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Reconciling anthropogenic climate change and variability on decadal timescales: narratives and hypotheses

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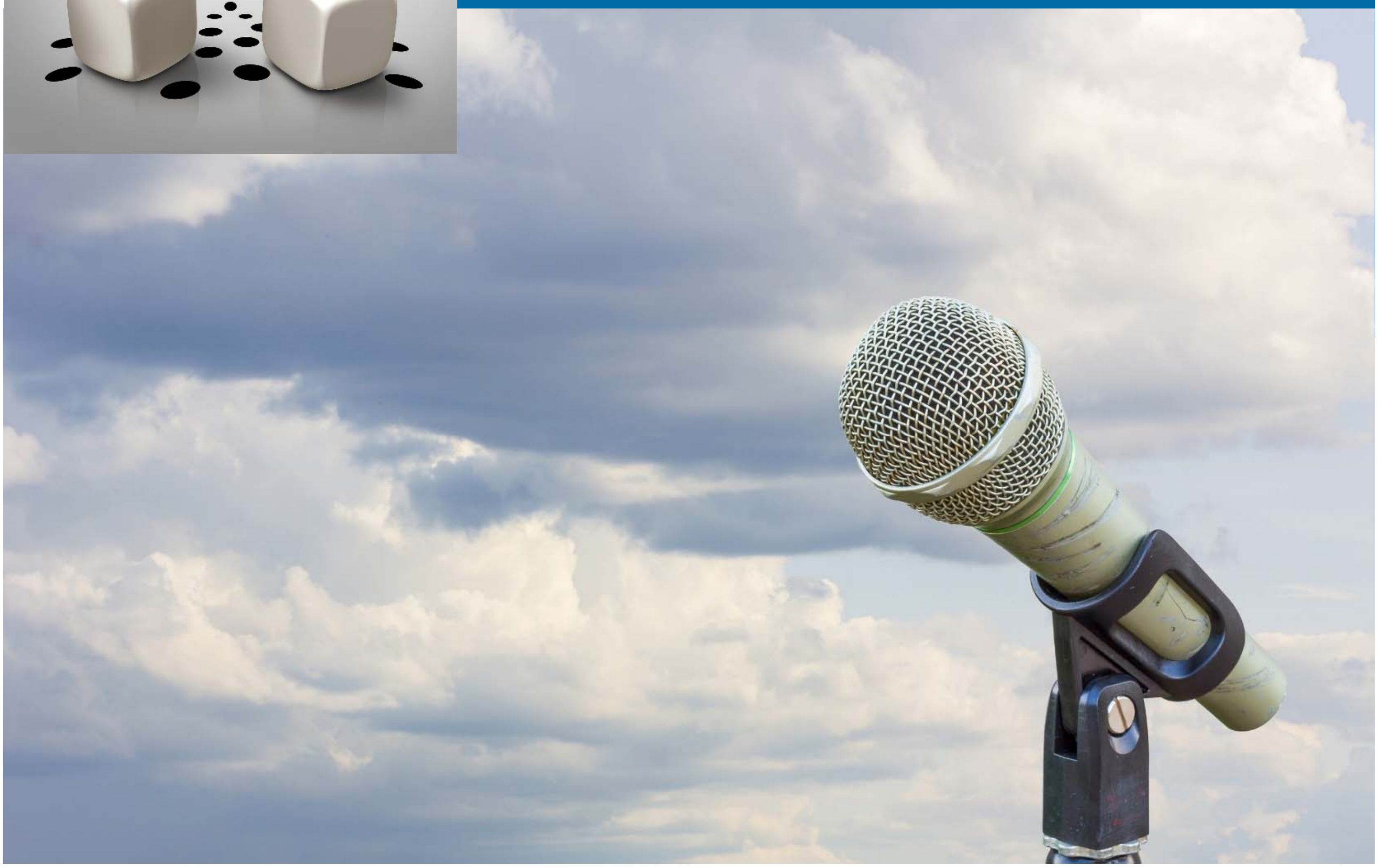

Key words: decadal variability, climate change, regime change, nonlinear dynamics, hypothesis testing, scientific narrative

