Reconciling anthropogenic climate change and variability on decadal timescales

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Contents

Introduction

Scientific narratives overwhelmingly communicate anthropogenic climate change as a gradual process. As part of those narratives, the predictable but uncertain signal of climate change is distinct from the unpredictable noise of climate variability (Jones et al., 2013). Changing climatic means are portrayed as smooth curves, contributing to a narrative of gradual change that feeds into decision making for both adaptation and mitigation – forming the gradualist narrative (Figure 1). Decision makers therefore assume that climate-related risks change gradually and are mediated by climate variability. The gradualist narrative and its accompanying methods comprise the dominant paradigm describing how the climate changes under greenhouse gas forcing. In this paper, these changes are considered as being linear, in that they can be described using a line, whether straight or curved (e.g., Figure 1b).

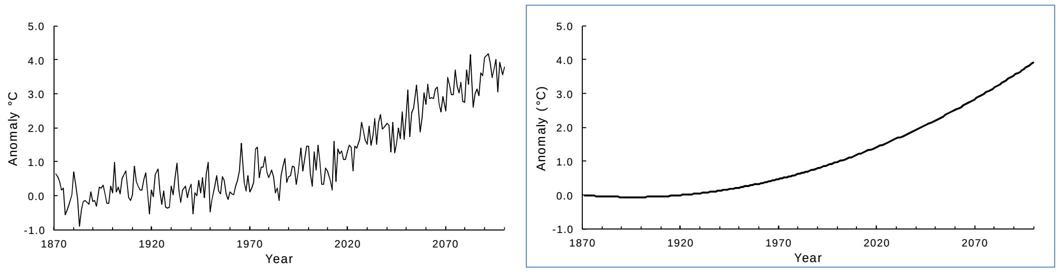


Figure 1. Single climate model simulation for south-east Australian minimum temperature (CSIRO Mk3.5 A1B $Tmin_{AGW}$) showing annual variability (left) and mean change (right) for a high emissions pathway.

This issue is most important at decadal timescales, where projected climate change and climate variability are likely to produce variations in climate of similar magnitude (Deser et al., 2012). Because of the diverse contexts within which decisions are being made, decision-making needs to consider a range of timescales from the short- to the long-term (Jones et al., 2014). This paper concentrates on the links between climate change theory, practice and decision-making over decadal time scales (5–50 years).

The theoretical understanding of climate change processes 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). Evidence of rapid climate change in response to gradual external forcing is a feature of past climates (Mayewski et al., 2004;Shuman et al., 2005;Herweijer et al., 2007;Dakos et al., 2008;Wanner et al., 2008). For example, lake levels in western Victoria, Australia show that large and rapid changes in regional moisture regimes occurred throughout the Holocene in response to slowly changing orbital forcing (Jones et al., 1998).

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).

The inherent non-linearity 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 non-linearity or do they combine (e.g., Corti et al., 1999;Palmer, 1999;Hurrell and Deser, 2010)? These alternative explanations should be testable.

Recent work shows that on decadal time scales, many climate variables change in a step-wise manner (Jones, 2010b;Jones, 2012;Jones et al., 2013). Variables include air temperature, sea surface temperature, tide gauge measurements, ocean heat content, rainfall, fire danger indices and stream flow (Jones et al., 2013). This work was prompted by a shift in 1997–98 in south-eastern Australian climate.

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). Some impact studies have been rendered obsolete (Jones, 2010a;Jones et al., 2013) because they failed to anticipate such large changes. Further investigation shows such changes are widespread on regional to global scales (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.

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, which it must, if one system component exhibits regime changes and the other does not? Clearly, a physical explanation that explains how this can be possible – or not – is needed.

There is currently no clear scientific narrative of how the climate changes, which is 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 this narrative and has testable conditions to distinguish it from alternatives.

Part I of this paper describes the two existing scientific hypotheses for how climate changes – and briefly describes the conditions required to sustain them. Part II provides substantial evidence for step changes and shows that the anthropogenic component of warming can shift abruptly at the regional scale. Part III addresses the paradigms relating human-induced climate change and variability, using a sociological model derived from Kuhn (1962, 1970), Laudan (1984) and others that addresses changing methods, values and theory. It concludes that the hypothesis sustaining the gradualist narrative is preferred for largely historical, rather than theoretical, reasons.

In Part IV, proposes an alternative hypothesis for how the climate changes over decadal timescales that combines human-induced climate change and natural variability within a single process. This process is more physically realistic than the default gradualist paradigm, and is more consistent with the findings of Lorenz (1963, 1975), Hasselmann (1976, 1979) and complex system behaviour in general.

Part I Hypotheses

Current hypotheses linking climate change and variability

The scientific literature contains two competing hypotheses that describe how anthropogenic climate change and variability may be linked (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 plotted along a single line, straight or curved.

The first hypothesis (H1) supports a gradual and linear atmospheric response to greenhouse forcing, mediated by climate variability. Solomon et al. (2011) suggest that this mediation may involve a preference for certain natural modes (e.g., a more El Niño-like world) or may feedback with variability to produce a non-linear (but gradual) response. Non-linear responses may occur, but will be independent of natural variability. These include thresholds, or tipping points, such as ice sheet collapse, loss of tropical forest or methane outbursts.

The second hypothesis (H2) supports non-linear responses where change imprints on natural variability. Charney and Shukla (1981) suggested that the boundary conditions in the low latitudes may lead to longer-scale predictability. Palmer (1993) showed that if forcing is added to Lorenz' equations then the climate response is predictable, even with weak forcing (Slingo and Palmer, 2011). Charney and Shukla (1981);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. As briefly described earlier, such changes in natural variability are often associated with step-like regime changes. The result, therefore, would be a non-linear response involving change plus variability.

Research on whether the climate responds in a linear or non-linear 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. Stratospheric cooling could be explained by both step and trend and simple trend models.

Changes in decadal-scale oscillations have also more recently been implicated in changes in the rate of global mean warming but their underlying interactions remain unclear (Tsonis et al., 2007;Swanson et al., 2009;Swanson and Tsonis, 2009;Wang et al., 2009). The role of complex system behaviour is an increasingly studied phenomenon in climate studies, while the methods used to project future climate and manage climate risk are almost overwhelmingly linear.

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 decadal climate change. The issue of methods selecting hypotheses by default is discussed further in Part III.

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.

These two types can largely be allocated to the first and second laws of thermodynamics. The first law applied to Earth's climate system means that energy is balanced between the Earth and its radiative inputs–outputs. A radiation imbalance at the top of the atmosphere caused by greenhouse gases trapping radiation in the lower atmosphere will prevent its re-emission into space. This will prompt the climate system to move towards energy equilibrium and the Earth will warm until such time as balance is re-established (Pierrehumbert, 2011).

Around 93% of the energy trapped by greenhouse gases goes into the oceans (Rhein et al., 2013). Earth experiences transient warming in the meantime 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).

Ozawa et al. (2003) conclude that the conversion of radiative energy to terrestrial temperatures is a linear process but also state that due to a non-linear 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. However, 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). It is also worth saying that in systems that exhibit self-organised criticality and that inhabit metastable states, gradual change is an anomaly.

The behaviour of climate on decadal time scales is most important for decision making on human time scales. Any forced response on such time scales can be considered a second-order response within a physical hierarchy, but it doesn't make this aspect less important to decision-making.

An alternative way to consider physical impacts in decision making is to ask why do they occur and how do they manifest? The answer to the first question would address why the climate system may or may not be prompted to change and the answer to the second would describe how it may change. This paper focuses on the how, using inferences from the complex system behaviour while the why is embedded in complex thermodynamic theory (e.g., Ghil, 2012).

Both types of predictability affect model simulations over decadal timescales (Collins, 2002;Collins and Allen, 2002). A climate model run multiple times under 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 communicating long-run average change, climate science is only relaying part of the information required to better understand and manage climate risk.

Methods for analysing change and variability

Methods for analysing climate change and variability fall into three main groups:

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

Group 1 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.

