Figure 4.53 Validation of annual TSS, TN and TP at site-1

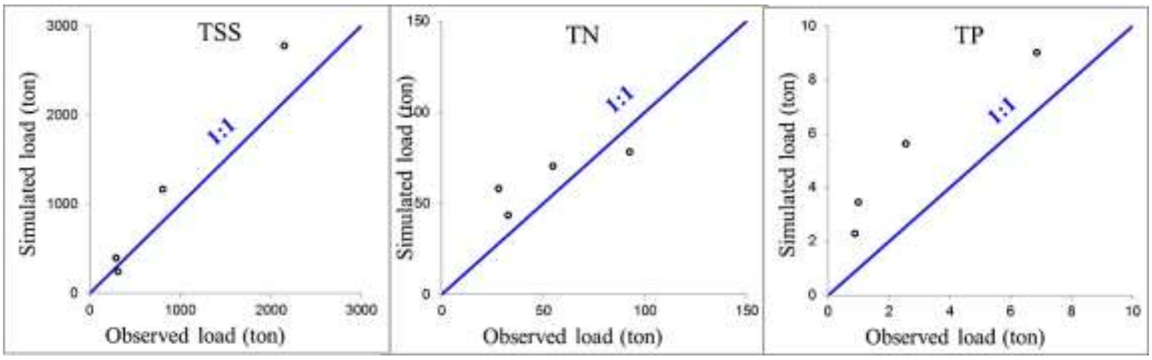


Figure 4.54 Scatterplot of annual TSS, TN and TP for validation at site-1

(B) SITE-2

At site-2, the MYWQM performances were satisfactory for monthly TSS loads (E_{NS}^2 > 0.65, R^2 > 0.85, PBIAS < ±30% but RSR < 0.70 as shown in Tables 4.18 and 4.19), and good for annual TSS loads (E_{NS}^2 > 0.65, R^2 > 0.85, RSR < 0.60, and PBIAS < ±30% as shown in Tables 4.18 and 4.19). Also the performances of monthly and annual TN loads were very good (E_{NS}^2 > 0.75, R^2 > 0.80, RSR < 0.50, and PBIAS < ±25% as shown in Tables 4.18 and 4.19).On the other hand, the monthly TP results were satisfactory (E_{NS}^2 > 0.50, R^2 > 0.95, RSR < 0.70 and PBIAS ≤ ±70 as shown in Tables 4.18 and 4.19), but annual TP results were unsatisfactory (E_{NS}^2 < 0.50 and RSR > 0.70 as shown in Tables 4.18 and 4.19).

Figure 4.55 shows that the model overestimated the peak monthly loads. The scatter plots (as shown in Figures 4.56 and 4.58) and Figure 4.57 also show that the model overestimated loads. This can also be seen in Tables 4.18 and 4.19 where PBIAS values are negative (which means overestimation). Causes of this overestimation were discussed in detail with Site-1. The overestimation rate of TP was much higher than those of TSS and TN.

(C) SITE-3

At site-3, the MYWQM performances were good for monthly and annual TSS loads (E_{NS}^2 > 0.65, R^2 > 0.75, RSR < 0.60, and PBIAS < ±30% as shown in Tables 4.18 and 4.19). Also the performances of monthly and annual TN loads were very good (E_{NS}^2 > 0.75, R^2 > 0.80, RSR < 0.50, and PBIAS < ±25% as shown in Tables 4.18 and 4.19). On the other hand, the monthly TP results were satisfactory (E_{NS}^2 > 0.65, R^2 > 0.95, RSR < 0.60 but PBIAS ≤ ±70 as shown in Tables 4.18 and 4.19), but the annual TP results were unsatisfactory (E_{NS}^2 < 0.50 and RSR > 0.70 as shown in Tables 4.18 and 4.19).

Figure 4.59 shows that the model overestimated the peak monthly loads. The scatter plots (as shown in Figures 4.60 and 4.62) and Figure 4.61 also show that the model overestimated loads. This can also be seen in Tables 4.18 and 4.19 where PBIAS values are negative (which means overestimation). Causes of this overestimation were discussed in detail with Site-1. Also the overestimation rate of TP was much higher than those of TSS and TN.