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Abstract

This paper is one of a series aiming to reconcile the scientific understanding of how external forcing and internal variability interact on decadal timescales. These papers examine the theoretical basis of, evidence for, and the history and philosophy of the scientific effort to understand how the climate changes under gradual radiative forcing. Does the change follow the gradual forcing pathway, or is does the climate system respond nonlinearly? This paper investigates the current narratives and hypotheses describing how the relationship between externally-forced and internally-generated climate variations are viewed. Two hypotheses describe how these processes combine: anthropogenic climate change is independent of natural climate variability (*H1*), or they interact (*H2*). In *H1*, anthropogenic climate change is gradual, its rate of change being mediated by climate variability. In *H2*, climate has a nonlinear response, arising from the interaction between the external and internal components of the climate system. Current methods to analyse and communicate climate change overwhelmingly self-select *H1*. This has resulted in a scientific narrative of gradual change that dominates discourse within climate science. This imbalance is not supported by current theoretical understanding, which considers either *H1* or *H2* as being possible, and evidence of step-like changes in climate, which supports *H2*.

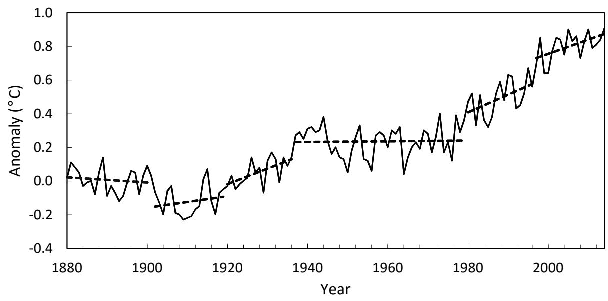
Introduction

The dominant scientific narrative and its underpinning paradigm overwhelmingly frames and communicates anthropogenic climate change as a gradual process. Changing climatic averages are typically portrayed as smooth curves, contributing to a narrative of gradual change – the gradualist narrative (Jones et al., 2013). This narrative frames how climate risks are analysed and communicated, feeding into decision making for both adaptation and mitigation. Uncertainty from climate variability is widely acknowledged as part of a changing climate, but is interpreted as unpredictable noise, while the smooth curve of mean change provides the signal.

Despite the dominance of the gradualist narrative in scientific practice, its theoretical support is nowhere near as strong. Two hypotheses, discussed further in the next section, describe the process of climate change as either being a linear or nonlinear response to gradual forcing. Current scientific thinking is that either is possible, with no strong preference for one over the other (Solomon et al., 2011;Kirtman et al., 2013). If a linear response is treated as the status quo, climate-related risks will be inadequately managed if change turns out to be nonlinear, as the risk from nonlinear change is greater (Schneider, 2004;Lemoine and Traeger, 2014).

This paper introduces a series that puts the case for climate change being nonlinear on decadal time scales (Jones, 2015a, b;Jones and Ricketts, 2015a, b). They document and analyse shifts in a range of variables from observations and models. Much of the evidence is provided by the application of the multi-step bivariate test. This is a rule-based test based on the Maronna-Yohai (1978) bivariate test that identifies multiple shifts in serially independent time series including climate data (Jones and Ricketts, 2015a, b;Ricketts, 2015).

Recent work shows that on decadal time scales, many climate variables change in a step-wise manner (Jones, 2010;Jones, 2012;Jones et al., 2013;Jones and Ricketts, 2015a, b). Variables include air temperature, sea surface temperature, tide gauge measurements, ocean heat content, rainfall, fire danger indices and stream flow (Jones et al., 2013). Much of this work was prompted by a shift in 1997–98 in south-eastern Australian climate (Jones, 2012). In that region, post 1997 means and extremes for average temperature, heat extremes, fire, and water supply are equivalent to projected levels for 2030–2050 (Jones et al., 2013). Step changes can lead to rapid shifts in the size and number of extreme events, potentially leading to rapid escalation in damage and loss (Jones et al., 2013). If such changes cross critical thresholds, these losses can be unexpected and perhaps irreversible. Figure 1a shows the Goddard Institute of Space Studies (GISS) record of global mean surface temperature (Hansen et al., 1999;Hansen et al., 2010) analysed for statistically significant step changes and Figure 1b shows the Max Planck Institute MPI-ESM-MR RCP4.5 run3 simulation from the CMIP5 archive analysed the same way. They show internal trends separated by step changes



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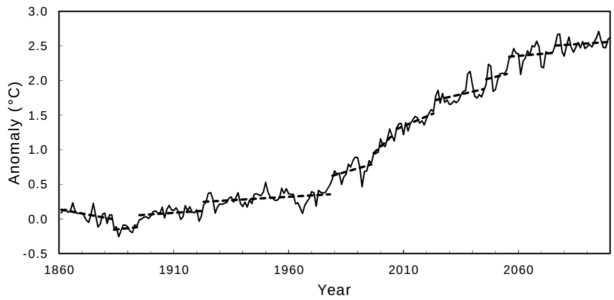

b

Figure 1a) Annual anomalies of mean global surface temperature from the GISS record of global mean surface temperature showing internal trends (bold dashes) separating significant step changes; b) the Max Planck Institute MPI-ESM-MR RCP4.5 run3 simulation from the CMIP5 archive.