Direct attribution involves detection of a 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):

- 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 detection and attribution studies and forecasting climate 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 detection and attribution 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 detection and attribution 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 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 shortand long-memory processes (Imbers et al., 2013;Imbers et al., 2014). 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).

Skill scores of climate models in observing current climate (Suppiah et al., 2007), and common experimental standards requiring certain standards for model structure (Taylor et al., 2012) are common methods, although various weighting methods have been 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 rather than assess the 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 (Suppiah et al., 2007). 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. 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 2) (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. Values attached to methods, reasoning and goals such as gradualism, simplicity and prediction are examined further in Part II.

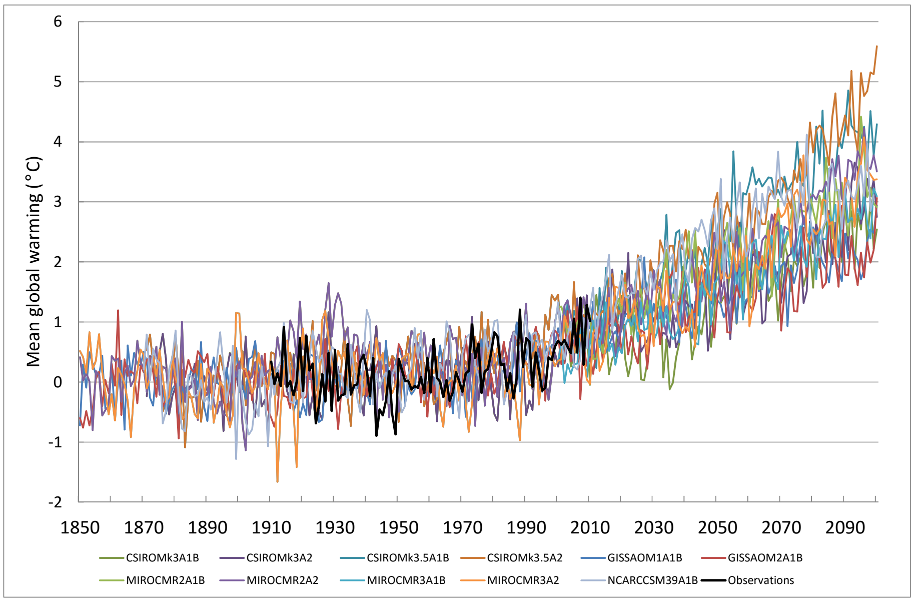


Figure 2. Annual maximum anthropogenic warming projections for south-eastern Australia from eleven climate models plotted with observed temperature from the Australian Bureau of Meteorology.

The default hypothesis of gradual climate change

There is a disjuncture in the literature concerning discussions of the links between climate change and variability as understood at the theoretical scale, and the practice of preparing and using climate information for decision making. Theoretical discussions carefully describe the alternative hypotheses for how externally forced and internally forced climate interact without selecting one over the other.

For example, in the latest IPCC Report, when the method 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 the same chapter are centred on trend analysis from model ensembles that combine internally and externally forced trends.

This is common – discussions of theory admit both possibilities with strongly favouring one over the other, whereas descriptions of methods overwhelmingly self-select H1 over H2. Therefore, we have two separate scientific narratives:

1. The methodological narrative overwhelmingly selects H1 over H2.
2. The theoretical narrative proposes both H1 and H2 as potentially valid hypotheses.

At present, these two narratives are incommensurate. Would research be conducted and climate risk formulated differently, according to whether H1 or H2 was considered more likely? The answer is a resounding yes. Evidence supporting H2 is presented in Part II.

Part II Evidence

Methods for measuring step changes

Step, or change-point analysis, has been widely used in a range of areas including finance, ecology and climatology (Peterson et al., 1998;Chen and Gupta, 2001;Bai and Perron, 2003;Andersen et al., 2009) but is less used than it might be. One major reason why is because of the difficulty in identifying methods free of false positives, particularly when autocorrelated data (red noise) and multiple change points are present (Bai and Perron, 2003;Beaulieu et al., 2012). Linear methods often appear successful by overlooking these concerns in favour of simplicity, but this does not solve the issue if a system really is influenced by red noise and/or contains multiple shifts. This raises the risk of the fallacy of formative measurement, where the measure becomes the cause (Edwards, 2010). Theoretical considerations should not be overlooked for the convenience of obtaining concrete results, but they often are.

For climatology, the success of linear methods lies in explaining long-run changes to climate and historical climate change. The persistence of these methods is in part due to the evolution of climate models from simple to complex. Initially, only linear methods could be used to analyse the results from the early models, because of their limited representation of climate variability and feedback processes. As models evolved, the representation of thermodynamic processes improved, complex system behaviour emerged gradually revealing interannual and decadal variability.

The principal method used here to detect step changes is the bivariate test of Maronna and Yohai (1978), which has been used to identify artificial inhomogeneities in climate data (Potter, 1981;Bücher and Dessens, 1991;Kirono and Jones, 2007) and statistically significant shifts in environmental variables (Lettenmaier et al., 1994;Gan, 1995;Vivès and Jones, 2005;Jones, 2012). Due to the difficulty of detecting multiple change points in time series, a forty-year window is progressively passed through an annual climate time series to identify potential change points. Subsequent individual sampling of time periods is undertaken to ensure that within a single time series, the minimum number of time periods with no statistically significant shift ($p<0.01$) is selected. This procedure tests the available data between alternate significant step changes, applying an iterative process until a stable configuration is reached with the minimum of statistically significant shifts while maximising the total test statistic (Ti0) within a single time period. To date, this has been carried out by the author, but is in the process of being automated.

Autocorrelation or ‘red noise’, which will not provide reliable probabilities with the bivariate test, is managed by identifying a break point then shuffling or randomising data either side of that point. If that point remains the dominant date, then it is considered robust. Tests with artificial data combining red noise and step changes shows that sometimes small random shifts become amplified by trends and will show up as significant. However, in data with steps and trends, steps may be amplified or suppressed by red noise but most remain apparent.

A second test, Rodionov (2005) STARS test is also used to ensure the robustness of shift dates. This method was tuned using an artificial training data set with autocorrelated (2 and 7 year) data containing both induced and imposed step changes. The STARS method is considered less reliable due to the dependence of the analysis on a single time-scale, which influences the results. The full methodology is described in Jones (2012).

Step changes in observations and models

A wide range of observed variables have been tested for statistically significant step changes using both the bivariate and STARS tests (Figure 3). Mean air temperature on global, hemispheric and zonal scales are shown. Global sea surface and land temperatures are shown. Regional maximum and minimum temperature and rainfall from south-eastern Australia are also shown. Marine observations include tide gauge records and ocean heat content (0–700 m).

The timing and magnitude of the change point is shown for a number of temperature records and for ocean heat content. The correspondence for the bivariate and STARS tests is fairly close in most of those records except for high latitude temperature.