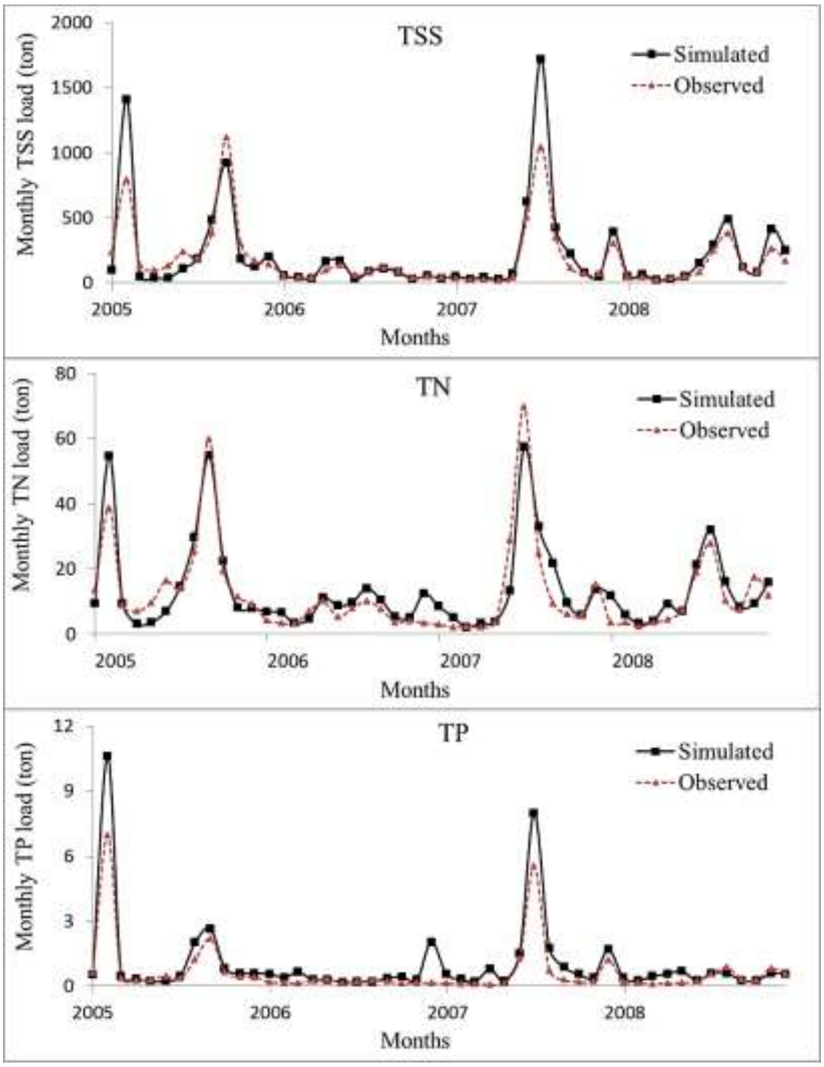


Figure 4.55 Validation of monthly TSS, TN and TP at site-2

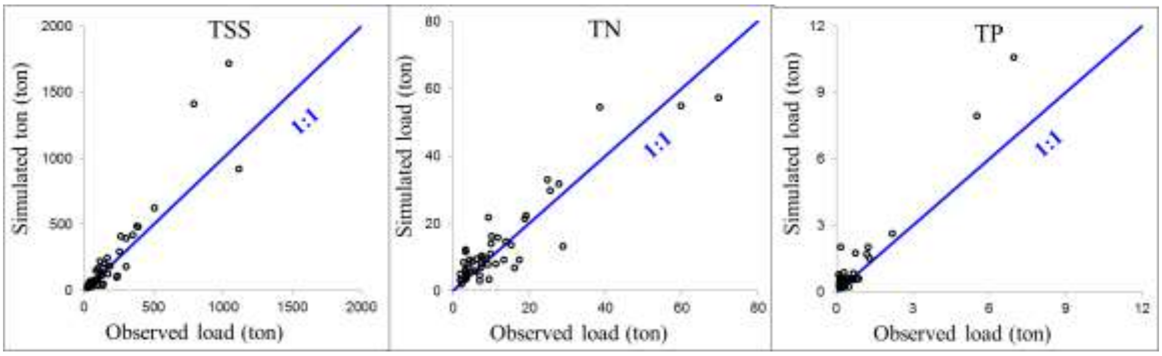


Figure 4.56 Scatterplot of monthly TSS, TN and TP for validation at site-2

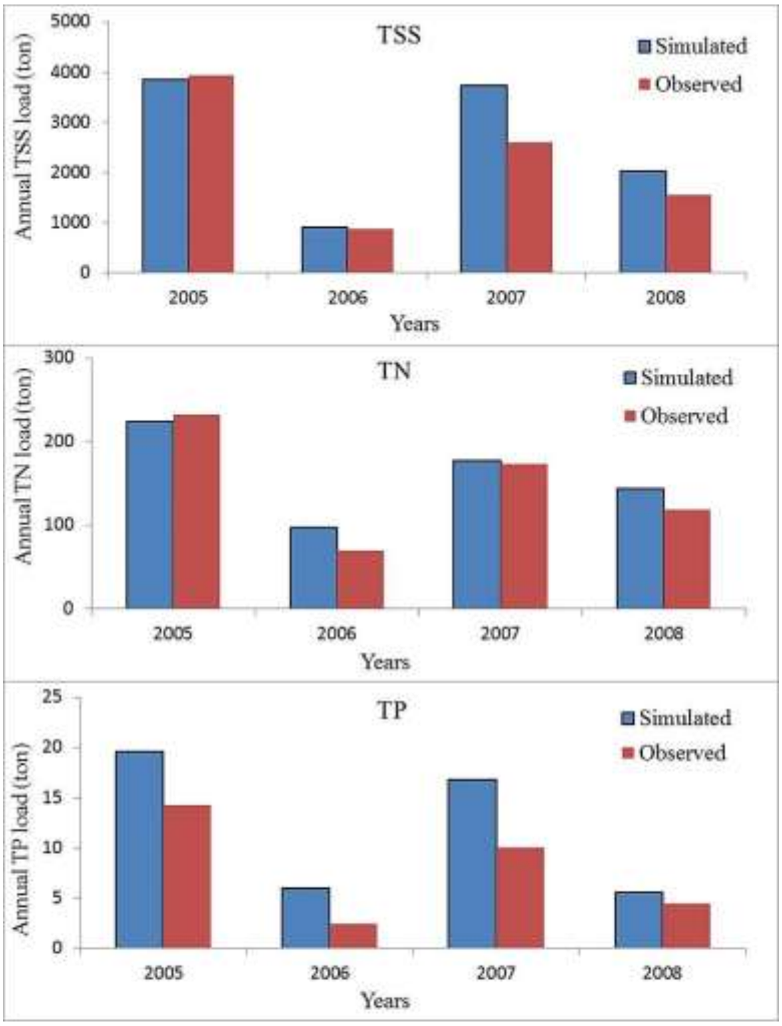


Figure 4.57 Validation of annual TSS, TN and TP at site-2

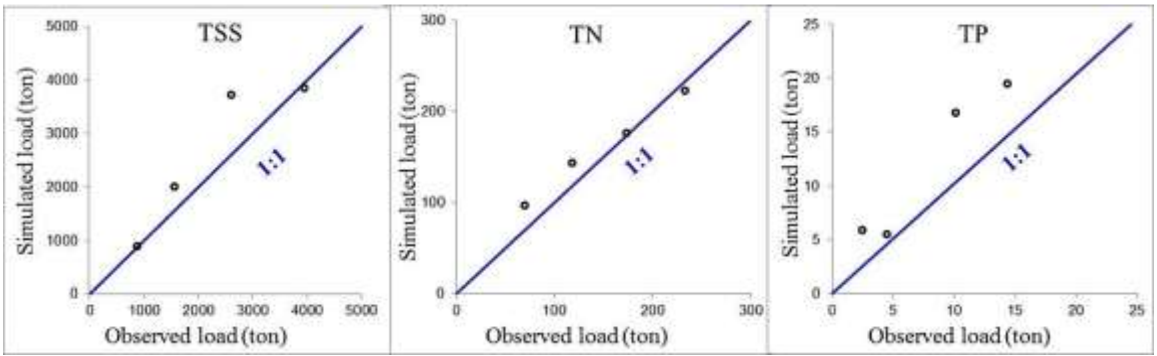


Figure 4.58 Scatterplot of annual TSS, TN and TP for validation at site-2

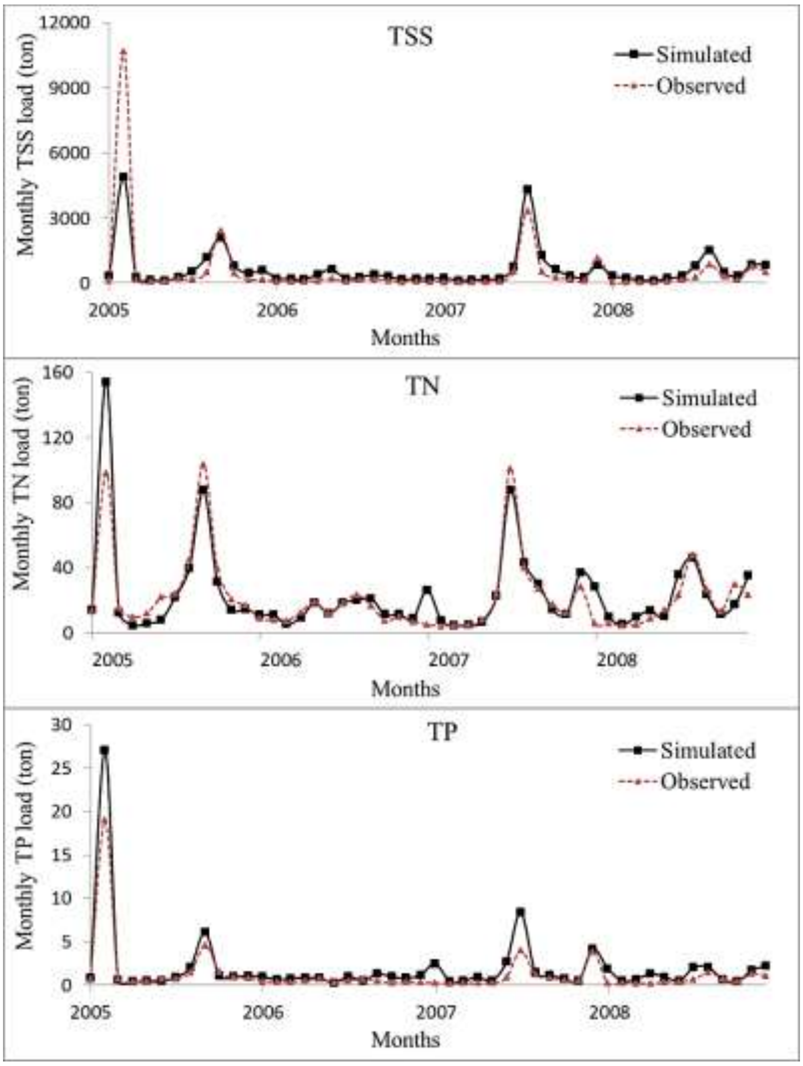


Figure 4.59 Validation of monthly TSS, TN and TP at site-3

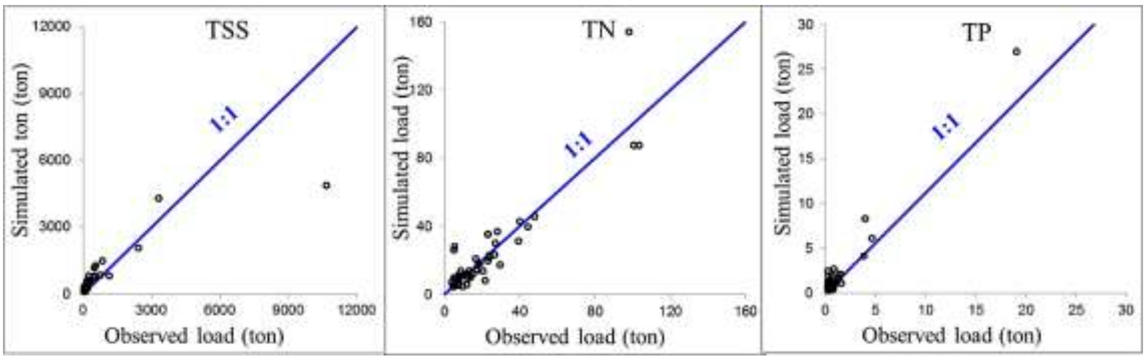


Figure 4.60 Scatterplot of monthly TSS, TN and TP for validation at site-3

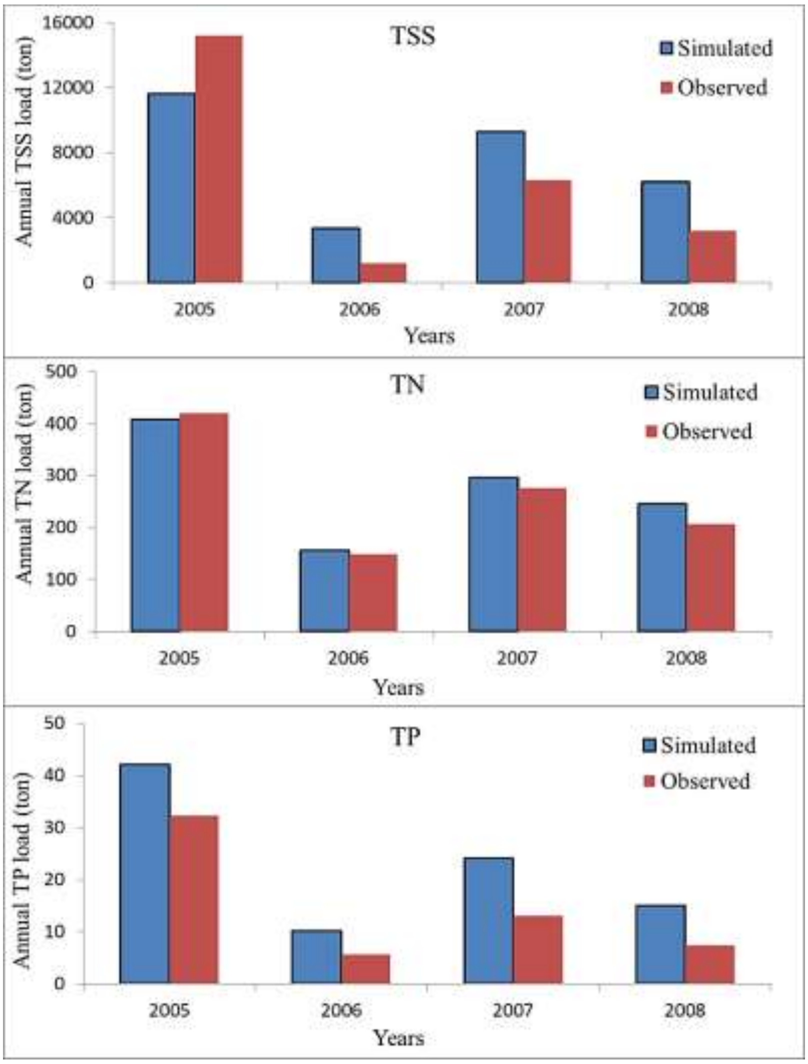


Figure 4.61 Validation of annual TSS, TN and TP at site-3

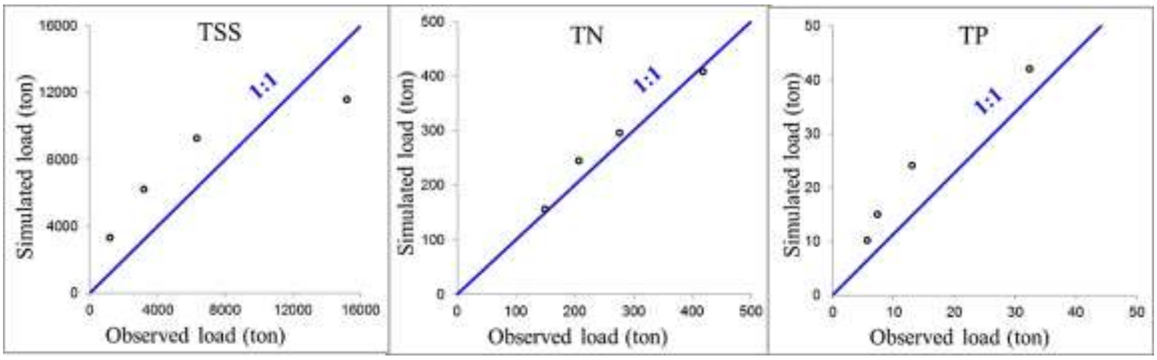


Figure 4.62 Scatterplot of annual TSS, TN and TP for validation at site-3

4.5. UNCERTAINTY ANALYSIS OF THE MYWQM

As discussed in Section 2.5.1, the model uncertainty analysis aims to quantitatively assess the reliability of model outputs. The sources of modelling uncertainties are often categorized as input uncertainties, parameter uncertainty, model structure/model hypothesis uncertainties and uncertainties in the observations. Abbaspour et al (2004) proposed *p-factor* and *d-factor* for quantifying the degree to which uncertainties are accounted for. The *p-factor* is simply the percentage of observed data bracketed by the 95% prediction uncertainty (95PPU) band, calculated at 2.5^{th} and 97.5^{th} percentiles of cumulative distribution of the simulated variable. The ideal value for *p-factor* is where all of observed values are enclosed by the 95PPU (*p-factor* equals 100%). On the other hand, *d-factor* is the average distance between upper and lower limits of 95PPU normalized by the standard deviation of observed variables. On the basis of *d-factor* definition, it is obvious that the magnitude of *d-factor* is directly related to the amount of uncertainty in the simulated outputs. In other words, the larger is the *d-factor*, the larger is the uncertainty. The ideal value for the *d-factor* is when it is close to zero (uncertainty in predicted output is minimum).

ParaSol with uncertainty analysis (SCE-UA) tool embedded in SWAT2005 was used for uncertainty analysis in the MYWQM. Once the optimization was done in ParaSol, the uncertainty analysis divided each simulation that has been performed by the SCE-UA optimization into 'good' simulation and 'not good' simulation based on a threshold value of the objective function whether falling or not within a user-defined confidence interval (e.g. 95% probability). Then good simulations were used to estimate the *p-factor* and *d-factor* from the 95PPU band for each simulated variables (Q, TSS, TN and TP). Sum of the squares of the residuals (SSQ) was used as the objective function. The χ^2-statistic was used to define the threshold value. Details about ParaSol with uncertainty analysis were discussed in Section 2.5.1.4(C).

The results of uncertainty analysis for streamflow (Q), sediment (TSS) and nutrients (TN and TP) in the MYWQM are shown in Table 4.20. The *d-factor* values shown in Table 4.20 indicated that the model's streamflow, sediment and nutrients predictions were reasonably consistent in the sense that the uncertainty bounds were narrow (very small values of *d-factor*). However, the values of *p-factor* were also very small. Setegn et al (2008) found similar ParaSol uncertainty results for hydrology at four tributaries in Lake Tana catchment in Ethiopia. They found *p-factor* ranges 15% to 21% and *d-factor* ranges 0.02 to 0.10. The uncertainty results also indicated that more uncertainties were associated with TSS and TP prediction which are expected.

Table 4.20 Uncertainty results in the MYWQM

	Streamflow			TSS			TN			TP		
	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3
p-factor (%)	14	31	19	8	13	5	17	25	17	1	13	10
d-factor	0.16	0.12	0.10	0.12	0.09	0.02	0.19	0.14	0.09	0.04	0.15	0.12

Mainly for two reasons, the *p-factor* values were very small in the MYWQM. Firstly, ParaSol uses very low threshold value of the objective function (SSQ) determined by χ^2-statistics to separate 'good' and 'not good' simulations. As a result, the uncertainty bounds are narrow, and bracket small numbers of observed data. Yang et al (2008) compared five uncertainty analysis procedures for an application of SWAT to the Chaohe Basin in China. They found the ParaSol *p-facto*r of 18% and *d-factor* of 0.08 in the calibration period. They pointed out that ParaSol uses high threshold value of Nash-Sutcliffe efficiency of 0.82 (or low threshold value of SSQ; the value of Nash-Sutcliffe efficiency was converted from SSQ) determined by χ^2-statistics to separate 'good' and 'not good' simulations. As a result the number of 'good' simulations is very small and the corresponding parameter ranges are very narrow i.e. narrow *d-factor* which bracketed less numbers of observed data (small *p-facto*r). When they used the threshold value of 0.70, the *p-factor* increased to 60%.

Secondly, ParaSol considers only parameter uncertainty out of many other uncertainties. For example, SUFI-2 uncertainty analysis method (Abbaspour et al, 2004) considers default ±10% uncertainty in observed streamflow data used for calibration. If similarly ±10% uncertainty in streamflow and ±15% uncertainty in sediment and nutrients observed data are considered in the ParaSol analysis of the MYWQM, the *p-factor* values substantially increased as shown in Table 4.21 compared to the *p-factor* values in Table 4.20.

Table 4.21 Uncertainty results in the MYWQM
(considering uncertainty in observed data)

	Streamflow			TSS			TN			TP		
	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3	Site-1	Site-2	Site-3
P-factor (%)	27	56	53	25	37	13	31	50	39	15	29	25
d-factor	0.16	0.12	0.10	0.12	0.09	0.02	0.19	0.14	0.09	0.04	0.15	0.12

4.6. SUMMARY

Although developing reliable catchment water quality models and validating them on real-world catchments are challenging, they can save time and money because of their ability to understand the problems and find solutions through land use changes and best management practices. For the same purposes, the MYWQM was developed for the Middle Yarra Catchment (MYC).

All the spatial datasets and database input files processed in Chapter 3 were organized following the guidelines of Winchell et al (2009) and Neitsch et al (2004; 2005) to develop the MYWQM. The main methods used in modelling the hydrologic processes were the curve number (CN) method for runoff estimating, the Penman-Monteith method for PET and the Muskingum method for channel routing. Moreover, in-stream nutrient transformations were modeled using the QUAL2E equation embedded in the SWAT2005 modelling software. The MYWQM delineated the MYC into 51 sub-catchments and 431 HRUs based on the MYC topography, land use, soils and slopes.

The SWAT inbuilt Latin-Hypercube and One-factor-At-a-Time (LH-OAT) random sampling procedure was used for sensitivity analysis. ParaSol (SCE-UA) method was used for Multi-site (three sites), multi-variable (Q, TSS, TN and TP) and multi-objective (one objective for each variable) autocalibration and uncertainty analysis. Based on the sensitivity analysis, 15 streamflow parameters, and 13 sediment and nutrient parameters were selected for autocalibration. The calibration and validation periods for streamflow were different from sediment and nutrients. Therefore, streamflow was calibrated first at the three sites simultaneously. Then sediment and nutrients were calibrated simultaneously at the three sites. Surface runoff, baseflow and in-stream process parameters were adjusted manually before autocalibration.

Sensitivity analysis was performed globally on 41 parameters related to streamflow, sediment and nutrients. The results showed that globally the hydrologic parameters dominated the highest parameter ranks. The result also indicated that both in-stream and upland processes were significant in the MYC. Moreover, the water quality variables (TN and TP) were potentially capable of contributing to the identification of streamflow parameters within SWAT, and a single parameter is correlated to multiple variables.

In general, the calibration results of streamflow showed good agreement between observed and simulated flows (total streamflow, baseflow and runoff) without any unsatisfactory ratings based on the Moriasi et al (2007) guidelines. The validation results of streamflow were also good but with some exceptions. Moreover, the calibration and validation results of streamflow at site-1 showed that the Woori Yallock creek is an intermittent creek i.e., it may cease flowing during dry periods which in general affected the model performance on this site. On the other hand, the calibration and validation results of TSS and TN were good in general with some exceptions. However, the calibration and validation results of TP were unsatisfactory in general.

In general, the MYWQM under predicted flows in wet years and over predicted in dry years. Moreover, the model underestimated peak monthly TSS, TN and TP loads in their calibration period, but overestimated in their validation period. It was observed that as the periods become drier, the MYWQM generated higher percentage of runoff in the streamflow prediction. This has caused the significant over prediction of the sediment and nutrients in their validation periods (which were drier than their calibration periods) which means the climate has significant impact on the hydrology and water quality in the MYC. Moreover, lack of storm event samples in the water quality monthly grab samples has caused underestimation of the observed TSS, TN and TP loads by the LOADEST model in the validation period which affected the MYWQM performances on that period.

The results of uncertainty analysis for streamflow, sediment and nutrients in the MYWQM showed that the model's streamflow, sediment and nutrients predictions were reasonably consistent in the sense that the uncertainty bounds were narrow (very small values of *d-factor)*. However, the values of *p-factor* were also very small i.e., bracketed less numbers of observed data between the uncertainty bounds. The uncertainty results also indicated that more uncertainties were associated with TSS and TP prediction which are expected.

The process of configuring SWAT for the MYWQM in the MYC was greatly facilitated by the GIS-based interface ArcSWAT, which provides a straightforward means of translating digital land use, topographic, and soil data into model inputs. In-stream water quality processes were considered in the model development which had significant impact on the model performance. The multi-site, multi-variable and multi-objective autocalibration makes the MYWQM performance good not only at the catchment outlet, but also throughout the MYC, reducing complexity and labor in the calibration process. The calibration and validation, and uncertainty results showed that the MYWQM reasonably replicated the MYC with some exceptions which means SWAT is capable of predicting streamflow, sediment and nutrient loads in the MYC.

5. DEVELOPMENT OF THE WATER QUALITY MANAGEMENT PLAN

5.1. INTRODUCTION

In Chapter 4, the SWAT based MYWQM was developed for the study area - Middle Yarra catchment (MYC). The model sensitivity analysis, calibration and validation, and uncertainty analysis were also performed to evaluate the ability of the model on how it replicates the real world catchment. A scientifically sound and robust modelling tool helps to understand water quality problems and find solutions through best management practices (BMPs) (Borah and Bera, 2004). Various studies as discussed in Section 2.3.2.2 showed that BMPs are effective and practical conservation practices which prevent or reduce the movement of sediment and nutrients from the land to surface water or groundwater, or which otherwise protect water quality from the potential adverse effects of agricultural activities in a catchment. Thus, the model through the “what-if” scenario analysis can provide scientific information on the impacts of various BMPs (individual or integrated effects of several BMPs) and can assist stakeholders and policy-makers with decisions for ensuring effective water quality management and protection of their catchments.

As per the Moriasi et al (2007) guidelines on model performance ratings and uncertainty analysis as discussed in Chapter 4, the MYWQM was found potentially capable of predicting streamflow, sediment and nutrient loads in the MYC. The purpose of the current chapter is to evaluate the performance of the MYWQM on simulating different types of management scenarios in the MYC.

The chapter starts with a description of the baseline scenario (current conditions of the MYC replicated in the model) of the MYWQM in Section 5.2. Simulation of different types of selected BMPs in the MYWQM are discussed in Section 5.3 to test their efficiency in reducing sediment and nutrient loads/yields in the MYC comparing with the baseline scenario. In Section 5.4, effects of in-stream processes in the MYC are described. Finally a water quality management plan was developed through the what-if scenarios of the BMPs (Section 5.5) followed by a summary of the chapter at the end.

5.2. BASELINE SCENARIO FOR WATER, SEDIMENT AND NUTRIENTS

The baseline scenario corresponds to the current catchment condition of soil erodibility, land use and crop management practices in the MYC. In the development steps of the MYWQM, the MYC was divided into 51 sub-catchments and 431 HRUs as discussed in Section 4.2.2. There were two slope classes (≤10% and >10%) considered in the MYC. The dominant soil types in the catchment were Sodosol (about 54%) and Dermosol (about 35%) as shown in Figure 3.10. The dominant land use was pasture covering around 32% of the total catchment area as shown in Figure 3.12. Specific management operations used in the MYWQM are shown in Tables 5.1, 5.2 and 5.3.

No crop rotation was considered in the baseline scenario because of unavailability of the data. Fertilizer and manure were applied during the tillage operation as shown in Table 5.1. The specific dates in the management operations as shown in Tables 5.1 and 5.2 were considered tentatively by the author while applying the management operations in the MYWQM as these specific dates were not available. The fertilizer and manure types and rates used in the calibration of the MYWQM are shown in Tables 5.1 and 5.2. Nitrogen based fertilizers were urea (46-00-000) and potassium nitrate (13-00-46), and phosphorus based fertilizer was single superphosphate (00-09-00). The fertilizer and manure application rates were not available at sub-catchment or catchment level (Table 3.7). Therefore, by inverse modelling techniques (which mean determining unknown causes, based on observation of their effects), fertilizer and manure application types, rates and dates were adjusted and fixed based on their effects on the simulated nutrient loads during the calibration process as discussed in Section 2.6.5. Moreover, livestock types and number were not same for all the sub-catchment in the MYC. So livestock types were varied according to the sub-catchment as shown in Tables 5.2 and 5.3. A simple excel based calculator “Grazing Winter Cereals Feed Budget Calculator” developed by Scott Vanderkley (2008) was used for the grazing plan downloaded from the Land and Water Australia (http://lwa.gov.au/products/pn21197).

The water, sediment and nutrient yields in the MYC were estimated based on the baseline scenario in the MYWQM for the period of 1990-2008. The baseline scenario was then used as a benchmark against which the results of the other management scenarios were evaluated.