This paper outlines the two existing scientific hypotheses for how climate changes and describes the conditions required to support them. A second paper addresses the paradigms relating human-induced climate change and variability, using a sociological model derived from Kuhn (1962, 1970), Laudan (1984) and others, which addresses changing methods, values and theory. It concludes that the hypothesis sustaining the gradualist narrative is preferred for reasons that are largely historical rather than theoretical (Jones, 2015a).

A third paper discusses the implications of these findings for the characterisation of climate risks, covering detection, attribution, prediction, adaptation, mitigation and communication (Jones, 2015b). Two more papers provide evidence for step-like changes in observed and modelled temperature (Jones and Ricketts, 2015a, b). This evidence supports the characterisation of climate as a nonlinear, complex system. Atmospheric warming is described as episodic, caused by short-term discharges of heat from the ocean to the atmosphere, manifesting as shifts that bookend periods of relative stability. This process is more physically realistic than the default gradualist paradigm, and is consistent with the findings of Lorenz (1963, 1975), Hasselmann (1976, 1979) and complex system behaviour in general.

The issue of <u>how</u> the climate changes on decadal timescales is very important, because projected climate change and climate variability are expected to produce climate variations of similar magnitude over coming decades (Deser et al., 2012). The focus here is on the links between climate change theory, practice and decision-making over decadal time scales (5–50 years) as they are currently understood. Currently, there is no clear scientific narrative of how the climate changes, capable of reconciling the relationship between climate change and variability while fully accounting for the available evidence. The challenge therefore, is to develop a scientific hypothesis that can sustain such a narrative and has testable conditions that will distinguish it from alternatives.

Hypotheses

The theoretical understanding of how the climate changes provides no clear support for gradual change in preference to other forms of change (Corti et al., 1999;Solomon et al., 2011;Kirtman et al., 2013), but scientific practice overwhelmingly selects gradual change as the default. The reasons why are complex, and include (Jones, 2015a):

- The application of Ockham's razor to support the simplest method at hand, ordinary least squares analysis, when the alternatives are unclear.
- The long history and success of analytic methods derived from least squares analysis and the way it is taught as foundational knowledge. To understand complex system behaviour, most graduates have to unlearn what they have been taught.
- A perception of the need to defend the trend from attacks by the merchants of doubt (Oreskes and Conway, 2010) and their camp followers.
- The lack of an analytic test that can assess nonlinear behaviour with a high degree of confidence.

The following paragraphs summarise the main threads of evidence supporting climate change as being a nonlinear process.

Past climate contains many examples of abrupt changes, even during interglacial periods when ice-sheet interactions are largely absent (Overpeck and Webb, 2000;Alley et al., 2003;Shuman, 2012). These changes are most often associated with singular events, but as Alley et al. (2003) warn "even a slow forcing can trigger an abrupt change, and the forcing may be chaotic and thus undetectably small." Evidence of rapid climate change in response to gradual external forcing is extensive (Mayewski et al., 2004;Shuman et al., 2005;Herweijer et al., 2007;Dakos et al., 2008;Wanner et al., 2008). For example, in reponse to slowly changing orbital forcing, lake levels in western Victoria, Australia oscillate between wet and dry regimes several times between 3 and 2.5 ka (Bowler, 1981;Jones et al., 1998). The evidence of rapid shifts on a wide range of time scales in the past keeps amassing (Shuman, 2012), but this is not feeding through into how future climate risk is being characterised in scientific practice .