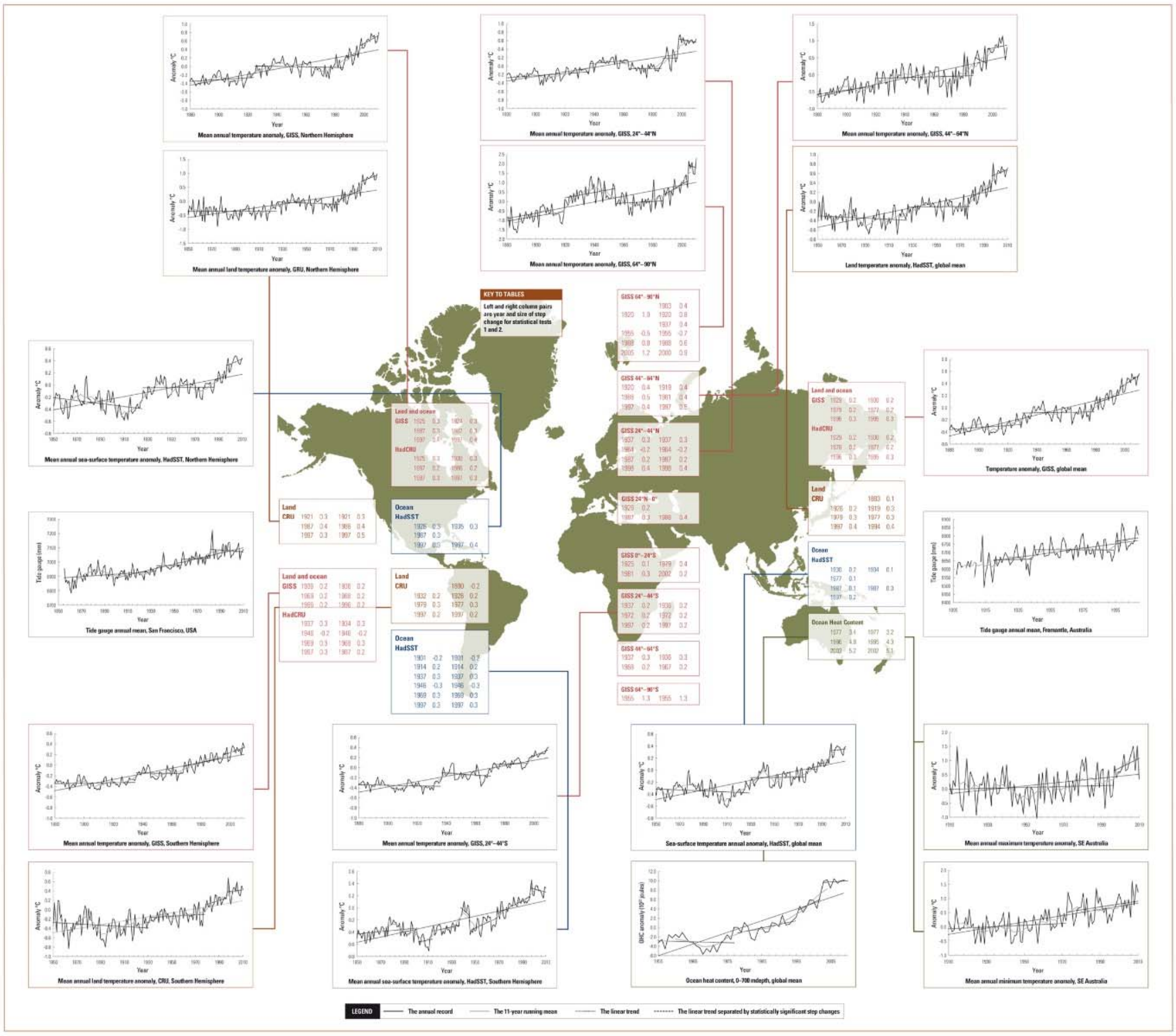


Figure 3. Step change analysis of a range of observed climate and climate-related variables using the bivariate and STARS tests. Data sets include mean global and regional warming anomalies from a pre-1900 baseline for the HadCRUt3 data set (HadCRU mean temperature, CRU land temperature, HADSST sea surface temperature)(Brohan et al., 2006), and GISS data set (Hansen et al., 2001) showing global hemispheric and zonal results. Tide gauge data was extracted from the PSMSL data set. Temperature from SE Australia is from a stationary climate baseline (Jones, 2012). Ocean heat content is described in Levitus et al. (2005). For tables, statistical test 1 is the bivariate test in the first two columns and the STARS test is in the second two columns. Graphs show annual data (thin black line), trends between statistically significant steps (bold dashed line), 11-year running means (thin grey line) and simple linear trends (faint dotted line).

The timing of step changes in temperature records is largely coincident with dates associated with change in decadal climate regimes, particularly in the northern hemisphere. Dates clustered around brief periods such as the early 1920s, 1977–78, 1986–87 and 1995–98 are common. Shift dates in the southern hemisphere occur in the mid-1930s, 1968–72 and 1996–97 being prominent. Temperature reversals occur in northern hemisphere locations, mainly in the post Second World War period.

Most of these records show an upward step-ladder like progression. Sea surface temperature, tide gauge and air temperature over largely oceanic regions, show a shift and gentle decline pattern throughout the 20th century until 1996. After 1996, upward trends are common. Few of the interpolated trends in between shift dates are statistically significant.

Climate model data shows similar behaviour. All CMIP3 and CMIP5 records of mean global warming tested so far have shown multiple step changes – none have fewer than 5. To date, only one region – south-eastern Australia – has been tested. However, the relationship between regional and global changes in the models mirror those in observations, suggesting that such phenomena are ubiquitous within climate models.

Eighteen climate simulations of maximum and minimum temperature for south-eastern Australia starting at dates from 1950 to 1900 and continuing to 2099 or 2100, show at least 3 shifts of $p<0.01$ each. These occur at a higher frequency in the 21st compared to the 20th century. Seventy-two individual climate simulations of precipitation from 21 models and 14 modelling groups, from the same data set, show at least one shift of $p<0.01$ for 34 simulations and one of $p<0.05$ for another 9 simulations. Eleven pairs of maximum and minimum temperature and precipitation temperature from this data set have been examined in detail, as summarised in the next section.

One consistent finding gained from testing a range of variables in both models and observations, is that local observations (locations and small regions) tend to show more pronounced step-like changes than very large-area averages (hemispheric and global; figures 4 and 5). For example, all the high-quality tide gauge records examined show a pronounced step ladder-like progression, whereas mean global sea level rise is clearly a non-linear trend (Figure 4). This is consistent with the Jevrejeva et al. (2006) finding that regions cannot be represented by a single curve but are influenced by multiyear cycles. Step changes can perhaps be identified within the global averages time series, but the serial dependence in the data renders the statistical tests less effective. This trend-like appearance is consistent with the global mean being an integration of many step-wise changes in regional sea level.

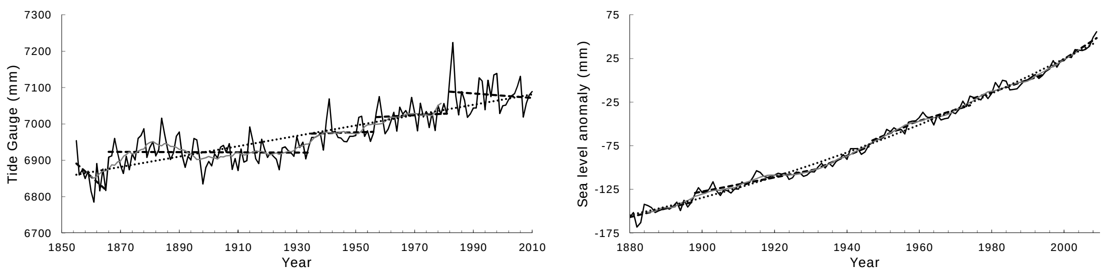


Figure 4. Annual tide gauge averages from San Francisco (1855–2010) and global mean sea level anomalies (Church and White, 2011) (1880–2009) showing statistically significant step changes using the bivariate test (dashed lines) combined with simple trends (dotted lines).

Likewise, mean global warming shows a step-like progression in the 20th century, changing into an elevator-like progression in the 21st century under increasing emissions (Figure 5). This is consistent with shifts becoming more frequent and widespread. All simulations of global mean warming under increasing greenhouse gas emission show a similar evolution of step changes, with fewer in the 20th century, increasing throughout the 21st century. The step and trend behaviour of the 21st century escalator is consistent with mean global warming being the integration of many local step-wise changes, the number of which increases with increasing forcing. Both Figures 4 and 5 tell a similar story in that regard.