Table 5.1 Management operations used in the MYWQM

Pasture	
Season-1(Autumn)	
1. Tillage operation	1st January (Generic Spring plowing operation)
2. Fertilizer application	1st January: 13-00-46 (50kg/ha); Manure
3. Plant begin/growth	1st February
4. Grazing operation	1st May (45 days)
5. kill/end of growing season	15th June
Season-2(Spring)	
1. Tillage operation	1st July (Generic Fall plowing operation)
2. Fertilizer application	1st July: 00-09-00 (25kg/ha); Urea 46-00-00 (50kg/ha); Manure
3. Plant begin/growth	1st August
4. Grazing operation	1st November (40 days)
5. kill/end of growing season	15th December
Hay	
Season-1(Autumn)	
1. Tillage operation	1st January (Generic Spring plowing operation)
2. Fertilizer application	1st January: 13-00-46 (50kg/ha); Manure
3. Plant begin/growth	1st February
4. Harvest and kill Operation	15th June
Season-2(Spring)	
1. Tillage operation	1st July (Generic Fall plowing operation)
2. Fertilizer application	1st July: 00-09-00 (25kg/ha); Urea 46-00-00 (50kg/ha); Manure
3. Plant begin/growth	1st August
4. Harvest and kill Operation	1st December
Apple and Grape	
1. Tillage operation	1st May (Generic Conservation Tillage)
2. Fertilizer application	1st May: 13-00-46 (50kg/ha); 00-09-00 (25kg/ha); Manure
3. Plant begin/growth	1st June
4. Harvest only Operation	31st December
Potato	
Season-1(Autumn)	
1. Tillage operation	1st January (Generic Spring plowing operation)
2. Fertilizer application	1st January: 13-00-46 (50kg/ha); Manure
3. Plant begin/growth	1st February
4. Harvest and kill Operation	30th June
Season-2(Spring)	
1. Tillage operation	1st August (Generic Fall plowing operation)
2. Fertilizer application	1st August: 00-09-00 (25kg/ha); Manure
3. Plant begin/growth	1st September
4. Harvest and kill Operation	31st December

Table 5.2 Manure application used in the MYWQM

Pasture and Hay		
Sub-catchment	Manure (500 kg/ha each time)	
21	Sheep 1st and 2nd of January	Beef 1st and 2nd of July
23, 25	Beef 1st and 2nd of January	Beef, Horse 2nd and 3rd of July
28, 29, 31, 33, 36, 37, 39, 40, 41, 42, 44, 45, 48, 49	Beef , Layer 1st and 2nd of January	Layer 1st and 2nd of July
22, 35, 43	Beef 1st and 2nd of January	Layer 1st and 2nd of July
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 17, 20, 24, 30	Broiler 1st and 2nd of January	Layer, Boiler 1st and 2nd of July
15, 16, 18, 19, 26, 27, 32, 34, 38, 46, 47	Broiler 1st and 2nd of January	Layer 1st and 2nd of July
50, 51	Broiler 1st and 2nd of January	Layer 1st and 2nd of July
Apple and Grape		
Sub-catchment	Manure (500 kg/ha each time)	
36, 39, 41, 44,	Beef, Layer (3times) 27th to 30th of April	
4, 5, 10, 11, 14, 17	Broiler 27th to 30th of April	
27, 32, 38, 47	Broiler (2 times), Layer (2 times) 29th and 30th of April; 5th and 6th of May	
51	Broiler (2 times), Layer (2 times) 29th and 30th of April; 4th and 5th of May	
Potato		
Sub-catchment	Manure (500 kg/ha each time)	
50, 51	Broiler 1st and 2nd of January	Layer 1st and 2nd of August

Table 5.3 Grazing operation (pasture) used in the MYWQM

Sub-catchment	Dry manure deposited	
21	sheep (0.13 kg/ha/day)	beef (0.92 kg/ha/day)
23, 25	sheep (0.01 kg/ha/day)	beef (0.32 kg/ha/day)
28, 29, 31, 33, 36, 37, 39, 40, 41, 42, 44, 45, 48, 49	dairy (0.45 kg/ha/day)	beef (1.65 kg/ha/day)
22, 35, 43	dairy (0.03 kg/ha/day)	beef (0.22 kg/ha/day)
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 17, 20, 24, 30	sheep (0.14 kg/ha/day)	beef (1.41 kg/ha/day)
15, 16, 18, 19, 26, 27, 32, 34, 38, 46, 47,	dairy (0.57 kg/ha/day)	beef (1.41 kg/ha/day)
50, 51	dairy (2.88 kg/ha/day)	beef (2.38 kg/ha/day)

5.2.1. WATER YIELD IN THE MYC

Table 5.4 shows the annual water yield components of the MYC. On average, ET accounts for 54% of the precipitation, the largest of all components. Surface runoff and lateral flow account equally about 5% of the precipitation and groundwater accounts slightly higher (about 6%). Available water holding capacity of the soils varies considerably and very low compared to other components (average annual about 14 mm).

Table 5.4 Water yield components of the MYC for 1990-2008 period

Year	PRECI (mm)	ET (mm)	SW (mm)	SURQ (mm)	LATQ (mm)	GW_Q (mm)	WYLD (mm)
1990	1125.5	575.6	7.3	48.6	54.7	18.7	122.8
1991	1222.5	530.4	28.1	95.9	59.1	32.6	188.5
1992	1357.5	636.4	20.1	59.5	70.0	78.8	209.9
1993	1385.3	660.7	27.3	81.0	67.4	90.1	239.8
1994	892.0	584.2	4.1	28.4	40.5	56.6	126.1
1995	1299.9	580.9	14.0	65.7	66.3	125.2	258.8
1996	1384.1	627.5	11.4	84.1	71.8	180.4	338.3
1997	698.2	485.6	3.8	19.3	28.2	10.8	58.3
1998	1028.1	584.9	19.6	41.9	46.2	44.4	132.8
1999	1027.1	601.7	27.7	39.2	45.4	63.4	148.3
2000	1072.5	585.3	11.5	42.6	52.0	97.0	192.3
2001	950.9	542.9	12.2	35.7	44.3	63.1	143.4
2002	810.3	560.5	6.2	24.0	33.2	24.4	81.8
2003	1001.8	550.3	7.7	41.0	48.2	66.9	156.3
2004	1146.7	537.9	15.0	64.4	58.7	123.1	246.7
2005	966.1	568.0	6.9	66.6	42.1	61.2	170.2
2006	747.5	488.9	15.4	22.2	31.4	22.0	75.6
2007	981.8	525.0	11.8	66.4	48.1	53.0	167.4
2008	843.6	503.0	13.4	27.9	39.4	46.1	113.4
Average	1049.6	564.7	13.9	50.2	49.8	66.2	166.9
Percent	-	54%	1%	5%	5%	6%	16%

Note: PRECI = Precipitation, ET = Evapotranspiration, SW =Soil water storage, SURQ = Surface runoff, LATQ = Lateral flow, GW_Q = Groundwater flow, WYLD =Water yield

The average annual water yield in the MYC is 166.9 mm. About 30% of the water yield is contributed by surface runoff, another 30% is from lateral flow and 40% is groundwater flow. The highest water yield occurred in 1996 and the lowest in 1997 as shown in Figure 5.1a. The water yield decreases from 1997 onwards because of the drought period in the MYC. Moreover, the highest water yield occurred in the month of August and the lowest in March as shown in Figure 5.2a. About 60% of water yield occurred in the months of Jun to October (Figure 5.2a).

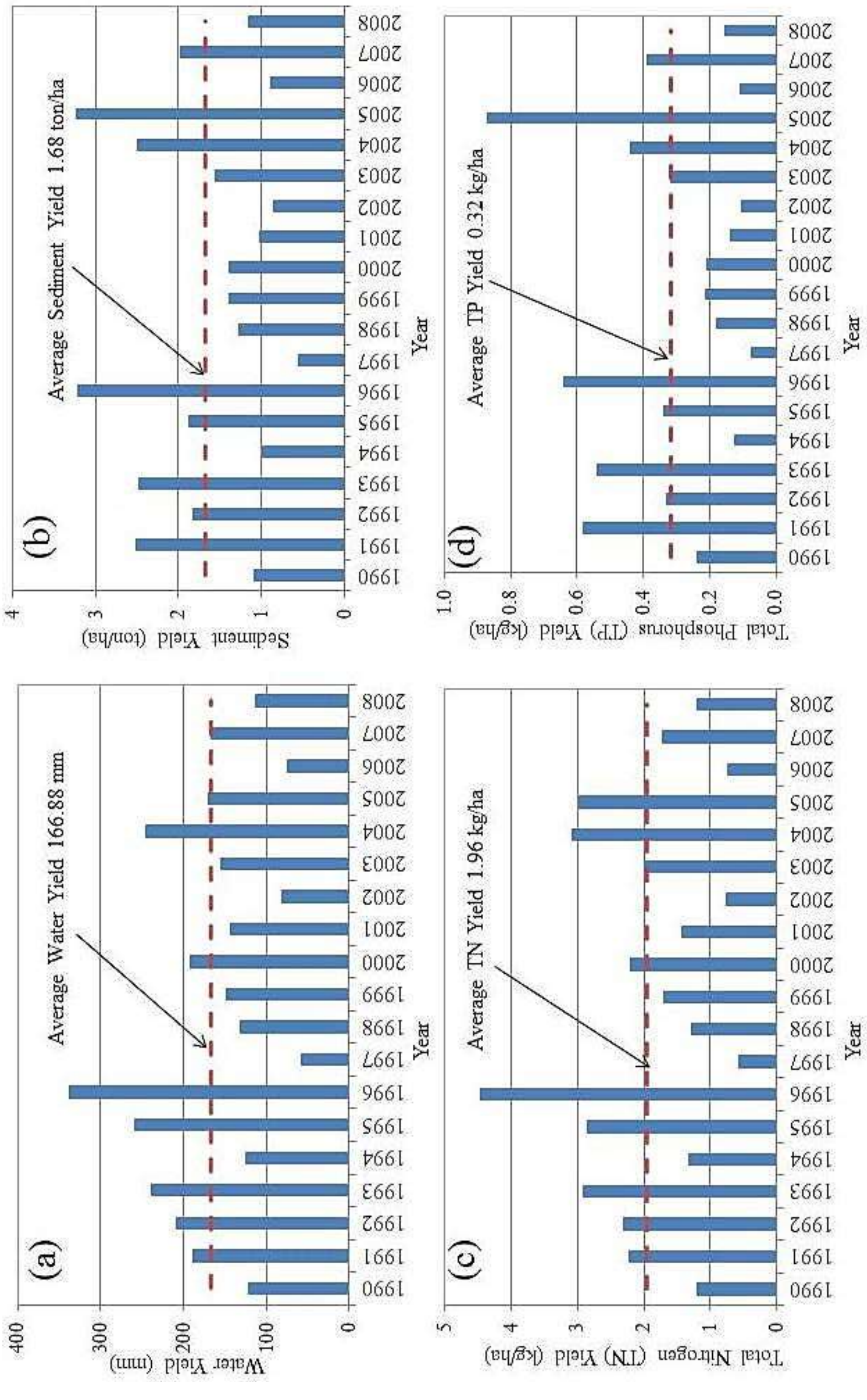


Figure 5.1 Annual yields in the MYC (a) Water yield (b) Sediment yield (c) TN yield and (d) TP yield

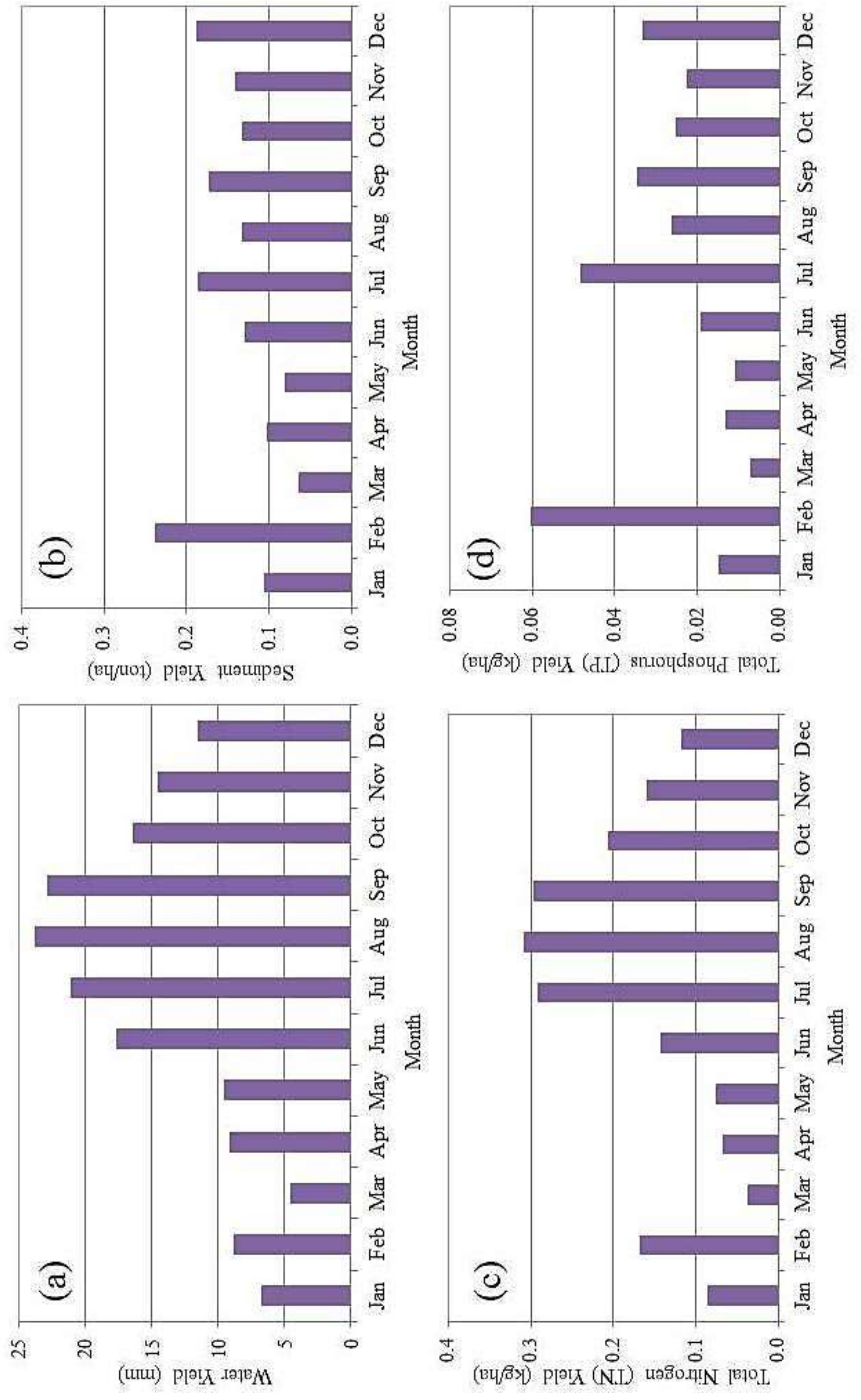


Figure 5.2 Monthly yields in the MYC (a) Water yield (b) Sediment yield (c) TN yield and (d) TP yield

The major water yielding areas of the MYC concentrated in the upper eastern and southern part of the catchment which is mainly mountainous and forest areas. About 41% of the catchment area has an annual water yield of over 230 mm contributing 65% of the water yield in the MYC, and the rest has less than 230 mm. The source areas and their relative contributions are shown in Table 5.5, and in Figures 5.3a and 5.4a. Table 5.5 is based on the sub-catchment wise spatial variation of water yield related to Figure 5.3a. Figures 5.3a and 5.4a also show that SWAT has estimated higher yields at the HRU scale than at the sub-catchment level.

Table 5.5 Water yield versus areal coverage

Water yield (mm)	Area coverage (%)	Water yield contribution (%)
14-46	17	4
46-105	11	7
105-176	13	10
176-230	18	14
230-300	19	25
>300	22	40

5.2.2. SEDIMENT YIELD IN THE MYC

Table 5.6 shows that the average annual sediment (Total Suspended Solid –TSS) yield in the MYC is 1.68 ton/ha. In general, the sediment yield has a consistent pattern with the water yield components. The highest sediment yield occurred in year 2005 and lowest in 1997 as shown in Table 5.6 and in Figure 5.1b. Moreover, the highest sediment yield occurred in February and the lowest in March as shown in Figure 5.2b. The highest sediment yield occurring year and month are different from those of the water yield. This is because of the most extreme rainfall event (as shown in Table 3.15) occurred in the month of February 2005. This means that the sediment yield is more influenced by the extreme rainfall event than the water yield. This can be seen in Table 5.6 that although the runoff and water yield are much higher in year 1996 than in year 2005, the sediment yield is higher in year 2005. About 47% of sediment yield occurs in the four months of February, July, September and December (Figure 5.2b).