Widespread regime shifts associated with climate variability also produce rapid changes in the thermodynamic characteristics of a particular region, affecting variables such as temperature, rainfall and storminess (Christiansen, 2003;Rodionov, 2005;Overland et al., 2008). Decadal-scale climate processes such as the North Atlantic Oscillation and Pacific Decadal Oscillation are widely recognised as having several modes that they oscillate between, sometimes individually and at other times in concert (Schwing et al., 2003;Rial et al., 2004;Enfield and Cid-Serrano, 2006). Such regime changes affect a range of systems including fisheries, agriculture, water resources and marine and terrestrial ecosystems (Ebbesmeyer et al., 1991;McCabe and Wolock, 2002;Rial et al., 2004) and change the frequency and magnitude of extreme events (Warner, 1995;Erskine and Warner, 1998;Swetnam and Betancourt, 2010).

Regime shifts are widely recognised as part of climate variability (e.g., see Section 5.5.5, Masson-Delmotte et al., 2013), but shifts attributable to climate change are considered to be uncommon, and are rarely recognised in climate model output (Valdes, 2011;Drijfhout et al., 2013). However, if the atmosphere cannot tell the difference between CO_2 of natural or anthropogenic origin, why then, would the climate system distinguish between natural and anthropogenic heat energy, where one system component exhibits regime changes and the other does not? The inherent nonlinearity of the climate system has been recognised since the seminal work of Lorenz (1963), which begs the question: does human-induced forcing affect the climate system independently of such nonlinearity or do they combine (e.g., Corti et al., 1999;Palmer, 1999;Hurrell and Deser, 2010)? These alternative explanations should be testable.

Current hypotheses linking climate change and variability

The two competing hypotheses that describe how anthropogenic climate change and variability may be linked are (Corti et al., 1999;Hasselmann, 2002):

1. Anthropogenic climate change occurs independently of climate variability (*H1*).
2. Anthropogenic climate change interacts with climate variability (*H2*).

Corti et al. (1999) state:

> *a crucial question in the global-warming debate concerns the extent to which recent climate change is caused by anthropogenic forcing or is a manifestation of natural climate variability. It is commonly thought that the climate response to anthropogenic forcing should be distinct from the patterns of natural climate variability. But, on the basis of studies of nonlinear chaotic models with preferred states or 'regimes', it has been argued that the spatial patterns of the response to anthropogenic forcing may in fact project principally onto modes of natural climate variability.*

For the remainder of the paper, these hypotheses are referred to as *H1* and *H2*. Linearity is referred to as any change that can be expressed using a single line, whether straight or curved. Linear additivity is also referred to in the papers, but will be specifically identified when relevant.

H1 supports a gradual and linear atmospheric response to greenhouse forcing, mediated by climate variability. Solomon et al. (2011) suggest this may involve a preference for certain natural modes (e.g., a more El Niño-like world) or feedback with variability to produce a nonlinear (but gradual) response. This framing also accepts the risk of nonlinear responses occurring due to thresholds, or tipping points, being breached (e.g., ice sheet collapse, loss of tropical forest, permafrost methane outbursts).

H2 supports nonlinear responses where change imprints on natural variability (Corti et al., 1999) or where the two interact (Branstator and Selten, 2009). This hypothesis has a fifty-year history, building on the work of Lorenz (1963) on quasi-oscillatory weather systems. Charney and Shukla (1981) suggested that existing boundary conditions in the low latitudes may lead to a measure of climate predictability. Palmer (1993) showed that if forcing is added to Lorenz' equations then the climate response is potentially predictable, even with weak forcing (Slingo and Palmer, 2011). Corti et al. (1999) describe this as anthropogenic forcing onto Lorenz-like regions of relative stability and instability, which if seen in the climate system, would project climate change onto the principal modes of variability on timescales shorter than that of the forcing; i.e., decades or less. Such changes in natural variability are often associated with step-like regime changes (Overland et al., 2008). These regimes are a principle method by which thermodynamic energy in the climate system is transported from the equator to the poles, so any added energy due to external forcing would presumably behave in a similar manner.

Research on whether the climate responds in a linear or nonlinear manner with respect to gradually increasing greenhouse gas forcing has been inconclusive, with evidence supporting both alternatives. Seidel and Lanzante (2004) investigated temperature records from surface to the stratosphere, testing a number of statistical alternatives: linear trends, flat steps, piecewise linear and sloped step. They decided that for surface data (1900–2002), the piecewise linear and sloped step were the best statistical models. For upper air data, conclusions were more elusive. Results for tropospheric (mid and upper atmosphere) data (1958–2001) suggested that most warming occurred in the climate regime shift of 1977 (Seidel and Lanzante, 2004).