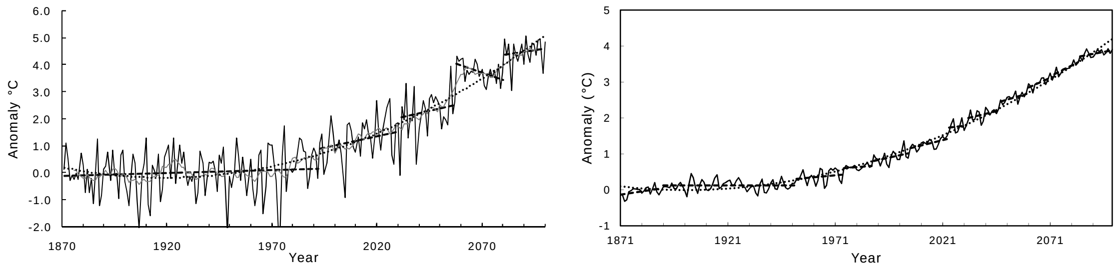


Figure 5. Annual mean temperature anomalies in south-eastern Australia from the CSIRO Mark 3.5 A1B run1 simulation (left) with annual global mean anomalies from the same simulation (right). Both charts show statistically significant step changes using the bivariate test (dashed lines) combined with simple trends (dotted lines).

Attribution of non-linear anthropogenic warming

Attribution of non-linear anthropogenic warming has been carried out in detail for two regions: south-eastern Australia (SEA) (Jones, 2012) and Texas, although it is clearly evident in data from other regions of Australia and continental USA where investigations have been carried out in less detail and are not reported here. Output for SEA from eleven model simulations was also analyzed but due to shared 20th century runs, only six 20th century simulations were independent.

The basic methodology is suitable for continental mid-latitude areas where annual average maximum temperature (Tmax) is correlated with total rainfall (P), and minimum temperature (Tmin) is correlated with Tmax (Power et al., 1998;Nicholls et al., 2004;Karoly and Braganza, 2005). The method uses the following steps:

1. Homogenous regional average data is obtained for Tmax, Tmin and P.
2. A period of stationary climate is calculated by testing when the relationship between Tmin and Tmax undergoes a statistically significant step change (Jones, 2012). The relationship between Tmax and P will change at the same, or later date.
3. Linear regressions are calculated between each pair (Tmax/P and Tmin/Tmax) for the stationary period.
4. $Tmax_{ARW}$ and $Tmin_{ARW}$ (anthropogenic regional warming) are estimated for the non-stationary period using these regressions. $Tmax_{ARW}$ and $Tmin_{ARW}$ are estimated as in (Jones, 2012).
5. The results are tested for step changes using both bivariate and STARS tests.

Table 1 shows the periods of stationarity for observations in SEA and Texas and climate models for SEA. Non-stationarity in observed climate in SEA began in 1968 and in Texas in 1990. Non-stationarity in simulated climate for SEA commenced between 1963 and 2002 with the Tmin/Tmax relationship shifting first or with Tmax/P. Initial step changes in Tmax/P ranged from 0.6°C to 1.5°C, compared to the historical shift of 0.7°C.

Table 1. Year of non-stationarity in regional temperature for south-eastern Australia (SEA) and Texas. Data source, year of first change greater than one standard deviation for Tmax against P and Tmin against Tmax using the bivariate test. The stationary period is also shown.

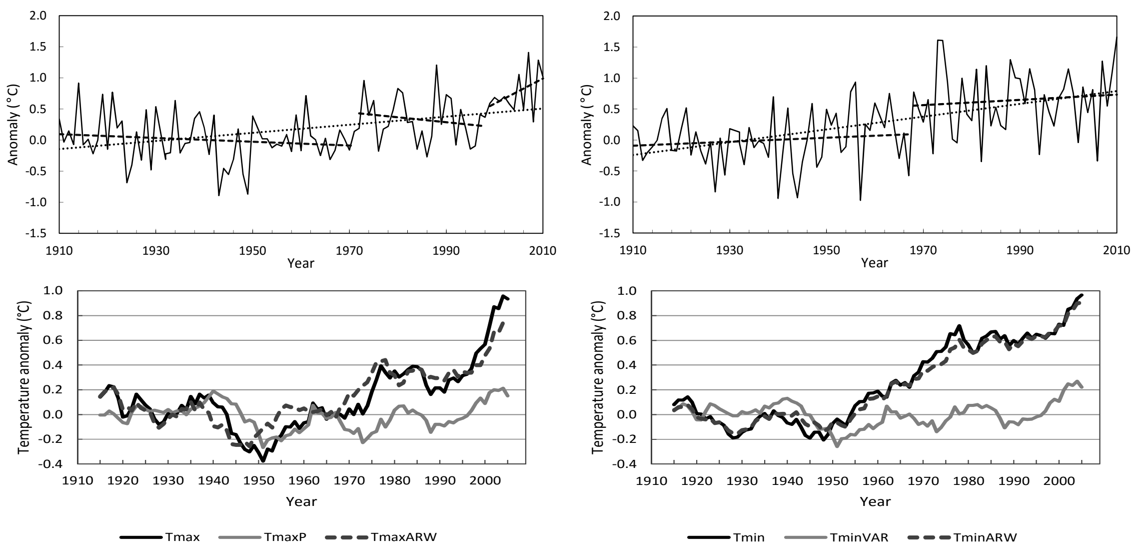
Data source	*Tmax/P*		*Tmin/Tmax*		Stationary Period
	Year	Change	Year	Change	(SEA)
Observations (SEA)	1999	0.7	1968	0.6	1910–1967
Observations (Texas)	1990	0.8	1998	0.5	1895–1990

Table 2 shows the dates of step changes in climate for the two regions. In south-east Australia, $\mathrm{Tmin}_{\mathrm{ARW}}$ changes significantly in 1968 and $\mathrm{Tmax}_{\mathrm{ARW}}$ in 1973. $\mathrm{Tmax}_{\mathrm{ARW}}$ shows a departure in 1973, the first of a series of wet La Niña years that affected rainfall during the 1970s perhaps counteracting underlying warming in Tmax. For Texas, $\mathrm{Tmax}_{\mathrm{ARW}}$ and $\mathrm{Tmin}_{\mathrm{ARW}}$ both change by 0.7°C from 1990. $\mathrm{Tmax}_{\mathrm{ARW}}$ behaves in a similar manner to that for SEA, actually showing an underlying change at the end of the calculated period in 1990. Again, potential increases in Tmax seem to be suppressed by higher than normal rainfall.

Table 2. Dates and changes of Tmax, Tmin, $\mathrm{Tmax}_{\mathrm{ARW}}$ and $\mathrm{Tmin}_{\mathrm{ARW}}$, from south-eastern Australia (SEA) and Texas using the bivariate and STARS tests.

Variable	Bivariate test			STARS test	
	Year	Change	Period	Year	Change
SEA					
Tmax	1997	0.80	1910–2010	1997	0.80
$\mathrm{Tmax}_{\mathrm{ARW}}$	1973	0.47	1910–2010	1973	0.38
				2005	0.54
Tmin	1973	0.69	1910–2010	1968	0.62
				2007	0.66
$\mathrm{Tmin}_{\mathrm{ARW}}$	1968	0.64	1910–2010	1970	0.63
				2007	0.64
Texas					
Tmax	1998	0.72	1895–2010	2005	0.79
$\mathrm{Tmax}_{\mathrm{ARW}}$	1990	0.70	1895–1989	1990	0.70
Tmin	1990	0.70	1895–2010	1990	0.70
$\mathrm{Tmin}_{\mathrm{ARW}}$	1990	0.69	1895–2010	1990	0.69

The anthropogenic components of warming in Tmax and Tmin for both SEA and Texas are shown in Figure 6 with step changes and running 11-year means compared with observations and attributed natural variability. Both sets of time series show the period of climate stationarity. Tmax is somewhat more complex than Tmin, with periods of higher rainfall masking the initial anthropogenic influence in both SEA and Texas. The use of 11-year running means makes the increase seem gradual in the figures but statistical analysis identifies both as being abrupt.