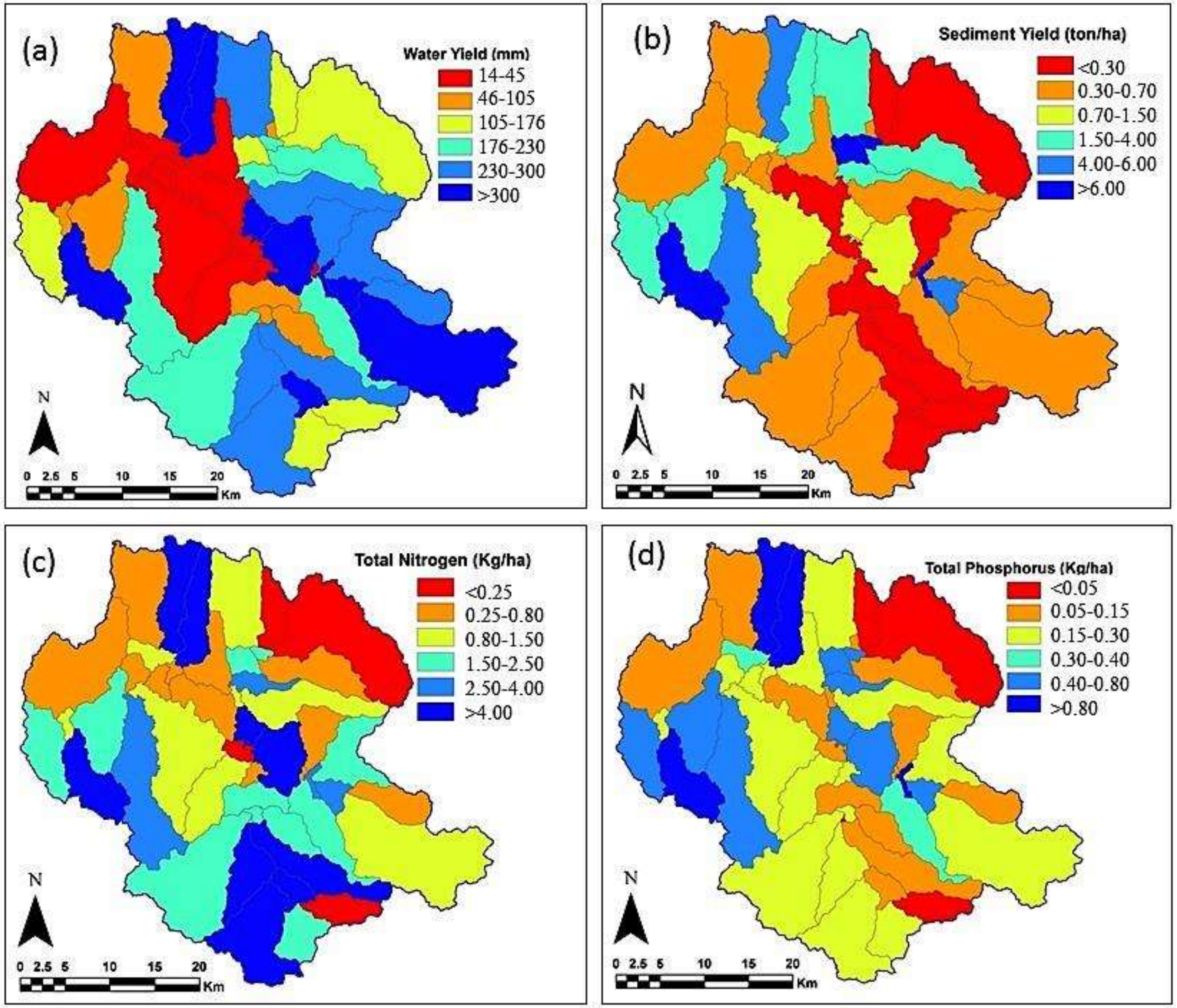


Figure 5.3 Sub-catchment based spatial distribution of average annual (a) Water yield (b) Sediment yield (c) TN yield and (d) TP yield

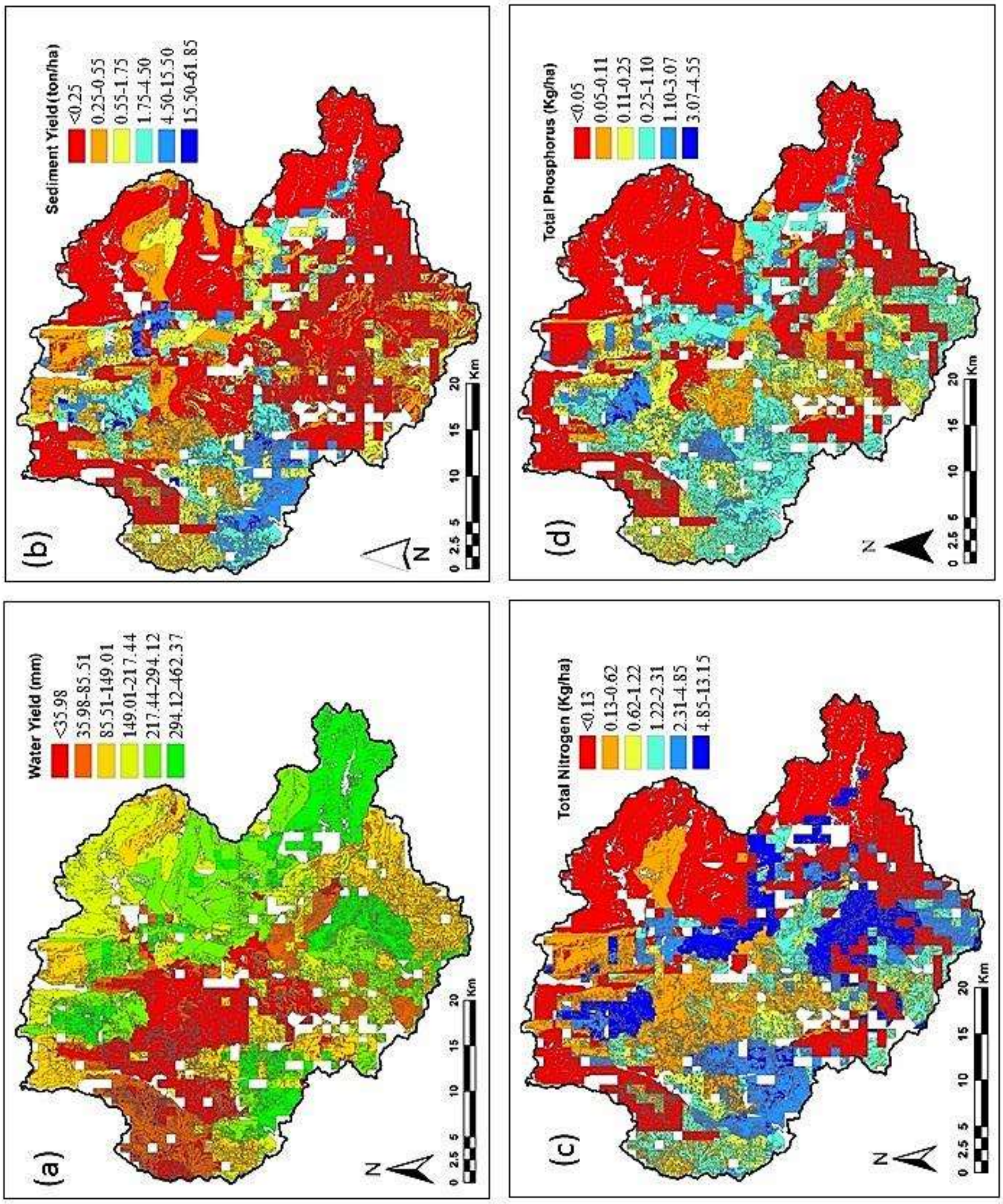


Figure 5.4 HRU based spatial distribution of average annual (a) Water yield (b) Sediment yield (c) TN yield and (d) TP yield

Table 5.6 Average annual water yield component and sediment yield of the MYC

Year	PRECI (mm)	SURQ (mm)	WYLD (mm)	SYLD (ton/ha)
1990	1125.52	48.57	122.79	1.09
1991	1222.55	95.92	188.51	2.51
1992	1357.53	59.50	209.88	1.82
1993	1385.33	80.96	239.76	2.48
1994	892.00	28.42	126.07	0.98
1995	1299.92	65.72	258.82	1.88
1996	1384.12	84.14	338.29	3.21
1997	698.17	19.31	58.34	0.56
1998	1028.12	41.94	132.81	1.27
1999	1027.15	39.18	148.28	1.39
2000	1072.53	42.61	192.27	1.39
2001	950.93	35.69	143.40	1.03
2002	810.26	24.02	81.80	0.86
2003	1001.83	40.98	156.31	1.56
2004	1146.72	64.43	246.69	2.50
2005	966.08	66.58	170.20	3.24
2006	747.48	22.15	75.64	0.89
2007	981.84	66.35	167.44	1.97
2008	843.58	27.90	113.39	1.16
Average	1049.60	50.23	166.88	1.68

Note: PRECI = Precipitation, SURQ = Surface runoff, WYLD = Water yield, SYLD = Sediment Yield

Figures 5.3b and 5.4b show that although high water yields occurred from the upper Eastern and Southern forest area of the catchment, high sediment yields occurred from the middle to downstream parts of the catchment. This part is mainly pasture land and urban area. About 14% of the catchment area has an annual sediment yield of over 4 ton/ha contributing 60% of the sediment yield in the MYC, and the rest has less than 4 ton/ha. The source areas and their relative contributions are shown in Table 5.7, and in Figures 5.3b and 5.4b. Table 5.7 is based on the sub-catchment wise spatial variation of sediment yield related to Figure 5.3b.

Table 5.7 Sediment yield versus areal coverage

Sediment yield (ton/ha)	Area coverage (%)	Sediment yield contribution (%)
<0.3	22	3
0.3-0.7	44	10
0.7-1.5	9	6
1.5-4	11	20
4-6	6	16
>6	8	44

5.2.3. TOTAL NITROGEN (TN) YIELD IN THE MYC

Table 5.8 shows the TN yield components in the MYC. The nitrogen losses occurred through surface runoff, lateral flow and groundwater flow. The average annual TN yield in the MYC is 1.96 kg/ha. Nitrate in groundwater accounts for 52% of the total yield whereas in surface runoff, it is only 3%. The organic and mineral nitrogen losses accounted for 36% and 64% of the total yield respectively.

Table 5.8 TN yield components of the MYC for 1990-2008 period

Year	ORGN (kg/ha)	NSURQ (kg/ha)	$LATNO_3$ (kg/ha)	$GWNO_3$ (kg/ha)	TN (kg/ha)
1990	0.55	0.06	0.17	0.42	1.21
1991	1.27	0.08	0.17	0.70	2.23
1992	0.75	0.07	0.18	1.32	2.32
1993	1.14	0.08	0.18	1.52	2.92
1994	0.31	0.04	0.16	0.83	1.34
1995	0.75	0.07	0.19	1.86	2.87
1996	1.39	0.08	0.18	2.83	4.47
1997	0.20	0.03	0.15	0.19	0.58
1998	0.43	0.05	0.18	0.62	1.29
1999	0.50	0.05	0.18	0.99	1.72
2000	0.49	0.05	0.19	1.48	2.21
2001	0.35	0.05	0.16	0.88	1.43
2002	0.27	0.04	0.16	0.32	0.78
2003	0.70	0.06	0.20	1.04	2.01
2004	0.94	0.06	0.18	1.90	3.08
2005	1.78	0.06	0.18	0.98	2.99
2006	0.27	0.04	0.16	0.28	0.75
2007	0.82	0.06	0.18	0.67	1.73
2008	0.37	0.04	0.17	0.64	1.22
Average	0.70	0.06	0.17	1.02	1.96

Note: ORGN = Organic nitrogen yield, NSURQ = Nitrate in surface runoff, $LATNO_3$ = Nitrate in lateral flow, $GWNO_3$ = Nitrate in groundwater

The highest TN yield occurred in 1996 and lowest in 1997 as shown in Table 5.8 and in Figure 5.1c. Moreover, the highest sediment yield occurred in August and the lowest in March as shown in Figure 5.2c. The TN yield has a similar pattern like the water yield as shown in Figures 5.1c and 5.2c. This is because of the nitrate in groundwater contributes the highest percentage in the TN yield and comparatively less influenced by extreme rainfall events (ORGN and $GWNO_3$ components in 1996 and 2005 years of Table 5.8). About 56% of TN yield occurred in the months of July to October (Figure 5.2c).

Figures 5.3c and 5.4c show that high TN yields occurred from the southern to downstream parts of the catchment. This part is mainly pasture land and urban area. About 26% of the catchment area has an annual TN yield of over 2.50 kg/ha contributing 59% of the TN yield in the MYC, and the rest has less than 2.50 kg/ha. The source areas and their relative contributions are shown in Table 5.9, and in Figures 5.3c and 5.4c. Table 5.9 is based on the sub-catchment wise spatial variation of TN yield related to Figure 5.3c.

Table 5.9 TN yield versus areal coverage

TN yield (kg/ha)	Area coverage (%)	TN yield contribution (%)
<0.25	10	0
0.25-0.80	19	7
0.80-1.50	23	8
1.50-2.50	21	25
2.50-4	7	12
>4	20	47

5.2.4. TOTAL PHOSPHORUS (TP) YIELD IN THE MYC

Table 5.10 shows the TP yield components in the MYC. The phosphorus losses occurred through surface runoff in soluble and attached to sediment form. The average annual TP yield in the MYC is 0.32 kg/ha. Organic phosphorus transported with sediment accounts for 65% of the total yield, the largest of all components. The organic and mineral phosphorus losses accounted for 65% and 35% of the total yield respectively, opposite to TN where mineral part was larger.

The highest TP yield occurred in 2005 and the lowest in 1997 as shown in Table 5.10 and in Figure 5.1d. Moreover, the highest sediment yield occurred in February and the lowest in March as shown in Figure 5.2d. The TP yield has a very similar pattern like the sediment yield as shown in Figures 5.1d and 5.2d. This is expected since the largest amount of phosphorus is transported with sediment. About 56% of the TP yield occurs in the months of February, July, September and December (Figure 5.2d).

Table 5.10 TP yield components of the MYC for 1990-2008 period

Year	ORGP (kg/ha)	SOLP (kg/ha)	SEDP (kg/ha)	TP (kg/ha)
1990	0.16	0.01	0.06	0.24
1991	0.39	0.03	0.16	0.58
1992	0.23	0.02	0.09	0.33
1993	0.35	0.03	0.17	0.54
1994	0.09	0.01	0.03	0.13
1995	0.23	0.02	0.09	0.34
1996	0.41	0.03	0.20	0.64
1997	0.06	0.00	0.01	0.08
1998	0.13	0.01	0.04	0.18
1999	0.15	0.01	0.06	0.22
2000	0.14	0.01	0.05	0.21
2001	0.10	0.01	0.03	0.14
2002	0.08	0.01	0.02	0.11
2003	0.20	0.01	0.10	0.32
2004	0.28	0.02	0.14	0.44
2005	0.51	0.03	0.33	0.87
2006	0.08	0.01	0.03	0.11
2007	0.24	0.02	0.12	0.39
2008	0.11	0.01	0.04	0.16
Average	0.21	0.02	0.09	0.32

Note: ORGP = Organic phosphorus yield, SOLP = Soluble phosphorus yield, SEDP = Mineral phosphorus attached to sediment

Figures 5.3d and 5.4d show that high TP yields occurred from the middle to downstream parts of the catchment. This part is mainly pasture land and urban area. About 22% of the catchment area has an annual TP yield of over 0.40 kg/ha contributing 61% of the TP yield in the MYC, and the rest has less than 0.40 kg/ha. The source areas and their relative contributions are shown in Table 5.11, and in Figure 5.3d and 5.4d. Table 5.11 is based on the Figure 5.3d.

Table 5.11 TP yield versus areal coverage

TP yield (kg/ha)	Area coverage (%)	TP yield contribution (%)
<0.05	10	1
0.05-0.15	23	9
0.15-0.30	42	25
0.30-0.40	3	4
0.40-0.80	15	35
>0.80	7	26

5.3. BEST MANAGEMENT PRACTICES (BMPs)

As discussed in Section 5.1, BMPs are effective and practical conservation practices which prevent or reduce the movement of sediment and nutrients from the land to surface water or ground water, or which otherwise protect water quality from the potential adverse effects of agricultural activities in a catchment.

5.3.1. SELECTION OF BMPs FOR THE MYC

As discussed in Section 2.3.2.1, regulatory agencies developed different types of structural and non-structural BMPs ranging from simplistic practices to more complex and capital-intensive practices. Structural BMPs include practices such as edge-of-field buffer and vegetative filter strips, parallel terraces, contour farming, cover crops, critical area planting, grad/streambank stabilization, and grassed waterways (USDA NRSC, 2012). Non-structural conservation practices**,** on the other hand**,** include practices such as fertilizer or manure management, and residue and tillage management (USDA NRSC, 2012). These BMPs were discussed in Section 2.3.2.1.

The Melbourne Water Corporation developed BMP guidelines as part of the Rural Land Program- Water Sensitive Farm Design (Melbourne Water, 2010b). These guidelines were collected through personal communication from Clinton Muller (Rural Land Program Coordinator, River Health (North East) section of the Melbourne Water organization). Based on these guidelines and other past studies, the following BMPs were selected to evaluate their effectiveness in the MYC as shown in Table 5.12. These were (1) Reduced rate fertilizer/manure application, (2) Conservation tillage, (3) Vegetative filter strips (VFSs), (4) Parallel terraces, (5) Contour farming, (6) Grassed waterways, (7) Streambank stabilization, and (8) combination of five BMPs from the above seven BMPs. The first two BMPs are non-structural and others are structural conservation practices. Moreover, the first five BMPs are upland conservation practices, and the grassed waterways and streambank stabilization are within-channel conservation practices.

SWAT has an established method for simulating non-structural BMPs. For structural BMPs, the model has no direct method to apply them. However, the model has the capacity to represent these practices through alteration of its input parameters. A number of previous modelling studies have used SWAT to evaluate conservation practices around the globe as discussed in Sections 2.3.2.2 and 2.4.3.2.