Climate models are widely assumed to not readily simulate rapid change (Valdes, 2011). This is partly due to a lack of precision concerning the language of rapid or abrupt change (Drijfhout et al., 2015), especially on the time scales upon which such changes are anticipated to occur. Most discussion concerns major dislocations that would be readily detectable when they occur but that have been primed by underlying processes that may not be fully understood. These are linked to known processes related to albedo change, ice sheet instability, ocean overturning and so on (e.g., Oppenheimer et al., 2014). Less attention has been given to nonlinear thermodynamic behaviour within the climate system and how that would affect phenomena such as warming, wetting or drying, although this emphasis is changing (e.g., Arias et al., 2012;Jacques-Coper and Garreaud, 2014;Coats et al., 2015).

Changes in decadal-scale oscillations have been implicated in changes in the rate of global mean warming but the underlying interactions between regime shifts and warming remain unclear (Tsonis et al., 2007;Swanson et al., 2009;Swanson and Tsonis, 2009;Wang et al., 2009). Solomon et al. (2011) review the issue of natural and anthropogenically-forced decadal climate variability, discussing the techniques used to separate the two in order to support decadal prediction. While they describe both H1 and H2 as being plausible, three of the five analytic methods they describe self-select H1 in the way that 'signal' is separated from 'noise'. These are the dominant methods in use, suggesting that methods are crowding out theory in assessments of climate change over decadal timescales.

Lorenz (1975) identified two kinds of predictability:

- The first is due to changing boundary conditions with fixed initial conditions and is associated with long-term (multi-decadal to centennial) climate predictability (Lorenz, 1975;Hasselmann, 2002;Collins et al., 2011), and;
- The second is due to initial conditions with fixed boundary conditions and is associated with weather and shorter term (interannual to decadal) climate predictability.

Both types of predictability affect model simulations over decadal timescales (Collins, 2002;Collins and Allen, 2002). A climate model ensemble of multiple simulation forced by the same greenhouse gas scenario will show significant uncertainty in its early stages but reproduce very similar trends over long periods (Meehl et al., 2007). By discarding decadal-scale uncertainties and communicating only long-run average change, climate science is only relaying part of the information required to better understand and manage climate risk.

These two types of predictability can largely be allocated to the first and second laws of thermodynamics. Applied to Earth, the first law means that the total energy within the climate system seeks to achieve a balance with its radiative inputs and outputs. Increasing greenhouse gases that trap radiation in the lower atmosphere thus preventing its re-emission into space will result in a radiation imbalance at the top of the atmosphere. This will prompt the climate system to move towards energy equilibrium, causing warming until such time as balance is re-established (Pierrehumbert, 2011). This process will be quasi-linear unless a singularity resulting in a positive or negative feedback occurs (e.g., ice sheet collapse).

Around 93% of the energy trapped by greenhouse gases goes into the oceans (Rhein et al., 2013). Earth experiences transient warming as ocean heat is re-emitted into the atmosphere. If greenhouse gases (and incoming radiation) stabilise, then Earth will warm until outgoing radiation at the top of the atmosphere equals incoming radiation. Over centuries to millennia, this approximates to a gradual process that can be represented using methods that linearize forcing and response. This is a first-order response to external forcing and can be represented with simple energy-balance models and smooth curves over those timescales (Houghton et al., 1997).

The second kind of predictability is related to entropy, where the ocean-atmosphere system acts as a large heat pump, transferring moist static energy into work through largely irreversible processes. Heat is transferred from the equator to the poles via both the atmosphere and ocean, which exhibits self-organised criticality (Ozawa et al., 2003). Climate will seek a stationary state until such time as energy stipulates that another state has maximum entropy – this can be thought as when one state becomes unlikely (or subcritical), it will transform into another that is more stable (Tsonis and Swanson, 2011;Tsonis and Swanson, 2012).

Metastable and quasi-periodic climate regimes, punctuated by rapid changes on timescales ranging from decades to millennia, are typical aspects of the climate system. Decadal scale oscillators that behave in this way include the Pacific Decadal Oscillation (PDO)/Interdecadal Pacific Oscillation (IPO) and the Atlantic

Multidecadal Oscillation (AMO) (Mantua et al., 1997;Hare and Mantua, 2000;Mantua and Hare, 2002;Newman et al., 2003;Enfield and Cid-Serrano, 2006;Zhang and Delworth, 2007). The mechanisms behind some of these shifts are beginning to be understood. Linked to an abrupt shift between El Niño–Southern Oscillation (ENSO) regimes in 1978, O'Kane et al. (2014) show that fast (weather) and slow build-ups of density anomalies combine to disrupt the thermocline in the equatorial Pacific. This is linked to a contemporaneous step change in global temperature (Jones and Ricketts, 2015a).