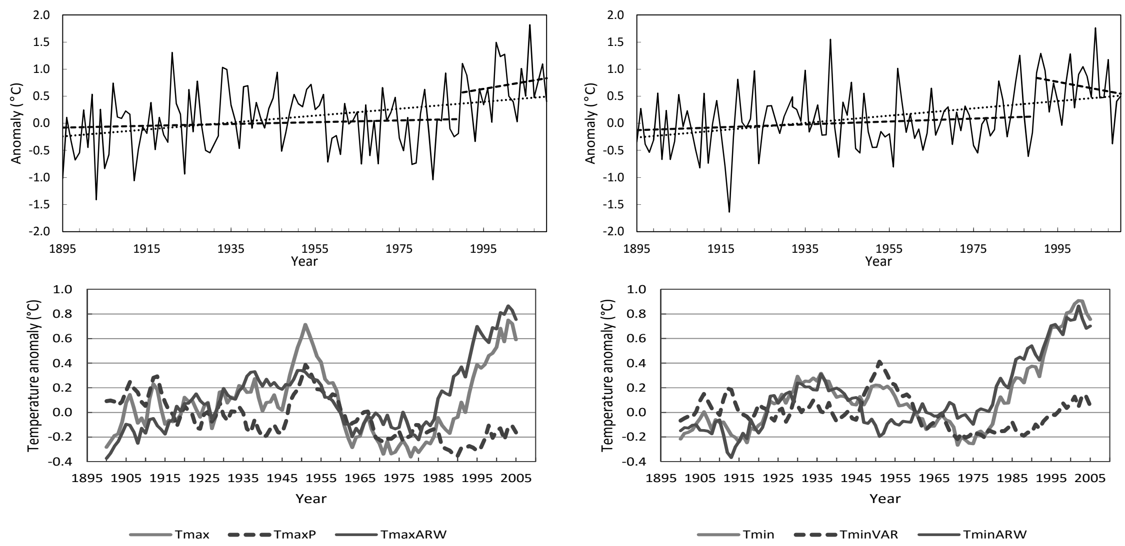


Figure 6. Trends and significant step changes from Tmax and Tmin, respectively, for SEA (top row), with 11-year running means of Tmax, $Tmax_P$ and $Tmax_{ARW}$ and Tmin, $Tmin_{Tmax}$ and $Tmin_{ARW}$ respectively (second row) for SEA. The same sequence for Texas are repeated on rows three and four. All changes are p<0.01 except for Tmax for SEA (update)

The same technique was used for eleven climate model simulations for SEA. The stationary period for all models ended with a statistically significant shift in Tmin between the years 1965 and 2003 (Table 3). Statistically significant step changes in each model averaged about 3.5 each simulation for Tmax and 4.5–5.5 for Tmin. No shifts p<0.01 were identified for P, but many of the step changes were large enough to produce significant hydroclimatic and ecological impacts if experienced. Further testing of 22 model simulations for a single grid cell over Melbourne Victoria, showed that 16 of these produced at least one shift p<0.05 under radiative forcing.

Table 3. Models and year of non-stationarity for the pairs *Tmax/P* and *Tmin/Tmax* using the bivariate test.

Data source	*Tmax/P*		*Tmin/Tmax*		Stationary Period
	Year	Change	Year	Change	(SEA)
CSIRO Mk3 A1B	2047	1.8	1992	0.6	1871–1991
CSIRO Mk3 A2	2006	0.9	1998	0.7	1871–1991
CSIRO Mk3.5 A1B	1996	1.1	1964	0.4	1871–1963
CSIRO Mk3.5 A2	1996	1.1	1964	0.4	1871–1963
GISS AOM R1 A1B	2000	1.5	1983	0.4	1850–1982
GISS AOM R2 A1B	1982	0.6	1982	0.6	1850–1981
MIROC Medres R2 A1B	1999	0.8	1999	0.5	1850–1998
MIROC Medres R2 A2	1999	0.9	1999	0.5	1850–1998
MIROC Medres R3 A1B	2007	0.7	2003	0.5	1850–2002
MIROC Medres R3 A2	2016	1.0	2001	0.5	1850–2000
NCAR CCSM3 A1B	1986	0.8	1971	0.5	1870–1970

All models in the SEA study showed a step-ladder-like process of change for TmaxARW and TminARW following a stationary period, with three to five statistically significant shifts to 2100 with generally insignificantly trending periods in between. Rainfall variability can also influence the timing and magnitude of step changes. Figure 6 shows Tmax, Tmin, $Tmax_{ARW}$ and $Tmin_{ARW}$ from the CSIRO Mk3.5 A1B and MIROC MR3 A1B simulations. In the CSIRO simulation, rainfall decreases amplify step changes in warming. Tmax undergoes four significant step changes of up to 1.5°C, whereas $Tmax_{ARW}$ undergoes more but smaller step changes and by 2100 warms by 0.6°C less. $Tmin_{ARW}$ also warms by slightly less than Tmin. In the MIROC simulation, increasing P suppresses step changes and total warming in Tmax and Tmin to 2100 by about 0.2°C.

This technique also allows individual years or seasons within a year to be attributed statistically to climate variability or change. Extreme high summer Tmax and Tmin during the Texas drought of 2011 were analysed to see whether they were better explained by climate variability or change. Tmax was regressed using P for both the stationary (1895–1989) and non-stationary periods (1990– 2011; correlations -0.82 and -0.95, respectively) and Tmin regressed using Tmax (correlations 0.81 and 0.86). Any given year can then be assessed for its likelihood with respect to either distribution. These likelihoods of occurrence described were then used to calculate a likelihood ratio of forced change versus natural variability.

The average Tmax in the summer of 2011 was 37.5°C compared to the 1961–90 average of 34.4°C and was six times more likely to have been due to external forcing than being a natural variation. Average summer Tmin in 2011 23.4°C compared to the 1961–90 average of 21.6°C was 21 times more likely to be due to external forcing. Figure 7 shows Tmax plotted against P and Tmin plotted against Tmax, showing both the stationary and non-stationary periods, and the anomalous summer of 2011.

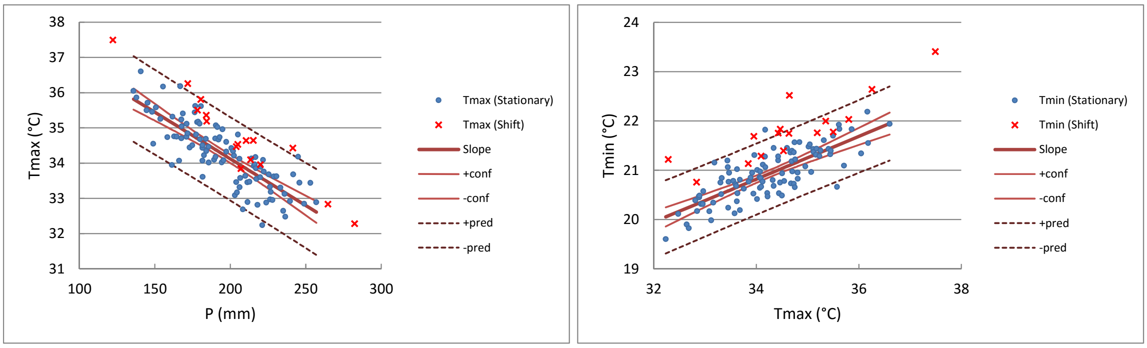


Figure 7. Summer maximum temperature plotted against rainfall (left) and minimum against maximum temperature (right) shown with 95% confidence limits for the slope (pred) and distribution (conf).

This methodology has been shown to work over the continental areas of Australia and the US. Step changes in these regions also coincide with step changes in zonal average data from the GISS data set (see Figure 3), suggesting widespread regional coherence of such changes. The timing of some of those changes can also be seen at the global scale, indicating that non-linearity in temperature at least can occur across a range of scales.