Table 5.12 Representation of different BMPs in the MYWQM

BMP	Purpose	Selection Criteria	SWAT representing parameter		Value when BMPs simulated	Reference
			parameter	Default/calibration value		
(1) Fertilizer/manure reduced application	Reduce nutrient load.	Cropland	--	Variable	Reduce by 30%	Cho et al (2010b) Panagopoulos et al (2011b)
(2) Conservation tillage	Facilitate sediment settling. Reduce velocity of flow. Reduce erosion.	Cropland	OV_N CH_N1 EFFMIX DEPTIL, mm CN2	0.14-0.15 0.079 0.50-0.95 125-150 35-98	0.20 0.14 0.25 100 CN2 reduced by 2	Chow (1959) Neitsch et al (2004) Neitsch et al (2005)
(3) Vegetative filter strips	Reduce sediment, dissolved contaminants, and sediment adsorbed organics in runoff.	Cropland	FILTERW	0.0 m	14 m 20 m	Cho et al (2010b) Melbourne Water (2010) Mbonimpa et al (2012)
(4) Parallel terraces	Reduce surface runoff and peak runoff. Reduce sheet and rill erosion.	Cropland	CN2 P-factor	35-98 0.27-0.70	CN2 reduced by 6 0.10, if slope ≤10% 0.12, if slope >10%	Wischmeier and Smith (1978) Arabi et al (2008) Tuppad et al (2010b)
(5) Contour farming	Reduce surface runoff. Reduce sheet and rill erosion.	Cropland	CN2 P-factor	Varies 0.27-0.70	CN2 reduced by 3 0.5, if slope ≤10% 0.6, if slope >10%	Wischmeier and Smith (1978) Arabi et al (2008) Tuppad et al (2010b)
(6) Grassed waterways	Reduce peak flow rate. Reduce channel erodibility. Increase sediment trapping. Reduce gully erosion.	Channel (1st stream class)	CH_COV CH_EROD CH_N2	0.02-0.25 0.01-0.45 0.01-0.031	0.001(completely protected) 0.001(completely protected) 0.24	Arabi et al (2008) Tesfahunegn (2012)
(7) Streambank stabilization	Reduce sediment load. Maintain channel capacity.	Channel (2nd and 3rd stream class)	CH_COV CH_EROD CH_N2	0.02-0.25 0.01-0.45 0.01-0.031	0.001 (completely protected) 0.001 (completely protected) 0.05	Chow (1959) Narasimhan et al (2007) Arabi et al (2008) Tuppad et al (2010b)

Note: CN2 initial SCS runoff curve number for moisture condition II, CH_COV channel cover factor, CH_EROD channel erodibility factor, OV_N Manning's "n" value for overland flow, CH_N1 Manning's "n" value for the tributary channel, CH_N2 Manning's "n" value for the main channel, DEPTIL depth of mixing caused by the tillage operation (mm), EFFMIX mixing efficiency of tillage operation, FILTERW width of edge-of-field filter strip (m), P-factor conservation support practice factor.

Arabi et al (2008) developed a general guideline to represent several agricultural BMPs with SWAT through changing the parameters' values. The representing parameters in SWAT and their values used to simulate the selected BMPs in the MYC are shown in Table 5.12. These values were selected based on the past studies and guidelines of Chow (1959), Wischmeier and Smith (1978b), Neitsch et al (2004; 2005), Narasimhan et al (2007), Arabi et al (2008), Cho et al (2010b), Melbourne Water (2010b), Tuppad et al (2010b), Panagopoulos et al (2011b), Mbonimpa et al (2012), Tesfahunegn et al (2012), (Giri et al, 2014) as shown in Table 5.12.

Two widths of vegetative filter strips (VFSs) of 14m and 20m were selected initially for this study. Melbourne Water (2010b) recommended minimum 20m wide strips between cultivated areas and waterways. A width of 14m is chosen as it produces an 80% trapping efficiency. SWAT separately simulates trapping efficiencies of a VFS for surface and subsurface components using the same parameter FILTERW as a user input for each HRU according to the following two equations (Neitsch et al, 2005; Arabi et al, 2008; Tuppad et al, 2010a; Panagopoulos et al, 2011b):

$$\text{Trapping efficiency}_{surface} = [0.367\ (\text{VFSs width, m})^{0.2967}]\ 100\ \% \quad (5.1)$$

$$\text{Trapping efficiency}_{subsurface} = [2.1661\ (\text{VFSs width, m}) - 5.1302]\ \% \quad (5.2)$$

The surface trapping efficiency Equation 5.1 is used for different constituents including sediment, organic nitrogen, nitrate-nitrogen in runoff, mineral phosphorus adsorbed to sediment in surface runoff, soluble phosphorus, and organic phosphorus. Similarly, the subsurface trapping efficiency Equation 5.2 is used for NO_3-N removal through lateral flow and groundwater (Cho et al, 2010a). A 30m and 50m width of a filter strip produce 100% surface and subsurface trapping efficiencies respectively as shown in Figure 5.5.

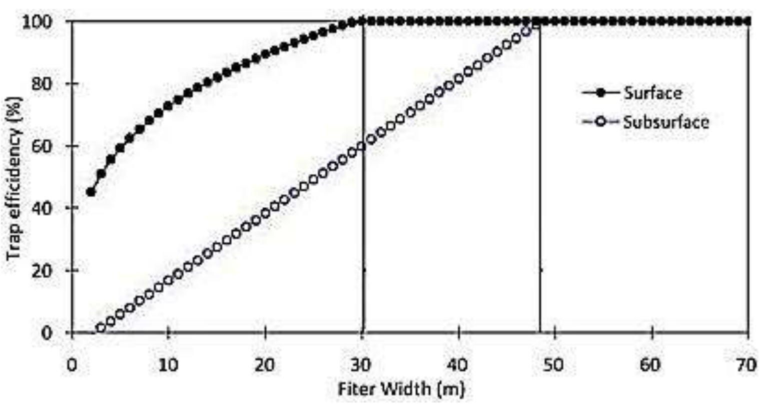


Figure 5.5 Surface and subsurface trapping efficiency of a VFS (Cho et al, 2010)

5.3.2. IMPLEMENTATION OF THE BMPs

As discussed in Section 2.3.2, identifying areas with high pollution potential and treating these areas first would be a more efficient way to allocate financial resources and control NPS pollution (Tuppad et al, 2010a). Effective water quality protection should target the BMPs on these high potential pollution areas instead of random distribution of BMPs within a catchment. Tuppad et al (2010a) found that the targeted approach required less area for implementing the BMPs (about 2.2 times less) in the catchment than the random approach. Tripathi et al (2003), Panagopoulos et al (2011a; 2011b), Giri et al (2012), Tesfahunegn et al (2012) and Giri et al (2014) have also found that the targeting approach is the most cost-effective and efficient way of managing river water quality.

In this research, a similar strategic targeting approach of Tuppad et al (2010a) is used. The average annual overland sediment-yield (ton/ha) from each sub-catchment of the MYWQM was used as the sole criterion to select sub-catchments for targeting. The MYWQM divided the MYC into 51 sub-catchments. The selected seven BMPs in Table 5.12 were implemented in these sub-catchments following the targeting approach. First the sub-catchments were ranked based on the MYWQM overland sediment yield estimated from the baseline scenario as shown in Table 5.13. Starting with the sub-catchment having the highest sediment yield, the next highest ranked sub-catchment was successively added until the cumulative area equalled the targeted percentage of total mixed-crop area. For this research, 25%, 50% and 100% targeted percentages were considered. The targeting was implemented in each sub-catchment on an "all-or-nothing" basis, which resulted in actual percentages of 32%, 50% and 100% of total mixed-crop area for the scenarios simulated in this research.

Table 5.13 shows that the selected BMPs were implemented in the first 16 high ranked sub-catchments for 32% targeted percentage, then in the first 26 high ranked sub-catchments for 50% targeted percentage and finally in all the 51 sub-catchments for 100% targeted percentage. It should be noted that the term "mixed-crop area" in Table 5.13 means summation of the areas of pasture, hay, potato, apple and grape in a sub-catchment. Moreover, 32%, 50% and 100% of treated mixed-crop area means about 13%, 20% and 41% of the total catchment area (1511 km^2) respectively. The first 16 high ranked sub-catchments that included the 32% of treated mixed-crop area or 13% of the total catchment area contributed about 84% of the total sediment yields.

Table 5.13 Ranking of targeted sub-catchments for implementation of BMPs

Rank	Sub-catchment number (related to Figure 4.1)	Sediment yield (ton/ha)	Mixed-crop area (km^2)	Cumulative area (km^2)	Percentage
1	11	8.73	2.60	2.60	0
2	35	7.75	5.70	8.30	1
3	6	7.56	0.00	8.30	1
4	33	7.26	0.43	8.73	1
5	43	6.07	24.68	33.41	5
6	36	5.20	2.46	35.86	6
7	5	4.83	18.19	54.05	9
8	1	4.06	3.11	57.16	9
9	25	3.52	8.97	66.13	11
10	12	3.43	5.45	71.58	12
11	8	3.20	15.54	87.12	14
12	7	2.47	0.00	87.12	14
13	22	2.46	35.03	122.15	20
14	23	2.23	0.67	122.82	20
15	10	1.47	7.22	130.05	21
16	**27**	**1.24**	**64.02**	**194.06**	**32**
17	30	1.17	21.09	215.15	35
18	24	1.16	10.11	225.26	37
19	41	0.69	12.95	238.21	39
20	32	0.69	32.76	270.98	44
21	20	0.66	6.81	277.79	45
22	31	0.66	9.51	287.30	47
23	37	0.59	0.00	287.30	47
24	3	0.58	0.00	287.30	47
25	15	0.56	7.28	294.57	48
26	**45**	**0.55**	**14.50**	**309.07**	**50**
27	46	0.52	17.49	326.56	53
28	17	0.47	7.48	334.04	55
29	13	0.44	2.85	336.89	55
30	14	0.44	17.27	354.15	58
31	4	0.42	19.45	373.60	61
32	47	0.38	48.27	421.87	69
33	51	0.37	36.87	458.74	75
34	21	0.36	42.04	500.78	82
35	18	0.32	0.08	500.86	82
36	40	0.28	1.73	502.58	82
37	28	0.27	2.08	504.66	82
38	2	0.26	0.00	504.66	82
39	38	0.25	16.13	520.79	85
40	50	0.25	12.37	533.17	87
41	19	0.24	1.35	534.52	87
42	34	0.24	4.39	538.91	88
43	39	0.23	13.44	552.35	90
44	9	0.21	0.00	552.35	90
45	16	0.20	28.51	580.86	95
46	48	0.15	5.45	586.31	96
47	26	0.12	3.23	589.54	96
48	29	0.12	0.73	590.27	96
49	44	0.11	22.25	612.52	100
50	42	0.01	0.24	612.76	100
51	**49**	**0.00**	**0.00**	**612.76**	**100**

Table 5.14 shows the fraction of stream class in the MYC. The MYC has three classes of streams. Stream class 1 covers around 63% of total stream length, and other two classes cover around 37% as shown in Table 5.14. Grassed waterways were applied in the streams of class 1, and streambank stabilization in the streams of other classes.

Table 5.14 Fraction of stream classes in the MYC
(The streams in the MYC were classified as per Arabi et al, 2008)

Stream class	Number of segments	Length (m)	Fraction of total stream length (%)
1	25	212605	63
2	16	60293	18
3	10	62752	19
Total	51	335650	100

5.3.3. EVALUATION OF THE BMPs

The effects of the BMP implementation on water quality are presented as percent reductions on average annual sediment, TN, and TP yields/loads (averaged over the period of 1990-2008) at the HRU, sub-catchment, and catchment outlet levels. The HRU and sub-catchment level percent reductions represent overland yield reductions due to the BMP implementation. Catchment level reductions include cumulative load reductions considering overland transport and routing through the stream network. The percent reduction was calculated as (Tuppad et al, 2010b):

$$reduction, \% = \frac{y_1 - y_2}{y_1} \times 100 \qquad (5.3)$$

where y_1 and y_2 mean model outputs before and after implementation of the BMPs.

Table 5.15 shows the percent reductions of sediment, TN and TP for the selected BMPs in the MYC. The percent reductions were higher at the HRU level, then at the sub-catchment level. This is because the yield reductions summarized at the HRU level consider only areas with BMPs, whereas the yield reductions summarized at the sub-catchment level consider both areas with BMPs (mixed-crop area) and without BMPs (other land use types). Also, since 32%, 50% and 100% of treated mixed-crop area is only about 13%, 20% and 41% of the total catchment area respectively, the reductions became lowest at the catchment outlet level. In general, the selected BMPs effectively reduced the sediment and nutrients loads/yields in the MYC except the VFSs. The combined effects of five BMPs (type ‘h’ in Table 5.15) are discussed in Section 5.5. Also the VFSs reductions as shown in Table 5.15 were only for 14m width; 20m was not considered further since VFSs has no effects on sediment and TP reductions.

Table 5.15 Percent reduction of Sediment, TN and TP loads/yields in the MYC for the selected BMPs

BMP	Cumulative Crop area (%)	Sediment reduction (%)			TN reduction (%)			TP reduction (%)		
		At catchment level	At sub-catchment level	At HRU level	At catchment level	At sub-catchment level	At HRU level	At catchment level	At sub-catchment level	At HRU level
(a) Application of fertilizer/manure at reduced rate	100	0	0	0	15	22	28	7	13	22
	50	0	0	0	8	18	25	5	10	21
	32	0	0	0	3	14	24	4	9	21
(b) Conservation tillage	100	0	20	51	-14	6	6	-24	20	25
	50	0	19	51	-11	6	8	-19	18	26
	32	0	17	48	-9	6	7	-17	13	21
(c) Vegetative filter strips	100	-	-	-	12	15	18	-	-	-
	50	-	-	-	6	12	15	-	-	-
	32	-	-	-	2	8	14	-	-	-
(d) Parallel terraces	100	1	20	88	2	12	19	24	48	81
	50	1	17	89	3	15	28	22	45	82
	32	1	13	90	2	17	34	17	38	83
(e) Contour farming	100	1	10	36	1	10	14	10	22	32
	50	0	8	36	0	8	13	6	19	31
	32	0	8	36	1	7	13	6	18	31
(f) Grassed waterways	100	72	-	-	48	-	-	55	-	-
	50	67	-	-	42	-	-	50	-	-
	32	14	-	-	18	-	-	39	-	-
(g) Streambank stabilization	100	55	-	-	0	-	-	0	-	-
	50	37	-	-	0	-	-	0	-	-
	32	32	-	-	0	-	-	0	-	-
(h) Combination of above (a), (b), (d), (f) and (g) type BMPs	32	44	23	93	16	30	53	38	43	87

Note: The figures in Table 5.15 were rounded up to the value of 0.50. Zero figures indicate very insignificant effect of a BMP on that level. The '-' spaces in case of grassed waterways and streambank stabilization indicate that these BMPs were simulated as in-stream processes, which have no effects on the overland processes (at sub-catchment and HRU level). The '-' spaces in case of vegetative filter strips indicate that it does not work on those cases in the MYC.

5.3.3.1 SEDIMENT LOAD/YIELD REDUCTION

At the catchment outlet level, within-channel BMPs (f and g in Figure 5.6 (A)) produced higher percentages of reduction for average annual sediment load where upland BMPs (a, b, c, d and e in Figure 5.6 (A)) have no or very insignificant impacts as shown in Table 5.15 and Figure 5.6(A). Reducing fertilizer/manure application rate (30% reduce rate) or conservation tillage has no effects on sediment reduction at this level. Also, parallel terraces and contour farming has very insignificant effects. This might be because of the upland BMPs implementation area is small compared to the catchment area. The 32%, 50% and 100% of treated mixed-crop area are equivalent to 13%, 20% and 41% of the total catchment area (1511 km^2) respectively. On the other hand, grassed waterways resulted in highest reduction with 14% - 72% and then streambank stabilization with 32% - 55% for the three targeted percentages of treated area as shown in Table 5.15 and Figure 5.6(A).

At the sub-catchment level, conservation tillage (17% - 20%) and parallel terraces (13% - 20%) resulted in higher percentages of sediment yield reduction, and then contour farming with 8% - 10% for the three targeted percentages of treated area as shown in Table 5.15 and Figure 5.6(B). Also Figure 5.6(B) shows that simulation of conservation tillage and parallel terraces had almost same impacts on sediment reduction at the sub-catchment level. Reducing fertilizer/manure application rate made zero effects on the sediment reduction which is expected as this BMP only affects the nutrient process. Also, grassed waterways and streambank stabilization had no effects at the sub-catchment level. Because these BMPs were simulated as within-channel process, and so had no effects on the overland processes.

At the HRU level, the highest sediment yield was reduced by parallel terraces around 90%, then around 50% by conservation tillage and around 36% by contour farming as shown Table 5.15 and Figure 5.6(C). At this level, the percent reductions did not vary among the targeted 32%, 50% and 100% treated areas as shown in Figure 5.6(C). This is because the yield reductions summarized at the HRU level consider only areas with BMPs. Also similar to sub-catchment level, reduced fertilizer/manure application rate or grassed waterways and streambank stabilization had no effects on sediment yield reduction at HRU level.