Ozawa et al. (2003) describe the conversion of radiative energy to terrestrial temperatures as a linearly additive process but also state that due to a nonlinear feedback mechanism, the rate of entropy production in a turbulent fluid system will adjust the transport process to generate the maximum possible work. This suggests that if increased radiative energy enters a turbulent fluid system; i.e., the ocean-atmosphere system, the rate of entropy production will increase. The understanding of these types of conversions within the climate system (from linear forcing to turbulent behaviour) is not well understood, although increases of energy will lead to new states that maximise entropy (Ozawa et al., 2003). However, in systems that exhibit self-organised criticality and that inhabit metastable states, gradual change is an anomaly.

By concentrating on the analysis of nonlinear responses in climate variables, this series of papers is looking at how the climate changes, not why. The focus on how, uses inferences from complex system behaviour while the why is embedded in thermodynamic theory (e.g., Ghil, 2012;Lucarini et al., 2014).

Methods for analysing change and variability

Beyond exploring the theory of how the climate changes, applied methods for analysing climate change and variability fall into three main groups:

1. Climatological analysis, including model testing and evaluation.
2. Detection and attribution (D&A) studies (past and present climate).
3. Forecasting: prediction, projection and scenario-building (future climate).

The first group is a catch-all description of general studies that aim to understand the climate of a place or time, or a specific process or model. A wide range of methods are used, with the signal-to-noise model being prominent. These are not discussed further here, as most aspects are covered under the next two groups.

Direct attribution involves detection of a statistically significant change in a variable of interest. Observed changes in that variable are then compared with expected changes due to external forcing typically derived from modelling approaches (Hegerl et al., 2007;Hegerl et al., 2010;Stott et al., 2010;Bindoff et al., 2013). If carried out with climate models, this method assumes that stationarity in control models runs adequately represents real-world stationarity. The null value theorem is then applied to show that observations are consistent with perturbed model runs. Statistical significance is obtained through the likelihood of observations matching control conditions (Stott et al., 2010).

Forecasting covers a spectrum of techniques ranging from (in order of increasing certainty (Carter et al., 2007)):

- Scenarios – plausible future states of climate with no specific likelihood of occurrence.
- Projections – model-based predictions conditional on a specific set of forcing and model assumptions. Probabilistic projections quantify the likelihood of a range of possible outcomes.
- Predictions – states of the future that are the best estimate developed from model and statistical approaches.

The dominant method for carrying out both D&A and forecasting assessments is the signal-to-noise model (STNM, Hasselmann, 1979;Santer et al., 1990;Wigley et al., 1999;Hasselmann, 2002). Santer et al. [2011] describe it thus: *The warming signal arising from slow, human caused changes in atmospheric concentrations* *of greenhouse gases is embedded in the background 'noise' of natural climate variability.* The main statistical model used to analyse and communicate climate change applies lines of best fit that largely remove this noise.

Signal-to-noise methods for D&A studies assess whether a signal exceeds the noise of natural variability (the signal to noise ratio) with statistical significance. Most important is how this noise is characterized. Most D&A studies utilise least squares regression of trends that are often, but not always, linear (Stone et al., 2009) or are modifications of that technique (Bindoff et al., 2013). Variability about the mean trend is considered as being random with respect to the trend, an assumption that has been used widely and successfully in analysing individual time series (Stone et al., 2009;Stott et al., 2010). These methods are also robust for temperature under different constructions of variability, taking into account short- and long-memory processes (Imbers et al., 2013a;Imbers et al., 2013b). Optimal fingerprint techniques combine spatial and/or temporal data to maximize the signal to noise ratio, thus identifying a pattern of change in response to external forcing (Bindoff et al., 2013).

Predictability is often explicitly linked to D&A techniques. For example, The International Ad Hoc Detection and Attribution Group (2005) state *that if a (known) change in external forcing occurs, the climate will respond by displaying a predictable change in its statistical characteristics. This should hold even if the climate displays "regimelike" behavior, because regime occupancy characteristics are part of the full description of the behavior of the climate system.*

Similar methods are used in climate forecasting. Regional climate change signals are assumed to be linear with respect to mean global warming allowing pattern scaling (Santer et al., 1990;Mitchell, 2003). Most regional climate change scenarios and projections are based on differences between time periods (Christensen et al., 2013) or scaled regional changes to mean annual temperature, rainfall and other variables (Whetton et al., 2005;IPCC-TGICA, 2007). Similar methods to pattern scaling are used to detect and project changes in decadal variability by describing a linear projection onto a set of indices (Christensen et al., 2013).