Trials with random data seeded with red noise shows that it will produce step changes when combined with a trend. This information may be consistent with H1, where a general trend in atmospheric climate, combines with random 'red noise' variability from ocean-atmosphere interactions, producing occasional but random shifts in the direction of the trend. Such shocks, which would also affect the frequency and magnitude of extremes, would be of concern to those who manage climate risks because they clearly imply such extremes will not change gradually.

However, the analyses from south-eastern Australia and Texas described above show that if annual variability can be removed from temperature data, the residual changes attributed to anthropogenic forcing, follow a step change pattern. In SEA, similar changes also occur in climate model data. This suggests that H2, where climate change and variability interact is more plausible than H1, where natural variability exhibits regime changes at the decal scale and anthropogenic warming proceeds smoothly. H2 is much more consistent with the general understanding of how complex systems, such as the earth system, will behave under external forcing.

Gradual versus punctuated change

The practical concern with step changes in climate on decadal time scales is how it may affect decision making. For example, conventional thinking on adaptation suggests that gradual climate change can be adjusted to over time, notwithstanding climate variability. However, punctuated step changes in the direction of forcing have the potential to deliver rapid changes in climate extremes, which may cause significant damage and loss if unplanned for.

This section provides further evidence showing that climate change is an episodic process on the decadal scale, rather than conforming to a trend. The preceding section (address) showed that most climate variables exhibit step changes. This section adds to that in the following ways, through:

- Tests using different ways of analysing the data,
- Tests linking different parts of the climate system, and
- Shifts in other variables (e.g., rainfall).

Applying the bivariate test to three main sources of global annual mean temperature, the HadCRUT4 (Brohan et al., 2006), GISS V3 (Hansen et al., 2010) and NCDC data sets (Smith et al., 2008), produces similar shift dates, in 1930, 1979 and 1997 (Figure 8). A further change occurs in 1987 at the 5% significance level. This explains the positive trend in the 1979–1996 time interval. All other trends are non-significant.

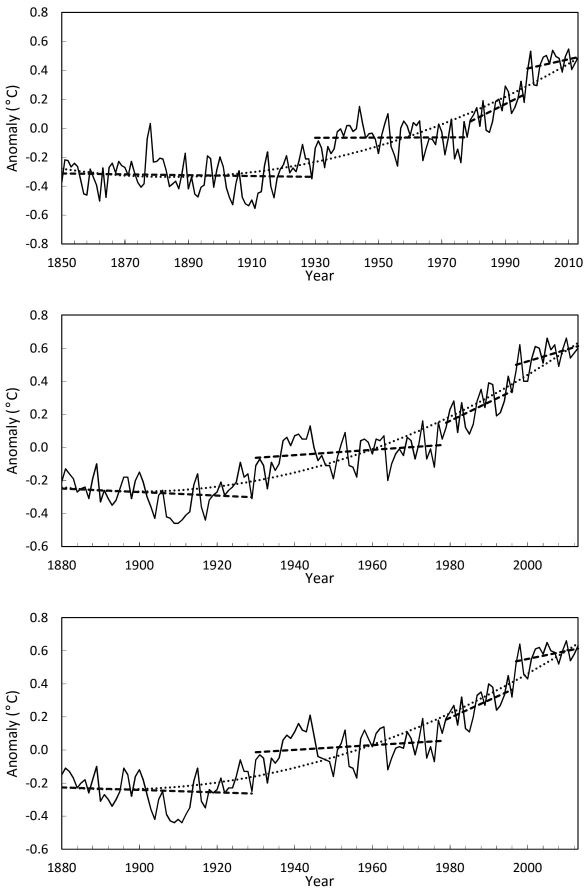


Figure 8. Time series analysis of annual mean global temperature anomalies from the HadCRUT4 (1850–2013, top), GISS V3 (1880–2013, centre) and NCDC (1880–2013, bottom) data sets using the bivariate test to identify steps (p<0.01) and linear trend analysis in the intervals (dashed lines). Also shown is a simple quadratic line of best fit (dotted lines).

A further test can be carried out using satellite data, in this case, satellite recorded temperatures of the lower troposphere from the RSS TLT record (Mears and Wentz, 2009), beginning in 1979. Using annual average data, a statistically significant shift is identified in 1995, but alternates with another date in 1997, which occurs at a slightly lower frequency. Because 1997 had been identified in surface temperature data as the most significant shift date, monthly average data were deseasonalised and then subject to the bivariate test to pinpoint the time of the shift. The results showed that the shift of 0.28°C occurred in July 1997 (79% of shift dates within ±1 month of the nominated date). This is just below the shifts in surface temperature of 0.30–0.32 °C identified for the three surface temperature records (Figure 9).

These data highlight a significant weakness of the bivariate test (and most other change point tests) in that these monthly data are not serially independent, so that small shifts will register as statistically significant when serially independent data would not (monthly satellite temperature shows memory effects whereas annual means do not show more than random data). This can be overcome by shuffling data randomly either side of nominated change points then re-running the bivariate test for 100 iterations (randomisation test). Changes amplified by red noise (or memory of the previous state) but below the relevant threshold for a step change, will fail to reproduce the nominated date.

A secondary shift point was located in December 1986, but only registered about 35% of shift dates within ±1 month of the nominated date using the randomisation test, so was not a clear result. However, this coincides with the step change at $p<0.05$ level in the surface temperature time series. This is associated with a step change of about 0.3 °C in northern hemisphere surface temperatures in 1987. Most of the trend observed in the first interval in Figure 9 is due to this warming event.

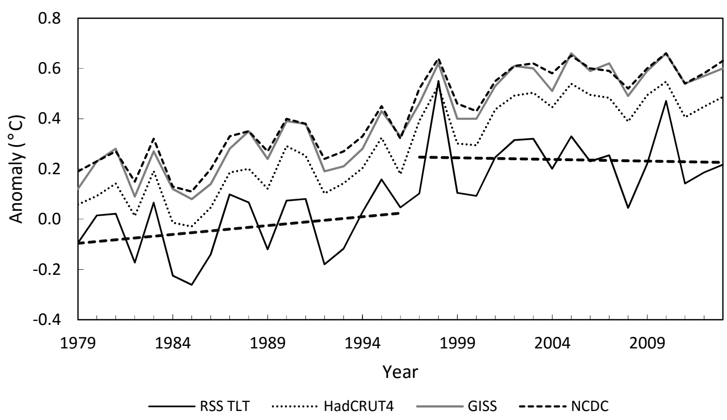


Figure 9. Annual anomalies for the lower troposphere (RSS TLT) and three surface temperature records (HadCRUT4, GISS and NCDC) 1979–2013, showing step change and intervening trends for the lower troposphere (dashed lines).

Natural influences on climate variability affects these results was tested by assessing both the raw and adjusted data for three surface and two satellite temperature records produced by Foster and Rahmstorf (2011). The influences of El Niño–Southern Oscillation (ENSO), volcanic aerosols and solar output were estimated using multiple regression then removed from the raw data over the period 1979–2010. If statistically significant step changes, such as those in Figure 9 were due to variability, then removing their influence from the record should smooth it out into a trend. However, if the step changes are part of anthropogenic warming, then those step changes should become more apparent.

Table 4 shows the results of the bivariate test for the raw and adjusted record. For the surface temperature records (GISS, NCDC and CRU), two show a shift in 1987 at $P<0.05$ and one is non-significant. All three show significant step changes in 1997 or 1998 at $p<0.01$ for the entire record, and varying dates when the period 1987–2010 is analysed. The adjusted records all show shifts of $p<0.01$ in 1987 and 1997. Note that the results for the period 1979–1996 are slightly different to those in Figure 8 because of the different periods of record used. The satellite records (RSS and UAH) show shifts in 1995 and 1998, respectively, but the adjusted records show shifts in 1997.

Table 4. Bivariate test results for three surface and two satellite temperature records for the raw data and adjusted for ENSO, volcanic and solar influences taken from Foster and Rahmstorf (2011). Note the year of shift is the year following Ti0 (maximum test value). NS is non-significant.