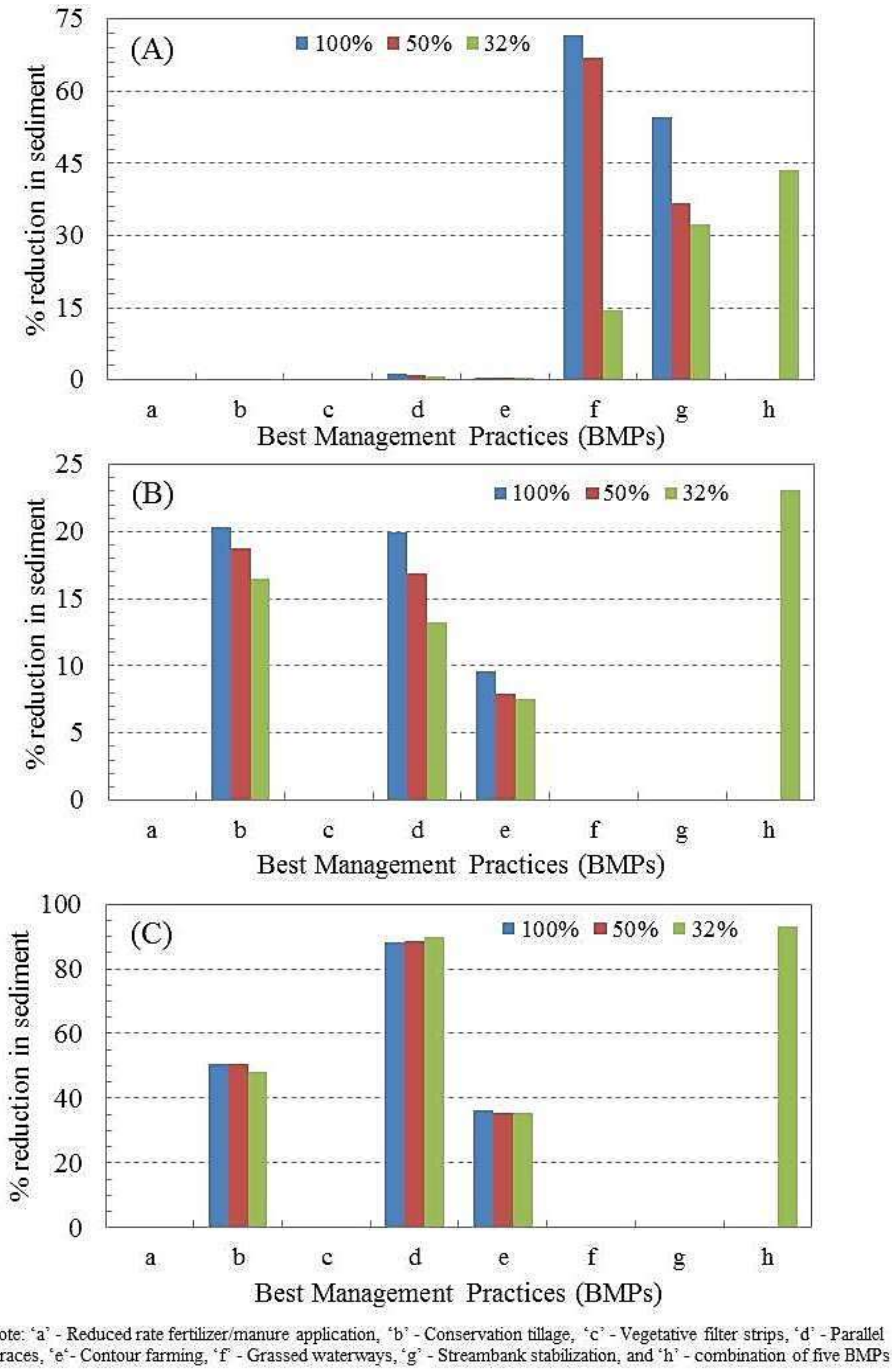


Figure 5.6 Percent reduction in sediment for different percentage of mixed-crop area treated (A) at catchment level (B) at sub-catchment level and (C) at HRU level

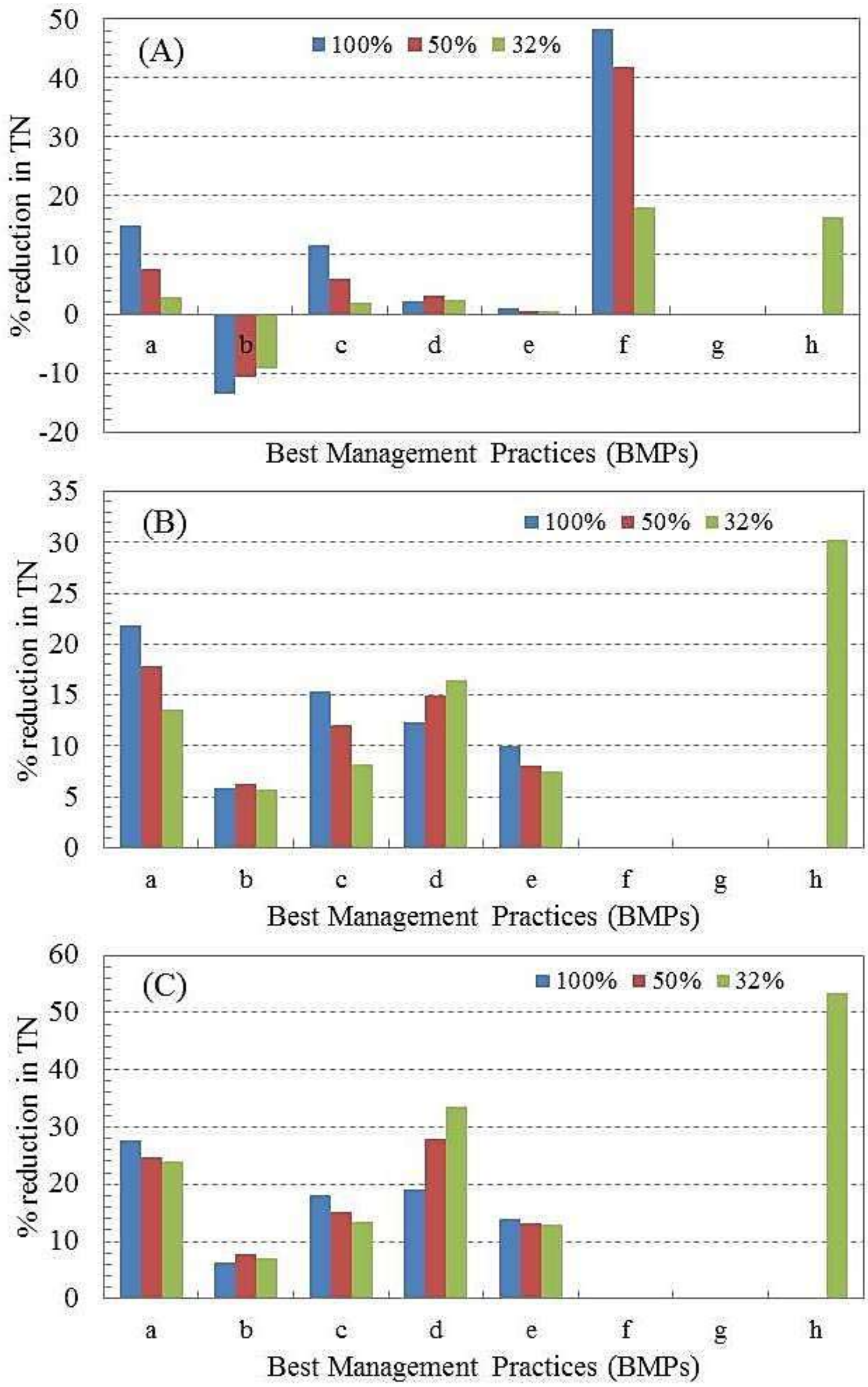
Table 5.15 also shows that the VFSs (c in Figure 5.6) have no effects on sediment reduction as shown by the '–'spaces. Details of VFSs are discussed with TN at the end of Section 5.3.3.2.

5.3.3.2 TOTAL NITROGEN (TN) YIELD/LOAD REDUCTION

At the catchment outlet level, the effectiveness of grassed waterways on the average annual TN load reduction was higher with 18% - 48% reduction. However, streambank stabilization had no effects as shown in Table 5.15 and Figure 5.7(A). The reason for this no-effect is the in-stream algorithms QUAL2E (Brown and Barnwell, 1987) in SWAT, which does not consider channel cover and erodibility in the in-stream nitrogen and phosphorus equations (Arabi et al, 2008; Tuppad et al, 2010b). Among the upland BMPs, parallel terraces and contour farming had very low/insignificant effects (maximum 3%), and reduced fertilizer/manure application rate had low effects with 3%-15% on TN load reduction. However, the conservation tillage notably increased TN at the catchment outlet level as shown in Table 5.15 (negative values) and Figure 5.7(A).

It was observed that although TN and TP reduced at the sub-catchment and the HRU level (Table 5.15), soluble nitrogen and soluble phosphorus increased at these levels. For example, in case of 100% treated area, soluble nitrogen and soluble phosphorus increased 1% and 15% respectively at the sub-catchment level. Similarly soluble nitrogen and soluble phosphorus increased 2% and 22% respectively at the HRU level. These soluble nitrogen and phosphorus leached through lateral and groundwater flow into the waterways which in turn resulted in overall increase in TN and TP at the catchment outlet as shown in Table 5.15. Other studies by Sharpley and Smith (1994); Gitau et al (2005; 2008) and Tappad et a (2010b) also found similar results due to the implementation of the conservation tillage. This increase is due to the increase of residue and the buildup of easily available soluble nitrogen and phosphorus at the surface area due to lack of soil mixing and overturn (Tuppad et al, 2010b).

At the sub-catchment level, within-channel BMPs produced no effects since these BMPs had no effects on the overland processes as shown in Table 5.15 and Figure 5.7(B). Among the upland BMPs, the effectiveness of reduced fertilizer/manure application rate (14%-22%) was little bit higher than parallel terraces (12%-17%). Conservation tillage and contour farming almost resulted in same reduction of TN ranging from 6%-10%.



Note: 'a' - Reduced rate fertilizer/manure application, 'b' - Conservation tillage, 'c' - Vegetative filter strips, 'd' - Parallel terraces, 'e'- Contour farming, 'f' - Grassed waterways, 'g' - Streambank stabilization, and 'h' - combination of five BMPs

Figure 5.7 Percent reduction in TN for different percentage of mixed-crop area treated (A) at catchment level (B) at sub-catchment level and (C) at HRU level

At the HRU level, within-channel BMPs produced no effects like at the sub-catchment level for the similar reason of being overland process as shown in Table 5.15 and Figure 5.7(C). Among upland BMPs, parallel terraces and reduced fertilizer/manure application rate resulted in higher percentages of reduction. Parallel terraces reduced 19%-34% of TN yields whereas reduced rate fertilizer/manure application resulted in 24%-28% reduction (Table 5.15). Also the conservation tillage reduced the lowest percentage of TN yields (around 7%) which is not significantly different from the sub-catchment level. Similar to sediment, at this level, the percent reductions did not vary significantly among the targeted treated areas as shown in Figure 5.7(C) except parallel terraces.

VFSs reduced 2%-12%, 8%-15% and 14%-18% of TN at the catchment, sub-catchment and HRU levels respectively as shown in Table 5.15. However, VFSs had no effects on sediment and TP reductions in the MYC as shown in Table 5.15 and Figures 5.6 and 5.8. It was found that the VFSs has no surface trapping efficient in the MYC, however it works effectively for the subsurface trapping. This is shown in Table 5.16 as an example for the 100% treated mixed-crop area at the sub-catchment level taken from Table 5.15. As discussed at the end of Section 5.3.1 for VFSs, the subsurface trapping efficiency is used for NO_3-N removal through lateral flow and groundwater (Cho et al, 2010a). Table 5.16 shows this where only NO_3-N in lateral flow and groundwater are reduced i.e. only subsurface trapping efficiency works. Moreover, Table 5.16 shows that 50m VFSs produce 100% subsurface trapping efficiency which is expected as per Equation 5.2 and Figure 5.5 of Section 5.3.1.

VFSs work effectively under uniform ideal sheet flow, but for concentrated or channel flow it has no surface trapping efficiency (Neitsch et al, 2011). Also as VFSs area acts as an area of increased infiltration, higher infiltration rate reduces surface trapping efficiency, but increases the subsurface trapping efficiency. Therefore, the result of VFSs indicates that the sediment erosion in the MYC mainly occurred from gully and channel processes with no or negligible amount of sheet and rill erosion. This can also be seen in sensitivity analysis (Section 4.3.1) where the channel processes parameters were found very significant in the MYC. SWAT2005 has only one option of VFSs width as an user input through the parameter FILTERW. SWAT has updated VFSs sub-model in SWAT2009 version which has more options like controlling what fraction of flow is fully channelized to apply VFSs effectively (Arnold et al, 2011). Betrie at al (2011) also recommended that VFSs can be simulated more effectively in SWAT2009.

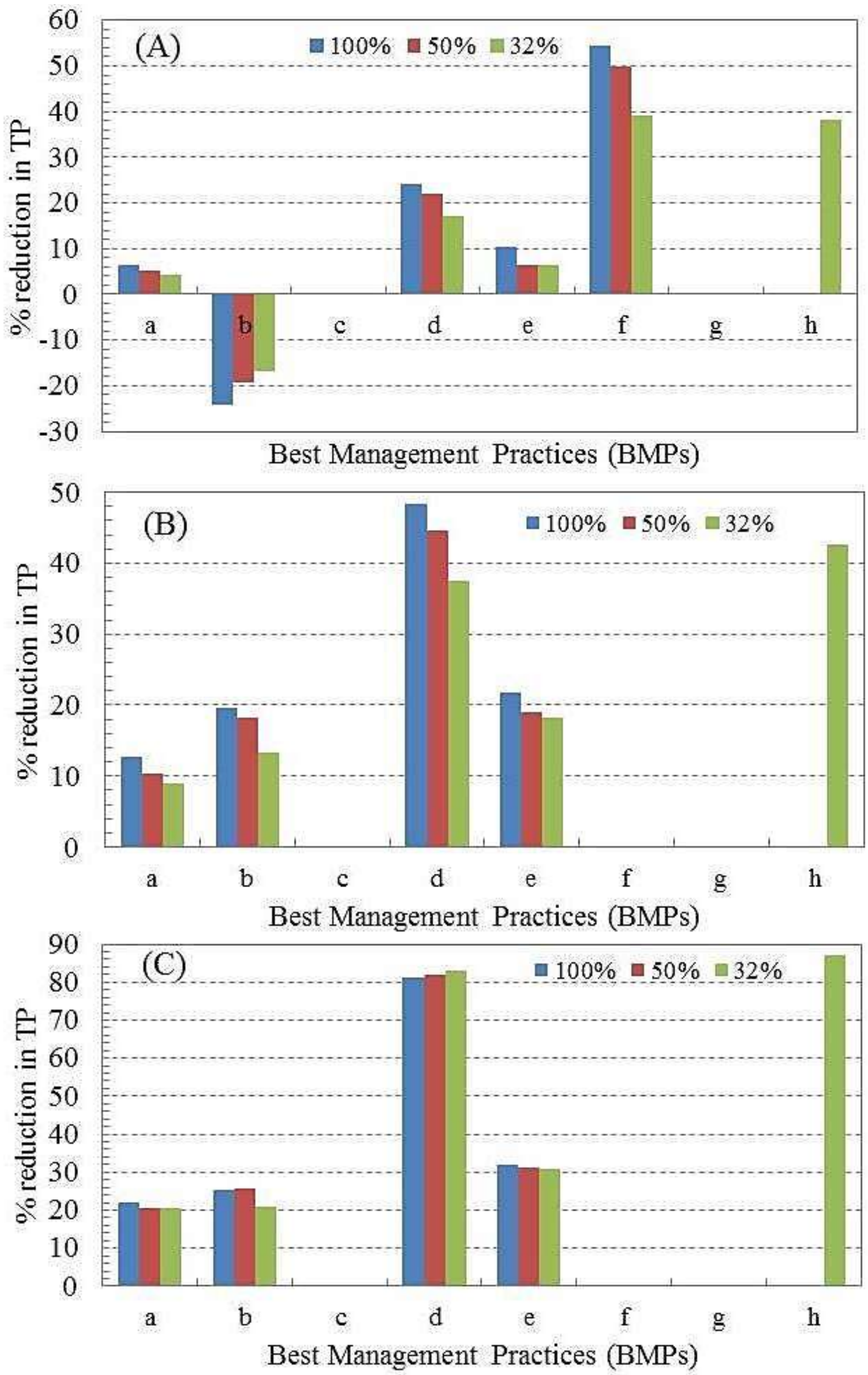
Table 5.16 Effects of VFSs on nitrogen in the MYC

	ORGN kg/ha	NSURQ kg/ha	LATNO3 kg/ha	GWNO3 kg/ha	TN kg/ha
Baseline condition	35.67	2.90	8.89	52.27	99.74
14m VFSs	35.67	2.90	6.66	39.11	84.35
Reduction for 14m VFSs	0%	0%	25%	25%	15%
50m VFSs	35.67	2.90	0	0	38.58
Reduction for 50m VFSs	0%	0%	100%	100%	61%

Note: ORGN = Organic nitrogen, NSURQ = Nitrate in surface runoff, LATNO3 = Nitrate in lateral flow, GWNO3 = Nitrate in groundwater, TN = Total nitrogen, VFSs = Vegetative filter strips

5.3.3.3 TOTAL PHOSPHORUS (TP) YIELD/LOAD REDUCTION

At the catchment outlet level, similar to TN, the effectiveness of grassed waterways on the average annual TP load reduction was higher with 39% - 55% reduction. Also for the same reason as in the case of TN, the within-channel BMP streambank stabilization had no effects at this level as shown in Table 5.15 and Figure 5.8(A). Among the upland BMPs, parallel terraces resulted in highest TP reductions (17% - 24%) at the catchment outlet level. Contour farming and reduced rate fertilizer/manure application had comparatively low effects (maximum 10%) on the TP load reduction. Also parallel terraces and contour farming had significant effects on TP reductions at this level compared to sediment and TN where sediment and TN had almost no effects (Table 5.15). Similar to TN, the conservation tillage had notably negative effects on TP reduction as shown in Table 5.15 and Figure 5.8(A). The reasons for this negative effect were discussed in Section 5.3.3.2 with the case of TN.



Note: 'a' - Reduced rate fertilizer/manure application, 'b' - Conservation tillage, 'c' - Vegetative filter strips, 'd' - Parallel terraces, 'e' - Contour farming, 'f' - Grassed waterways, 'g' - Streambank stabilization, and 'h' - combination of five BMPs

Figure 5.8 Percent reduction in TP for different percentage of mixed-crop area treated (A) at catchment level (B) at sub-catchment level and (C) at HRU level

At the sub-catchment level, within-channel BMPs produced no effects since these BMPs had no effects on overland processes as shown in Table 5.15 and Figure 5.8(B). Among the upland BMPs, the parallel terraces resulted in highest TP yield reductions (38% - 48%) similar to the catchment level. Contour farming and conservation tillage had almost similar effects on TP reduction, and reduced rate fertilizer/manure application had comparatively low effects among the upland BMPs as shown in Table 5.15 and Figure 5.8(B).