Experimental designs prescribing climate model capacities and inputs (Taylor et al., 2012) are used to set common standards, which allow skill scores of climate models in how they reproduce current climate to be calculated (Suppiah et al., 2007) and various weighting methods to be tried (Tebaldi et al., 2005;Tebaldi and Knutti, 2007;Watterson, 2008). Methods such as optimal fingerprinting strive to maximise the signal to noise ratio in climate model output by optimally fitting patterns rather than assessing direct output values (Hasselmann, 1993;Hegerl et al., 1996;Allen and Stott, 2003).

The development of ensemble techniques and probabilistic methods for regional climate projection borrow strongly from weather forecasting methods but concentrate on characterising uncertainty in the future signal of climate change means and extremes (Tebaldi et al., 2005;Tebaldi and Knutti, 2007;Watterson, 2008). This allows probabilistic projections for mean change encompassing a large span of scientific and socio-economic uncertainty to be constructed from a more limited number of climate model simulations based on pattern scaling methods (Jones, 2004). These methods manage future uncertainties at a given date but do not manage the potential uncertainties encountered over the time taken to reach that date.

The evolution of climate modelling has also influenced how the results are communicated. Climate models started out as relatively simple mathematical models containing little internal variability, gradually evolving into fully coupled representations of the climate system (Weart, 2008). The output from these early models was best represented as simple curves, creating a legacy in how a changing climate is communicated. The continuing use of simple models to explore and represent future uncertainty, especially in the response of global mean temperature to external forcing, also produces smooth curves of change.

However, showing too much uncertainty is also an important constraint on communication (Figure 1) (Patt and Dessai, 2005;Climate Change Science Program, 2009;Pidgeon and Fischhoff, 2011). For example, displaying the raw output of many climate models on a single chart, with large uncertainties in both mean and variability, promotes confusion and decision paralysis. To depart from using simple curves as a forecasting strategy would therefore require compelling evidence and a rethinking of how results are presented. Existing values attached to methods, reasoning and goals such as gradualism, simplicity and prediction are examined further in Jones (2015a) and implications for how they affect the characterisation and application of climate information is discussed in Jones (2015b).

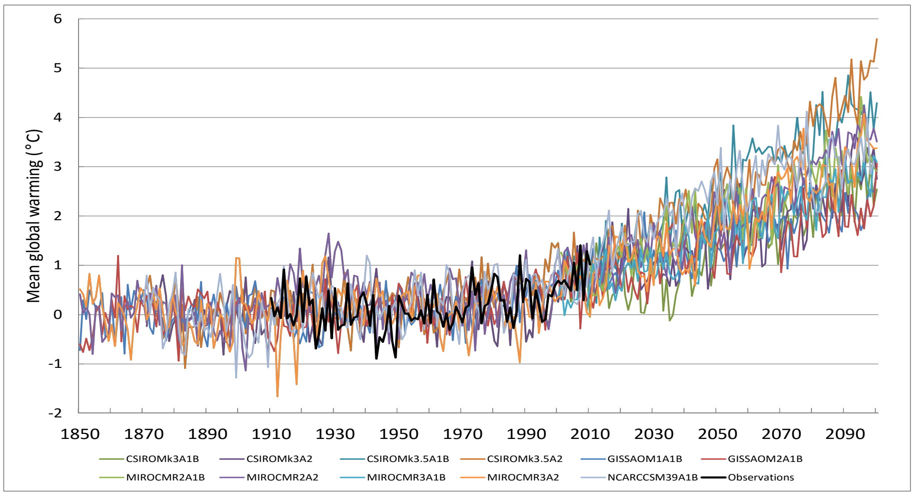

Figure 1. Annual maximum temperature projections for south-eastern Australia from eleven climate models from the CMIP3 database plotted with observed temperature from the Australian Bureau of Meteorology.