Temperature Record	Ti0	Year of Ti0	Shift	Test Period	Probability
GISS	6.2	1986	0.13	1979–1996	NS
	14.6	2000	0.25	1987–2010	0.01
	20.9	1996	0.30	1979–2010	0.01
GISS adjust	10.5	1986	0.15	1979–1996	0.01
	17.2	1996	0.23	1987–2010	0.01
NCDC	8.7	1986	0.13	1979–1996	0.05
	17.5	1996	0.24	1987–2010	0.01
	23.3	1996	0.29	1979–1996	0.01
NCDC adjust	12.1	1986	0.15	1979–1996	0.01
	18.5	1996	0.22	1987–2010	0.01
CRU	8.0	1986	0.12	1979–1996	0.05
	11.3	1997	0.24	1987–2010	0.01
	23.8	1996	0.29	1979–1996	0.01
CRU adjust	11.4	1986	0.14	1979–1996	0.01
	18.2	1996	0.21	1987–2010	0.01
RSS	17.3	1994	0.29	1979–2010	0.01
RSS adjust	19.3	1996	0.27	1979–2010	0.01
UAH	15.9	1997	0.28	1979–2010	0.01
UAH adjust	18.3	1996	0.27	1979–2010	0.01

These results are consistent with H2 because they have become more step-like and less trend-like. When climatic influences not directly linked to greenhouse gas forcing are removed from the temperature records, shifts become more statistically significant and more consistent between records rather than less. If shifts were directly influenced by natural factors such as volcanoes, ENSO and solar intensity, they would be reduced rather than enhanced.

Rainfall also shows step changes in selected locations, the timing of which may be anthropogenically influenced. South-west Western Australia shows a reduction in total annual rainfall of 12% in 1968, at the same time as the region commences warming. A significant downward step change also occurs in low pressure system generation (Jones et al., 2013). This reduction rainfall has at least in part been attributed to climate change (IOCI (Indian Ocean Climate Initiative), 2002). The Northern Territory of Australia shows an upward shift of 20% in 1973, shortly after sea surface temperatures increased in 1969. While the latter has not been formally attributed, it is broadly associated with warmer conditions over northern Australia. Neither of these records shows a long-term trend but remains stable while showing step changes. The potential for rainfall to change in a regime-like fashion when externally forced has significant ramifications for managing ensuing impacts (Jones et al., 2013).

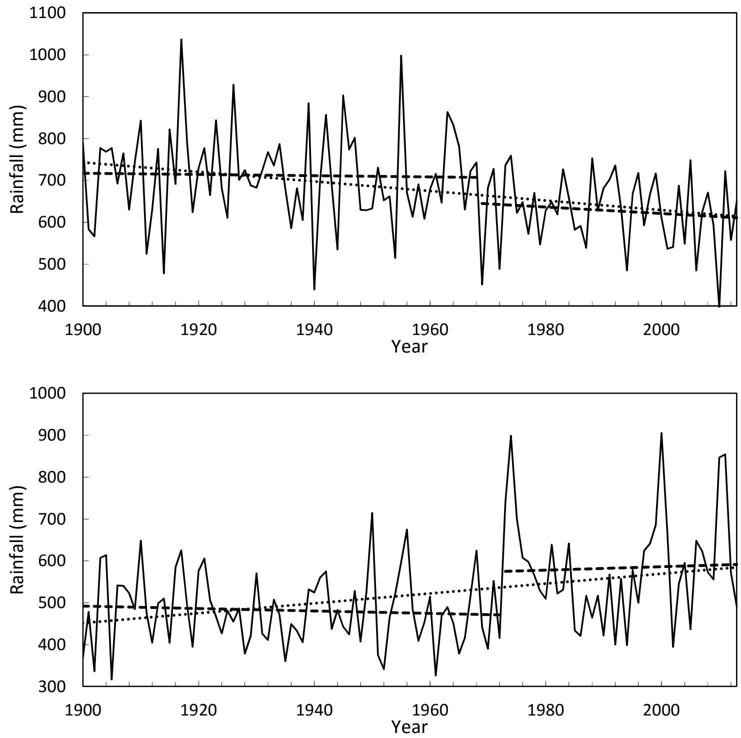


Figure 10. Step changes in total annual rainfall in south-western Western Australia (upper) and the Northern Territory (lower) 1900–2013.

The conclusion from the observed temperature record on the surface and in the troposphere, in model output regionally for south-eastern Australia and globally for the 20th century, is that temperature change is characterised by sudden shifts on decadal timescales interspersed with periods of relative stability. This is supported by changes in other variables such as rainfall and sea surface temperatures, where there is little sign of gradual change, but more commonly of stability and shifts.

Part III Paradigms

Kuhn (1996) described paradigms as 'scientific achievements that, for a time, provide model problems and solutions for a community of practitioners'. In line with this definition, the dominant view of future climate change, where anthropogenic climate change occurs independently of climate variability as a largely smooth process (H1), with its associated methods of modelling analysis and prediction of mean change, can be nominated as the dominant paradigm of greenhouse gas-driven climate change. Henceforth, it is called the gradualist paradigm.

This paradigm co-exists uneasily with the hypothesis that climate change interacts with variability (H2), so H2 is inherently non-linear, but lacks an established set of scientific achievements that link model problems and solutions. Therefore, H2 does not quality as a fully-fledged scientific paradigm.

Given that both H1 and H2 are both considered theoretically plausible, the main justification for the gradualist paradigm is value-based, in that it is widely accepted by the scientific community and is methodologically successful. To paraphrase Kuhn: a given set of model problems has an accepted set of model solutions and these solutions overwhelmingly favour H1.

This section examines the disjunct between theory and practice and how it has come about, culminating in a set of methods and values that self-select H1 over H2. The exploration here draws mainly on the history and philosophy of science as it pertains to current understandings of how greenhouse gas-induced climate change is analysed and communicated.

Styles, scientific values, paradigms and methods

Central to this history is the origin of the gradualist narrative, the values operating within the climatological community and how they have evolved. The gradualist narrative and the statistical and analytic methods underpinning this narrative resemble what Hacking (1992) called "models of relatively permanent, growing, self-modulating, revisable features of science." Hacking (2012) refers to these as styles of scientific thinking and doing and suggests that "the result of their persistence is a body of what is counted as objective ways of determining the truth, of settling belief, of understanding meanings, a body of nothing less than logic itself". This latter construction describes the foundation for many areas of science, where a discipline such as Earth Science (including climatology) will utilise a range of styles, developed over a period of time.

Styles as conceived by Crombie (1994) and developed philosophically by Hacking (1992, 2012) and historically by Kwa (2011) are ways of scientific thinking or reasoning. Scientific styles have entered European thinking since Ancient Greek times, therefore guide how science is developed and 'validated'. These styles differ from each other and evolve relatively slowly compared to methods and paradigms. Crombie's six styles as developed by Kwa (2011) are deductive, experimental, analytical-hypothetical, taxonomic, statistical, and evolutionary. Both Hacking (2012) and Kusch (2010) caution that this list is not exclusive and more may be added, including those that have existed in the past but are no longer active (e.g., hermeticism). Two important styles of the modern era that I would add are system complexity and simulation. The first involves an understanding of system complexity, networks and self-adaptive behaviour while the second uses models to envision plausible futures underpinned by a degree of scientific understanding, or to illustrate theorised or speculative behaviour. Both have become important in climatology.

Winther (2012) proposes an interweaving framework of styles, paradigms and models with the former underpinning the latter. Each manifests on decreasing time scales, with the lifetime and evolution being the longest/slowest for styles and shortest/fastest for models. Of those, styles and paradigms are examined here, and are related to methods and scientific values. Along with styles, values are recognised as changing more slowly, and often independently, of paradigms and methods.

Scientific values inform how science is carried out: as such, commitments to factual claims and to value judgements co-evolve (Kitcher, 2011). Kitcher (2011) suggests three levels of values within a broad ethical framework:

1. The broad scheme of values that society holds;
2. The personal set of values that relates to an individual's knowledge goals;
3. A probative set of values: which problems are most important and which rules best validate/invalidate scientific conclusions.