At the HRU level, within-channel BMPs had no effects on TP yield reduction as in the sub-catchment level as shown in Table 5.15 and Figure 5.8(C). Among the upland BMPs, parallel terraces resulted in highest TP reductions (81% - 83%) similar to the sub-catchment level. Contour farming resulted in second higher percentages of TP reduction (31% - 32%). Conservation tillage and reduced rate fertilizer/manure application had almost similar effects ranging from 21% - 26% as shown in Table 5.15 and Figure 5.8(C).

Table 5.15 also shows that the VFSs (c in Figure 5.8) have no effects on TP reduction as shown by the '-'spaces. Details of VFSs were discussed with TN at the end of Section 5.3.3.2.

5.4. EFFECTS OF IN-STREAM PROCESSES IN THE MYC

As water transports nutrients downstream, they cycle through the stream ecosystem in biotic and abiotic forms. During this cycle, the biochemical processes reduce or transform nutrient matter by plants and microorganisms through consumption of oxygen. As discussed in Section 2.2.2, the degradation of organic matter through biochemical processes involves mineralization and microbially decaying to reduce one form of water quality constituent to another. As algae grow and die, they also form part of the in-stream nutrient cycle. Since during in-stream processes, the nutrient matter changed (increase or decrease) or transform from one form to another form, the in-stream processes have significant effects on the development of a water quality model, especially when the model is calibrated at the catchment outlet as discussed in Section 2.2.

The in-stream algorithms incorporated in the MYWQM is adopted from QUAL2E (Brown and Barnwell, 1987). The model was developed considering the in-stream processes. Table 5.17 and Figure 5.9 show the effects of in-stream processes in the MYWQM at the three data sites of the MYC where the model was calibrated and validated. Site-3 and Site-2 are in the Yarra River, and Site-1 is in the Woori Yallock Creek as shown in Figure 3.18. Also Site-3 is the outlet of the MYC. At any sites of the MYC, the in-stream processes have no effects on sediment (SED) as shown in Table 5.17.

At Site-1, TN and TP were reduced around 10% when the in-stream processes were kept off in the MYWQM. When the in-stream processes were considered, the organic nitrogen (ORGN) was increased about 50% because of the conversion of algal biomass nitrogen to organic nitrogen. Then some portion of the organic nitrogen went through the transformation of organic nitrogen to ammonia (NH_4), to nitrite (NO_2) and finally to nitrate (NO_3). The nitrate again was reduced by the uptake of nitrate by algae. When the in-stream processes were not considered, there was no transformation of nitrogen from one form to another as shown in Table 5.17 and Figure 5.9 for Site-1 (amounts of NH_4 and NO_2 are zero). Similarly, the amount of organic phosphorus (ORGP) was increased by the conversion of algal biomass phosphorus to organic phosphorus. The mineral/soluble phosphorus (MINP) was decreased by the uptake of mineral phosphorus by algae.

Table 5.17 Effects of in-stream processes at the data sites of the MYC

Data site	In-stream process	SED (tons)	TN (tons)	ORGN (tons)	NO_3 (tons)	NH_4 (tons)	NO_2 (tons)	TP (tons)	ORGP (tons)	MINP (tons)
Site-1	on	2420	117.49	17.85	93.79	4.24	1.62	5.43	4.59	0.83
Site-1	off	2420	106.12	8.88	97.24	0.00	0.00	4.90	3.77	1.13
% change		0	10	50	-4	100	100	10	18	-36
Site-2	on	6241	281.07	37.25	225.50	12.73	5.59	12.29	9.91	2.38
Site-2	off	6241	263.43	55.42	206.40	1.18	0.43	15.25	11.83	3.42
% change		0	6	-49	8	91	92	-24	-19	-44
Site-3	on	19000	463.19	100.80	323.40	27.20	11.79	30.32	27.52	2.80
Site-3	off	19000	373.10	107.70	263.70	1.24	0.46	35.23	28.93	6.30
% change		0	19	-7	18	95	96	-16	-5	-125

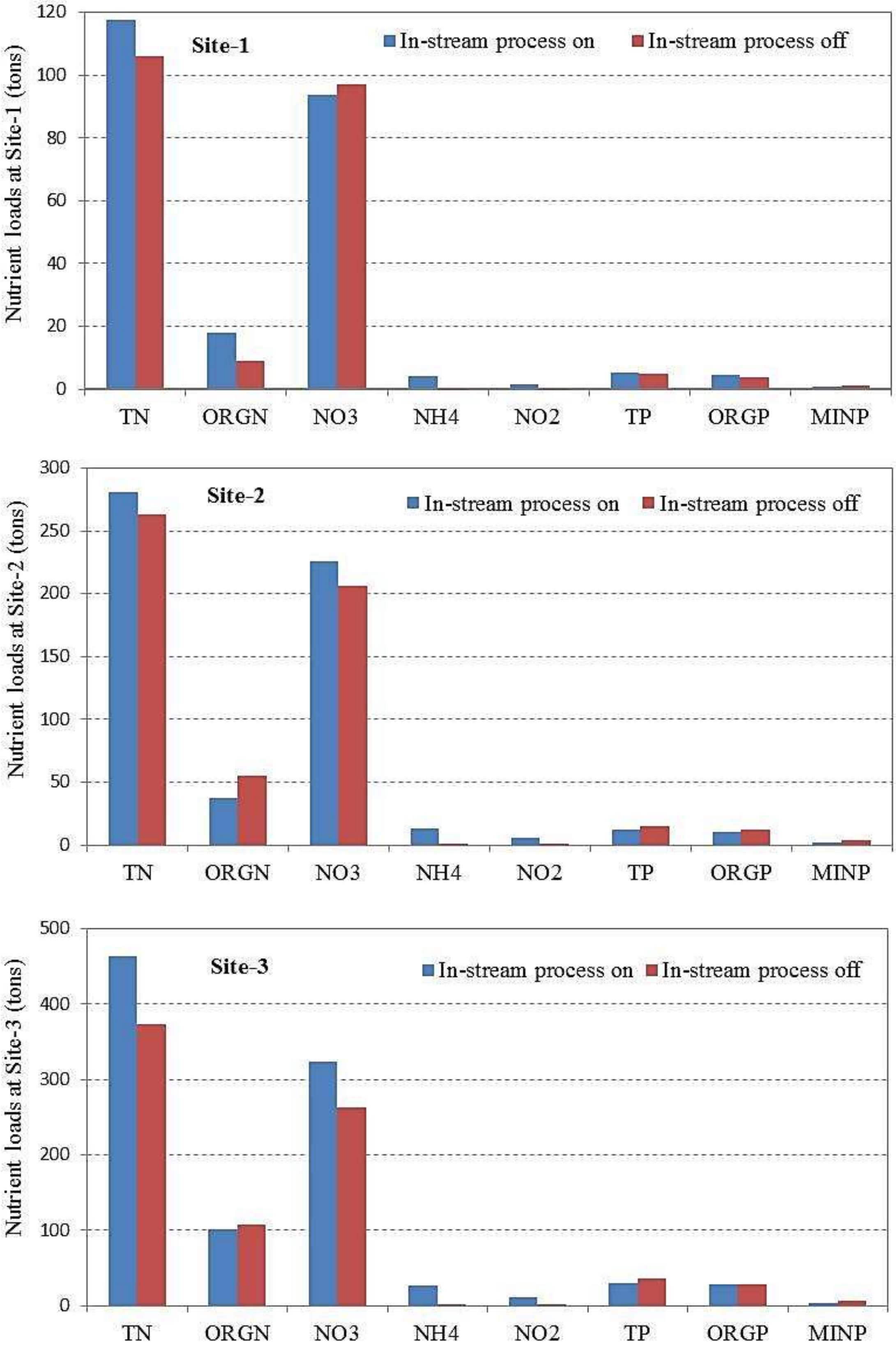


Figure 5.9 Effects of in-stream processes at the three data sites of the MYC

At Site-2, the components of TN went through the same transformation processes as Site-1 when the in-stream processes were considered. However, at Site-2, organic nitrogen was decreased about 49% and nitrate was increased about 8% (opposite to Site-1). As nutrient passes through upstream to downstream of the catchment, the in-stream processes become more effective. For this reason, the transformation of organic nitrogen to nitrate was higher than the conversion of algae biomass nitrogen to organic nitrogen at Site-2 as shown in Table 5.17 and Figure 5.9. Also the uptake rate of nitrate by algae was reduced compared to Site-1. Similarly the transformation of organic phosphorus to mineral phosphorus was higher than the conversion of algae biomass phosphorus to organic phosphorus when the in-stream processes were considered at Site-2. Also the uptake rate of mineral phosphorus by algae was higher compared to Site-1 as shown Table 5.17 and Figure 5.9.

At site-3, the components of TN went through the same transformation processes as in Site-2 when the in-stream processes were considered. Since Site-3 is the outlet of the MYC, the effects of in-stream processes were higher. Overall, TN was increased about 19%, but TP was decreased about 16% when the in-stream processes were considered. Most notably, the uptake of mineral phosphorus by algae was much higher than the uptake of nitrate by algae during the in-stream processes as shown in Table 5.17 and Figure 5.9. Mineral phosphorus was reduced about 125%, but nitrate was increased about 18% when the in-stream processes were considered at Site-3. This trend of uptake rate by algae can also be seen at other two sites. This means phosphorus is the key pollutant in the waterways of the MYC. Other previous studies (Harris et al, 1996; Yarra Valley Water, 1997; DSE, 2006a; Melbourne Water and EPA Victoria, 2009a) also found that phosphorus was the key pollutant in the waterways of the Yarra River catchment whereas in Port Phillip Bay, nitrogen was the key nutrient affecting algal growth as discussed in Section 3.2.3.2.

Table 5.18 shows the effects of in-stream processes when simulating BMPs in the MYWQM. In case of the BMP conservation tillage, TN and TP were increased about 9% and 17% respectively for 32% of the treated mixed-crop area instead of decreasing as shown Table 5.15 and 5.18. As discussed in Section 5.3.3.2, due to lack of soil mixing and overturn, the conservation tillage resulted in an increase of residue and buildup of easily available soluble nitrogen and phosphorus at the surface area which leached through the subsurface flow into the river systems. Table 5.18 shows that TN and TP and their components were increased (except mineral phosphorus) when conservation tillage was simulated against the baseline condition considering in-stream processes. When in-stream processes were not considered, there were no transformations or uptake of the nutrients by algae. Only organic nitrogen and organic phosphorus were settled down (5% and 9% respectively) which in turn resulted in 1% TN reduction and 8% TP reduction at the outlet of the MYC. This result shows that the in-stream processes not only will affect the calibration and validation of a water quality model, it can also result in wrong estimates if it is not considered when simulating BMPs in the model.

Table 5.18 Effects of in-stream processes for the conservation tillage at the MYC outlet

Scenario	In-stream process	SED (tons)	TN (tons)	ORGN (tons)	NO_3 (tons)	NH_4 (tons)	NO_2 (tons)	TP (tons)	ORGP (tons)	MINP (tons)
Baseline	on	19000	463.19	100.80	323.40	27.20	11.79	30.32	27.52	2.80
Conservation tillage	on	19180	506.59	134.10	326.00	32.49	14.00	35.42	32.69	2.73
% change		-1	-9	-33	-1	-19	-19	-17	-19	3
Baseline	off	19000	373.10	107.70	263.70	1.24	0.46	35.23	28.93	6.30
Conservation tillage	off	19180	368.69	102.80	264.20	1.24	0.46	32.52	26.25	6.27
% change		-1	1	5	0	0	0	8	9	1

5.5. WATER QUALITY MANAGEMENT PLAN FOR THE MYC

The loss of sediment and nutrients is affected in a catchment by several factors, including the occurrence, amount and intensity of rainfall and runoff, fertilizer/manure application amount and timing, and land management practices such as tillage. Thus, the BMPs that can affect these factors should be used to reduce the loss of sediment and nutrients in a catchment. Eight BMPs as discussed in Section 5.3 were simulated in the MYWQM. These were (1) Reduced rate fertilizer/manure application, (2) Conservation tillage, (3) Vegetative filter strips, (4) Parallel terraces, (5) Contour farming, (6) Grassed waterways, (7) Streambank stabilization and (8) combination of five BMPs from the above seven BMPs. As discussed in Section 5.3.3, these BMPs showed a significant reduction in the pollution of the MYC affecting the upland and within-channel factors responsible for the loss of sediment and nutrients.

In Section 5.3.3, the effectiveness of the BMPs was evaluated individually in reducing sediment, TN and TP pollution at three levels (catchment outlet, sub-catchment and HRUs) of the MYC. Table 5.15 shows that grassed waterways resulted in the highest reduction in sediment, TN and TP at the catchment outlet level. On the other hand, parallel terraces produced the highest reduction in sediment, TN and TP at sub-catchment and HRU levels. Streambank stabilization had no effects on TN and TP reduction whereas application of reduced rate fertilizer/manure had no effects on sediment reduction as discussed in Section 5.3.3. Although the application of reduced rate fertilizer/manure (30% reduced) resulted in significant reduction in TN and TP at the sub-catchment and the HRU level, the average yield of the mixed-crop were reduced about 15% at sub-catchment level. Table 5.15 also shows that the conservation tillage had negative impacts on TN and TP at the catchment outlet level, and vegetative filter strips had only subsurface trapping efficiency.

Table 5.19 shows that the ranges in percent reductions of sediment, TN and TP for the three targeted percentages of treated mixed-crop area were almost the same at sub-catchment and HRU level with slight exception for TP at sub-catchment level in case of 32% treated mixed-crop area. However, at the catchment outlet level, the ranges in case of 32% targeted percentage were significantly different than 50% and 100% targeted percentage, especially for sediment and TN area as this treated area was very small compared to the total catchment area (only 13% of the catchment area). Table 5.19 also shows that at the HRU level, the percent reduction ranges of sediment, TN and TP were slightly higher for less targeted area (32%). This was expected as 32% targeted area included the higher yielding HRUs. In general, applying BMPs on 32% of the treated mixed-crop area produced almost same reduction efficiency compared to the 50% and 100% targeted percentages in the MYC. Moreover, the first 16 high ranked sub-catchments that included 32% of the treated mixed-crop area or 13% of the total catchment area contributed about 84% of the total sediment yields in the MYC. Therefore applying the BMPs on 32% of the treated mixed-crop area will be most effective in achieving maximum pollution reduction while minimizing costs.

Table 5.19 Percent reduction ranges of sediment, TN and TP for the selected BMPs.

Pollutants	Cumulative mixed-crop area (%)	Ranges of percent reduction in the MYC		
		At catchment level	At sub-catchment level	At HRU level
Sediment	100	1 to 72	10 to 20	36 to 88
	50	1 to 67	8 to 19	36 to 89
	32	1 to 32	8 to 17	36 to 90
TN	100	1 to 48	6 to 22	6 to 28
	50	3 to 42	6 to 18	8 to 28
	32	1 to 18	6 to 17	7 to 34
TP	100	7 to 55	13 to 48	22 to 81
	50	5 to 50	10 to 45	21 to 82
	32	4 to 39	9 to 38	21 to 83

An integrated effect of five BMPs implemented on 32% of the treated mixed-crop area is shown in Table 5.15. Vegetative filter strips and contour farming were not considered in the integrated effects. Because, vegetative filter strips had only subsurface trapping efficiency, and contour farming was almost similar type of parallel terraces. Table 5.15 shows that the integrated effects of the five BMPs were not equal to the cumulative effects of the individual BMPs, because some BMP implementation parameters were common for several BMPs (Table 5.12).

The five BMPs combinely reduced 44%, 23% and 93% of sediment pollution at the catchment, sub-catchment and HRU levels respectively as shown in Table 5.15 and Figure 5.6. The reduction at the sub-catchment level was less than at the catchment level since grassed waterways and streambank stabilization had no effects at the sub-catchment and HRU levels as discussed in Section 5.3.3.1. Similarly the integrated effects resulted in 16%, 30% and 53% of TN reduction, and 38%, 43% and 87% of TP reduction at the catchment, sub-catchment and HRU levels respectively as shown in Table 5.15 and Figures 5.7 and 5.8. The negative effects of conservation tillage affected the reduction rates of TN and TP at the catchment level. In general, the integrated effects of the five BMPs were more effective in reducing TP pollution, and then reducing sediment pollution in the MYC as shown in Table 5.15 and Figures 5.6, 5.7 and 5.8.

The simulation of BMPs in the MYWQM shows that the selection of a BMP should be based on the goals stated in a BMP implementation project. For example,

- If the goal of a project is to protect aquatic health of the Port Phillip Bay (the mouth of the Yarra River), it will be useful to use a BMP that focuses on load reduction at the catchment outlet. Table 5.15 showed that grassed waterways will be the most effective for this goal.

- Conversely, if the goal of a project is to protect aquatic health of the waterways in the MYC, selecting a BMP that focuses in-stream pollutant concentration will be more appropriate. Table 5.15 showed that parallel terraces will be the most effective for this goal.

5.6. SUMMARY

The extensive clearing of land in the MYC has resulted in high runoff during storms with the consequences of erosion on stream banks and increases in sediment loading, causing major non-point source pollution in the Yarra River in terms of high nutrient runoff. The degradation of water quality in the Yarra River has prompted a need to assess fate and transport of pollutants in the catchment for development of appropriate management strategies to improve the water quality. The MYWQM was developed in the MYC to understand the water quality problems and find solutions through best management practices (BMPs). The model identified the critical areas within the MYC that are responsible for a disproportionate amount of water, sediment and nutrient yields.