Discussion

Readers will naturally point to the many papers in the literature that treat climate as a complex nonlinear system, exploring many aspects of nonlinearity and what that means for future climate risk. This is certainly true, but means there are two literatures that remain unreconciled. The one literature addressing theory is comfortable with climate as a nonlinear system, but the other literature dealing with the application of climate-related information to decision making, overwhelmingly treats climate as a linear system. Climate change is overwhelmingly being portrayed through the gradualist narrative (Jones et al., 2013). If *H2* is ultimately accepted as the more plausible hypothesis, current scientific practice will need to be revised substantially.

The other papers in this series deal with various aspects of why and how this situation has arisen, but one key issue is how perceived utility influences the provision of climate information. What is deemed useful will align with the cognitive values of the scientists themselves (Jones, 2015a), where knowledge and predictability are highly valued and ignorance is not. The other major factor affecting decision making in complex contexts is deep uncertainty: *uncertainty that results from myriad factors both scientific and social, and consequently is difficult to accurately define and quantify* (Kandlikar et al., 2005). Decision making that ignores deep uncertainty runs the risk of being unprepared for surprises (Gallopin, 2002;Schneider, 2004;Parker and Risbey, 2015), or of making set and forget decisions when ongoing change needs to be addressed.

While substantial effort has been invested in understanding the implications of deep uncertainty by addressing the context and needs of decision maker (e.g., Climate Change Science Program, 2009;Jones et al., 2014), less effort has been invested in reconciling these two literatures to provide the appropriate climate information to support these needs. For example, Risbey and O'Kane (2011) point out that because of nonlinear climate responses there is much that climate models cannot portray, but emphasise that ignorance and surprise can be incorporated into decision making in a meaningful way (Parker and Risbey, 2015).

Efforts are being made to overcome the predictability barrier, for example through typologies of change within which specific scenarios can be developed (CSIRO and Bureau of Meteorology, 2015) and user-focused programs within climate services (Hewitt et al., 2012;Krauss and von Storch, 2012;von Storch and Zwiers, 2013;WMO, 2014). Pressure on science to deliver utility also comes from funding organisations and national governments who may not understand the value of scenarios focussed on managing uncertainty and ignorance, despite the fact that this was the motivation for their development in the first place (Wack, 1985a, b). Embracing uncertainty would see the emphasis of climate risk management change from being a direct response to projected climate impacts to managing the effect of uncertainty (including future climate uncertainty) on objectives (Jones et al., 2014). The framing of what is useful climate information at its most basic level, would shift from whether a future risk can be predicted with skill, to whether it is plausible and can be described.

Conclusions

There is a disjuncture in the literature between theory-based discussions of the links relating climate change and variability, and the practice of analysing and applying climate information for decision making. Discussions concerning theory carefully describe the alternative hypotheses describing the relationship between externally forced and internally varying climate without selecting one over the other. Scientific practice, on the other hand, self-selects the hypothesis that the two act independently.

This disjointedness can be seen within a single chapter in the latest IPCC Report. When the technique for separating internally and externally generated components is explained, the following caveat is given: *This separation of T, and other climate variables, into components is useful when analyzing climate behaviour but does not, of course, mean that the climate system is linear or that externally forced and internally generated components do not interact* (Kirtman et al., 2013). However, methods for decadal predictions outlined in that same chapter focus on trend analysis from model ensembles that utilise a linear signal-to-noise model. This emphasis is widespread within climate practice.

Regarding starting assumptions, Wallace (1996) said:

> *Preconceived notions concerning the nature and causes of climate variability determine the datasets that scientists examine, the analysis tools they employ, and the questions they address in their research. Their choices, in turn, define and limit the range of possible outcomes. If these notions are wrong, the research is likely to get off on the wrong track. If they are lacking altogether, the course of the research may be determined by default, through ad-hoc choices, as in the maxim: "If all you have is a hammer, all you'll see is nails".*

At present, the two narratives describing H1 and H2 are incommensurate. Paraphrasing Wallace, we could ask "would research be conducted differently, depending on whether H1 or H2 was considered more likely?" This question is revisited in the final paper of this series that explores the implications of nonlinear change for the framing and conduct of climate-related risk assessment, covering detection, attribution, prediction, adaptation, mitigation and communication (Jones, 2015b). The reasons leading to H1 being self-selected over H2 are examined in a paper that investigates the history and philosophy of linear analysis methods in climatology Jones (2015a). Evidence for nonlinear climate change is presented for temperature in Jones and Ricketts (2015a, b) and climate more generally in (Jones, 2015c).

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