The MYWQM shows that average annual water yield in the MYC was 166.9 mm for the period of 1990-2008. About 30% of the water yield was contributed by surface runoff and 30% by lateral flow, and 40% was by groundwater flow. About 41% of the MYC area had an average annual water yield of over 230 mm contributing 65% of the water yield. High water yields were generated in the mountainous forest area. Average annual sediment yield in the MYC was 1.68 ton/ha. About 14% of the catchment area had an average annual sediment yield of over 4 ton/ha contributing 60% of the sediment yield.

The average annual TN yield in the MYC was 1.96 kg/ha. Nitrate in groundwater accounted for 52% of the TN yield whereas surface runoff contributed only 3%. About 26% of the catchment area had an average annual TN yield of over 2.50 kg/ha contributing 59% of the TN yield in the MYC. Average annual TP yield in the MYC is 0.32 kg/ha. Organic phosphorus transported with sediment accounts for 65% of the TP yield. About 22% of the catchment area has an annual TP yield of over 0.40 kg/ha contributing 61% of the TP yield in the MYC. High sediment, TN and TP yields occurred in the pasture land and urban area. Also, sediment and TP yields had similar pattern and more influenced by extreme rainfall events.

Individual and integrated effects of eight BMPs were evaluated against the baseline conditions of the MYC through simulation in the MYWQM. These were (1) Reduced rate fertilizer/manure application, (2) Conservation tillage, (3) Vegetative filter strips, (4) Parallel terraces, (5) Contour farming, (6) Grassed waterways, (7) Streambank stabilization and (8) combination of five BMPs from the above seven BMPs. A strategic targeting approach was used to evaluate the BMPs on the high potential pollution areas. Average annual overland sediment yield (ton/ha) for each sub-catchment from the MYWQM was used as the sole criterion for selecting the sub-catchments for targeting. The 32%, 50% and 100% of the treated mixed-crop area were used as targeted percentage after ranking the sub-catchments of the MYC. The first 16 high ranked sub-catchments which comprised 32% of the treated mixed-crop area or 13% of the MYC contributed about 84% of the total sediment yields in the MYC.

The individual simulation of the BMPs shows that grassed waterways resulted in the highest reduction in sediment, TN and TP at the catchment outlet level. On the other hand, parallel terraces produced highest reduction in sediment, TN and TP at the sub-catchment and HRU levels. Streambank stabilization had no effects on TN and TP reduction whereas application of reduced rate fertilizer/manure had no effects on sediment reduction. Moreover, the conservation tillage had negative impacts on TN and TP at the catchment outlet level, and vegetative filter strips had no surface trapping efficiency. Among the 32%, 50% and 100% targeted percentages, implementing BMPs on the 32% of the treated mixed-crop area was found to be most effective in achieving maximum pollution reduction while minimizing costs. The integrated effects of five BMPs implemented on 32% of the treated mixed-crop area were found to be more effective in reducing TP pollution, and then reducing sediment pollution in the MYC. However, their integrated effects were not equal to the cumulative effects of the individual BMPs, because some BMP implementation parameters were common for several BMPs.

As water transports nutrients downstream, the effects of in-stream processes became more significant in the MYC. TN and TP and their components changed significantly when in-stream processes were considered. The analysis of the in-stream processes in the MYC showed that the in-stream processes not only will affect the calibration and validation of a water quality model, it can also result in wrong estimates if it is not considered when simulating BMPs in the model.

The simulation of BMPs in the MYWQM shows that the selection of a BMP for developing water quality management plan should be based on the goals stated in a BMP implementation project.

In general, the MYWQM was found very effective and capable for simulating individual and integrated effects of different BMPs in the MYC. The model identified the critical areas of high potential pollution in the MYC. NPS pollution control resources and investments can then be targeted only on these critical areas to maximize improvements in downstream water quality. However, the pollution reduction efficiency of the BMPs simulated in the MYC can vary from other studies due to variability in topography, soils, weather, and extent of BMP implementation.

6. SUMMARY AND CONCLUSIONS, AND RECOMMENDATIONS FOR FUTURE STUDY

6.1. SUMMARY AND CONCLUSIONS

The main objective of this research was to investigate the applicability of data-intensive physics-based, distributed and continuous water quality models in data-poor catchments. This main objective was achieved by undertaking the following tasks:

1. Literature review
2. Selection of the study area, and data collection and processing
3. Development of the SWAT based MYWQM
4. Development of the water quality management plan

A brief summary and the conclusions drawn from each of these tasks are discussed in the following sections.

6.1.1. LITERATURE REVIEW

Agricultural non-point source (NPS) pollution is a major concern to the catchment water managers in many parts of the world. Successful management of NPS pollution requires an understanding of the pollutant transport mechanisms from runoff to surface water. Water quality models are effective tools to understand the water quality processes (overland and in-stream) responsible for the NPS pollution, and to develop water quality management plan through simulation of BMPs.

The conclusions from the literature review of this research are discussed below.

- Physics-based distributed and continuous catchment water quality models are better suited for agricultural NPS pollution modelling. However, because of high data requirement and processing, the applications of these models are limited in many data-poor catchments.
- Traditionally commonly used water quality models in Australia are lumped/semi-distributed conceptual models mainly because of data

limitations. Even within these modelling frameworks, water quality component is empirical or generation rates-based because of data limitation especially for water quality monitoring data and catchment scale land management data. In this context, developing an effective water quality management plan in the data-poor conditions of Australia still remains as a major challenge for catchment water managers despite huge investment on river health improvement programs.

- With the advent of computationally efficient computers and GIS software, the physics-based models are increasingly being called upon in data-poor regions. The extensive input data for the physics-based models are often generated from GIS and regional or local surveys. Moreover, most of the data can be collected from many global sources for these models.
- The ArcSWAT interface of SWAT2005 was chosen for this research with a view to justify the applicability of physics-based models in the data-poor conditions of Australian. SWAT is a public domain widely used catchment water quality modelling tool with GIS link. It is a physics-based distributed water quality modelling tool which can be used for long-term continuous simulations in predominantly agricultural catchments. The ability to simulate in-stream water quality dynamics is a definite strength of SWAT incorporated from QUAL2E. The ArcSWAT interface of SWAT2005 has also an automated sensitivity, calibration, and uncertainty analysis component.
- Physics-based models like SWAT need observed data (such as sediment and nutrient loads, surface runoff and baseflow) for calibration and validation. A regression based software tool LOADEST developed by the U.S. Geological Survey was found promising for load estimation from sparsely available water quality grab samples. Also, the software “Baseflow Filter Program” developed by USDA-AES based on automated digital filter technique was found promising for baseflow separation.

6.1.2. SELECTION OF THE STUDY AREA, AND DATA COLLECTION AND PROCESSING

The Yarra River catchment is an important water resources catchment for Victoria, Australia. It is also the largest generator of contaminants, both in terms of total load and load per unit area in the Port Phillip Bay region of Victoria. Intensive agricultural activities from the middle agricultural part of the Yarra River catchment contribute to a significant amount of non-point pollutants into the waterways. The middle agricultural part referred to as Middle Yarra Catchment (MYC) was chosen as the study area for this research. Data were collected and processed to understand the hydrology and water quality processes in the MYC and to develop the SWAT based MYWQM for the purpose of developing water quality management plan.

The conclusions from this task are discussed below.

- Two types of data were collected for the MYWQM to set up, and to calibrate and validate the model. These data were collected from local organizations except DEM. The set up data of the model were processed with ArcGIS tool. Crop and land management practices data (such as fertilizer/manure application rate and timing, tillage, grazing, crop rotation and residue management) were spatially very coarse compared to the MYC, and had to process based on published literature. Soil data were available for two layers, and land use data was static type.
- Stremflow data were processed for 1990-2008 periods. Baseflow and surface runoff were also processed along with the streamflow to represent surface and subsurface hydrological processes accurately in the MYC. Baseflow was separated from mean daily streamflow using automated baseflow separation software “Baseflow Filter Program”. In the MYC, baseflow contributes about 75% of the streamflow.
- Water quality grab samples were available on monthly basis without any storm event data for 1998-2008 periods. The LOADEST modelling tool was used to estimate observed TN, TP and TSS loads from these monthly grab samples for the calibration purposes of the MYWQM. The LOADEST models performed well for estimating the constituent observed loads ($R^2 \geq 0.85$).

- In general, streamflow pattern was consistent with rainfall, and water quality load generation was consistent with streamflow and rainfall in the MYC. Streamflow data were processed considering 1990-2002 as calibration period and 2003-2008 as validation period. Similarly water quality data were processed considering 1998-2004 as calibration period and 2005-2008 as validation period. A longer period for streamflow was chosen compared to the water quality constituents so that the model can capture all possible variations in stremflow pattern (wet, moderate and dry years). From 1997 onwards, the climate was very dry which affected the streamflow and pollutant load generation processes.

6.1.3. DEVELOPMENT OF THE SWAT BASED MYWQM

In order to use model outputs for tasks ranging from regulation to research, models should be scientifically sound, robust, and defensible. However, developing reliable catchment simulation models and validating them on real-world catchments with measured and monitored data are also challenging. In this regard, model sensitivity analysis, calibration and validation, and uncertainty analysis help to evaluate the ability of the model to sufficiently predict streamflow and constituent yields for a specific application. The MYWQM was developed and evaluated with a view to simulate the individual and integrated effects of several BMPs in the MYC.

The main methods used in modelling the hydrologic processes were the curve number (CN) method for runoff estimating, the Penman-Monteith method for PET and the Muskingum method for channel routing. Moreover, in-stream nutrient transformations were modeled using the QUAL2E equation embedded in the SWAT2005 modelling software. The MYWQM delineated the MYC into 51 sub-catchments and 431 HRUs based on the MYC topography, land use, soils and slopes.

The SWAT inbuilt Latin-Hypercube and One-factor-At-a-Time (LH-OAT) random sampling procedure for sensitivity analysis and ParaSol (SCE-UA) method for multi-site, multi-variable and multi-objective autocalibration and uncertainty analysis were used to evaluate the MYWQM performance. Based on the sensitivity analysis, 15 streamflow parameters, and 13 sediment and nutrient parameters were selected for autocalibration.

The conclusions from this task are presented below.

- The sensitivity results showed that globally the hydrologic parameters dominated the highest parameter ranks. The result also indicated that both in-stream and upland processes were significant in the MYC. Moreover, the water quality variables (TN and TP) were potentially capable of contributing to the identification of streamflow parameters within SWAT, and a single parameter is correlated to multiple variables.
- In general, the calibration and validation results of streamflow were good without any unsatisfactory ratings based on the Moriasi et al (2007) guidelines. On the other hand, the calibration and validation results of TSS and TN were also good in general but with some exceptions. However, the calibration and validation results of TP were unsatisfactory in general. Moreover, the calibration and validation results of streamflow at site-1 showed that the Woori Yallock creek is an intermittent creek i.e., it may cease flowing during dry periods which in general affected the model performance on this site.
- In general, the MYWQM under predicted flows in wet years and over predicted in dry years. Moreover, the model underestimated peak monthly TSS, TN and TP loads in their calibration period, but overestimated in their validation period. From 1997 onwards, the climate in the MYC was dry. It was observed that as the periods become drier, the MYWQM generated higher percentage of runoff in the streamflow prediction. This has caused the significant over prediction of the sediment and nutrients in their validation periods (which were drier than their calibration periods) which means the climate has a significant impact on the hydrology and water quality in the MYC. Moreover, lack of storm event samples with the water quality monthly grab samples has caused underestimation of the observed TSS, TN and TP loads by the LOADEST model in the validation period which affected the performance of the MYWQM on that period.
- The results of uncertainty analysis for streamflow, sediment and nutrients in the MYWQM showed that the model's streamflow, sediment and nutrients predictions were reasonably consistent in the sense that the uncertainty bounds were narrow (very small values of *d-factor)*. However,

the values of *p-factor* were also very small i.e., bracketed less numbers of observed data between the uncertainty bounds. The uncertainty results also indicated that more uncertainties were associated with TSS and TP predictions which are expected.

- The process of configuring SWAT for the MYWQM in the MYC was greatly facilitated by the GIS-based interface ArcSWAT, which provide a straightforward means of translating digital land use, topographic, and soil data into model inputs. In-stream water quality processes were considered in the model development which had significant impact on the model performance. The multi-site, multi-variable and multi-objective autocalibration makes the MYWQM performance good not only at the catchment outlet, but also throughout the MYC, reducing complexity and labor in the calibration process.
- The calibration and validation, and uncertainty results showed that the MYWQM reasonably replicated the MYC with some exceptions. This means data-intensive model like SWAT can be successfully applied in the data-poor conditions of Australia if the required data are collected and processed properly to develop and validate the model.

6.1.4. DEVELOPMENT OF THE WATER QUALITY MANAGEMENT PLAN

The MYWQM was developed in the MYC to understand the water quality problems and find solutions through best management practices (BMPs). The model identified the critical source areas within the MYC that are responsible for a disproportionate amount of water, sediment and nutrient yields.

Individual and integrated effects of eight BMPs were evaluated against the baseline conditions of the MYC through simulation in the MYWQM. These were (1) Reduced rate fertilizer/manure application, (2) Conservation tillage, (3) Vegetative filter strips (VFSs), (4) Parallel terraces, (5) Contour farming, (6) Grass waterways, (7) Streambank stabilization, and (8) combination of five BMPs from the above seven BMPs. A strategic targeting approach was used to evaluate the BMPs on the high potential pollution areas. The average annual overland sediment yield (ton/ha) for each sub-catchment from the MYWQM was used as the sole criterion for selecting the sub-catchments for targeting. The 32%, 50% and 100% of the treated mixed-crop area were used as targeted percentages after ranking the sub-catchments of the MYC.

The conclusions from this task are presented below.

- The MYWQM showed that about 70% of the water yields in the MYC contributed by the subsurface flow through which about 52% of TN yields leached into the waterways. On the other hand, organic phosphorus transported with sediment accounts for 65% of the TP yields. Sediment and TP yields were more influenced by extreme rainfall events. High water yields were occurred in the mountainous forest areas, but high sediment, TN and TP yields were occurred in the pasture land and urban areas.
- The individual simulation of the BMPs showed that the grassed waterways resulted in the highest reduction in sediment, TN and TP at the catchment outlet level. On the other hand, parallel terraces produced highest reduction in sediment, TN and TP at the sub-catchment and HRU levels. Streambank stabilization had no effects on TN and TP reduction whereas application of reduced rate fertilizer/manure had no effects on sediment reduction. Moreover, conservation tillage had negative impacts on TN and TP at the catchment outlet level, and vegetative filter strips had no surface trapping efficiency.
- The first 16 high ranked sub-catchments which comprised 32% of the treated mixed-crop area or 13% of the MYC contributed about 84% of the total sediment yields in the MYC. Implementing BMPs on this 32% of the treated mixed-crop area will be most effective in achieving maximum pollution reduction while minimizing costs. The integrated effects of five BMPs implemented on the 32% of the treated mixed-crop area were found to be more effective in reducing TP pollution, and then reducing sediment and TN pollution respectively in the MYC. However, their integrated effects were not equal to the cumulative effects of the individual BMPs, because some BMP implementation parameters were common for several BMPs.

- As water transports nutrients downstream, the effects of in-stream processes became more significant in the MYC. TN and TP and their components changed significantly when in-stream processes were considered. The analysis of the in-stream processes in the MYC showed that the in-stream processes not only affect the calibration and validation of a water quality model, if it is not considered it can also result in wrong estimates when simulating BMPs in the model.
- The MYWQM showed that the selection of a BMP should be based on the goals stated in a BMP implementation project. For example,
    - ✓ If the goal of a project is to protect aquatic health of the Port Phillip Bay (the mouth of the Yarra River), it will be useful to use a BMP that focuses on load reduction at the catchment outlet. The MYWQM showed that grassed waterways will be the most effective for this goal.
    - ✓ Conversely, if the goal of a project is to protect aquatic health of the waterways in the MYC, selecting a BMP that focuses in-stream pollutant concentration will be more appropriate. The MYWQM showed that parallel terraces will be the most effective for this goal.
- In general, the MYWQM was found effective and capable for simulating individual and integrated effects of different BMPs in the MYC. The model identified the critical areas of high potential pollution in the MYC. This information can assist stakeholders and policy-makers with decisions for ensuring effective water quality management. However, the pollution reduction efficiency of the BMPs simulated in the MYWQM can vary from other studies due to variability in topography, soils, weather, and extent of BMP implementation.
- Overall, the performance of the MYWQM on evaluating the BMPs in the MYC demonstrated that physics-based water quality models can be applied in data-poor conditions of Australia. However, uncertainties in the data used to develop the model should be considered while applying the model in catchment management programs.

6.2. RECOMMENDATIONS FOR FUTURE STUDY

Based on the findings of this research, the following future studies are recommended.

- The critical sources areas were identified by one targeting method (sediment yields –average load per unit area from each sub-catchment) for all pollutants in this study. Other targeting methods like total load per sub-catchment, pollutant load from the reach of a sub-catchment and pollutant concentration from the reach of a sub-catchment (Giri et al, 2012) individually for each pollutant are recommended for future studies.
- The BMPs were evaluated and selected based on the environmental factor (percent reduction of sediment, TN and TP). For future studies, the economic factor (consisted of total BMP cost) and the social factor (consisted of farmer preference in BMP implementation) should be included (Giri et al, 2012).
- Climate change impacts on spatiotemporal variability of critical source areas and on the efficiency of BMPs are also recommended for future studies.
- A survey can be conducted on the local farmers for catchment scale crop and land management data.

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