The latter two constitute a set of cognitive values that bestow value to scientific knowledge, applied at the personal and community scale, respectively.

Cognitive values that constitute the scientific world views maintained by a scientific community form the broad heuristics used by that community at any one time. These may be standardised into particular methodologies. These values inform how styles are applied and combined. Each style contains a probative set of values that will also change over time; these values also influence and are influenced by, the use of various methods. Kuhn (1977) lists five values: accuracy, consistency, scope, simplicity and fruitfulness. Such values wax and wane but are not linked to any one particular scientific style, and change quite independently of paradigms. Their evolution will therefore take place over different timescales to the waxing and waning of various scientific theories.

Cognitive values or ideals can be described as scientific world views. They describe how science, and its broad areas of disciplinary practice see the world. These interrelate with broader social (cultural) world views, being influenced by and influencing these world views.

Many values influencing scientific world views relate to structure and change. For the broad area of earth sciences including climatology, values include balance, gradualism, uniformitarianism, chaos, prediction and complexity. Styles such as experimental and statistical styles are interpreted through such values, influencing the development of paradigms and the methods used to analyse and illustrate them. For example, uniformitarianism as developed in classical geology has had a significant influence on climatology, despite a growing appreciation of the Earth system as a non-linear, self-adapting complex system. This point will be expanded upon in the following sections.

Together cognitive values and styles form a kind of historical epistemology that describes how science addresses concepts such as knowledge, belief, evidence, good reason, objectivity and probability over time (Hacking, 1999;Feest and Sturm, 2011). That these are informed by scientific and broader world views can be illustrated by a range of historical examples, not least Oreskes (1999) account of the delay in acceptance of Wegener's theory of continental drift by the American geological community because it challenged their existing standards and practice at the time. Of particular interest, is how the gradualist narrative has maintained its hold on the analysis, interpretation and communication of climate change science, even though it is currently understood at the theoretical level, that the climate system does not behave in a gradual manner.

Paradigm construction

Kuhn describes periods when science is operating within a particular paradigm as 'normal science' and activities within that as puzzle solving. Paradigm change, he interpreted as a scientific revolution (Kuhn, 1962), treating it in a holistic manner involving the wholesale over-turning of theory and practice. In the following discussions, Masterman (1970) recognised metaphysical, sociological and methodological aspects in paradigms, describing their sociological aspect as a "set of scientific habits".

For example, paradigms that form part of normal science become part of the furniture of doing science, consisting of a range of methods and practice that are generally accepted by the scientific community and are rarely questioned. They set up a set of simplified analogies that a community can accept as a series of core beliefs, while continuing to work on puzzles such as areas of incomplete knowledge, alternative explanations or system uncertainty. As such, they give rise to scientific narratives that tell the story of the model problems, solutions and achievements Kuhn refers to. Scientific narratives are very powerful in that they map out which values are the more important, which problems and solutions are accepted and delineates which methods are core, from those that are developmental and exploratory.

Laudan (1984) criticised Kuhn's holistic vision of the revolutionary overturning of paradigms, arguing that scientific revolutions did not involve a wholesale replacement of theory and practice. Instead he proposed a three-part reticulated structure for paradigms covering theory, methods and cognitive aims and values (consistent with Masterman's (1970) interpretation of Kuhn's paradigms), arguing that these elements do not all change at once but inform each other through a process of justification and harmonization. In this construct, any one of the three can change, but to have an internally consistent paradigm that involves all three aspects, the other elements will have to adjust in some way. This reflects the previous discussion on styles and cognitive values that evolve on very different timescales to particular scientific paradigms.

Figure 11 shows this model with the methodological and theoretical narratives supporting H1 and H2. The methodological narrative is dominated by methods and cognitive values relating to a set of criteria such as explanatory power, simplicity and predictability. The theoretical narrative addresses hypotheses H1 and H2 and is informed by set of cognitive values relating to how hypotheses are validated by evidence (probative values). Probative values consist of the rules for proof – scientifically, these relate the availability and quality of evidence to support a given hypothesis.

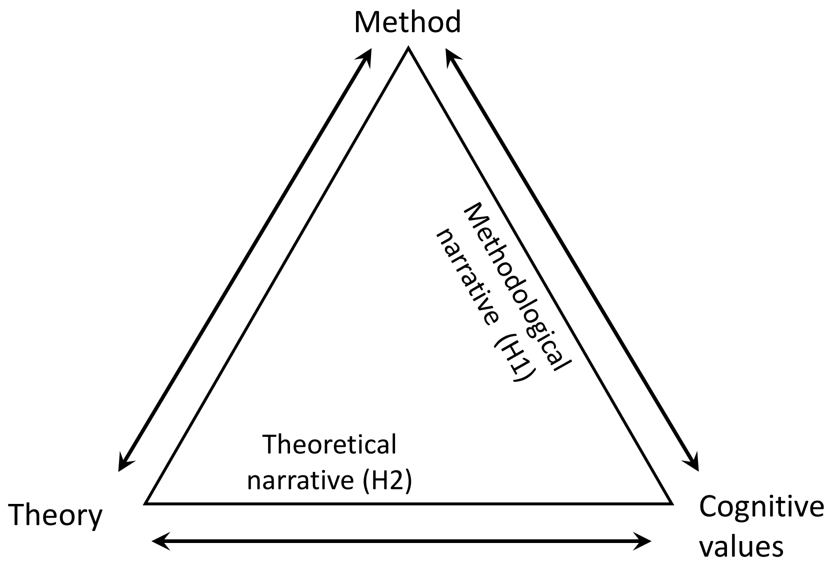


Figure 11. Theory, method and cognitive values within a scientific paradigm (Laudan, 1984) aligned with the methodological and theoretical narratives of how the climate changes.

As detailed above, statistical methods have failed to clearly distinguish between these two hypotheses, although my view is that theoretically, H2 is much more plausible than H1. The simplest objection to gradual atmospheric climate change is that abrupt change is widely recognised in palaeoclimatic reconstructions and regime changes at the decadal to millennial scale. If the atmospheric-ocean system has frequently changed abruptly in the past, as is generally accepted, smooth atmospheric change would be an exception to this process. Greenhouse gases would need to produce *in situ* warming in the atmosphere in a manner that is not governed by ocean or ocean-atmosphere processes, but could be influenced by them. This warming would have to be consistent and measurable. Given that the Earth system is a coupled ocean-atmosphere system, atmospheric variables would have to change in a gradual, rather than abrupt, manner.

Using an analogy, many scientists when faced with objections that natural and human-generated CO_2 will cause different responses in the climate system, argue that their radiative effects cannot be separated once they are mixed in the atmosphere. If the same principle follows for thermodynamically-driven change, then naturally driven and human-induced warming/cooling should also interact unless there is an identifiable process that shows they behave separately.

The two separate narratives shown in Figure 11 illustrate a conflict in how methodology and theory are being interpreted by the climatological community. These two narratives are often encountered within a single book, paper or chapter.

Historical influences on methods and values

If paradigm change is a reticulated structure as maintained by Laudan (1984), supported by the different timescales of evolution within styles, values, theory and methods, then the history and evolution of climatological thought will reflect these varying influences, similar to the variable take-up of continental drift within the earth sciences (Oreskes, 1999). This section surveys the evolution of climatology since the scientific enlightenment, taking particular note of values such as balance, gradualism, uniformitarianism, prediction, chaos and complexity.

Order and overcoming uncertainty are central themes in climatology that can be traced back to the scientific enlightenment. The act of obtaining balance from uncertainty (variability) and developing predictability through order are rarely questioned. These ideals were a feature of the scientific enlightenment, especially France during 1770–1810, and informed the development of the physical sciences and economics (Wise, 1993). Particularly influential was Newton's gravitational model. His distance squared model of gravitational force was adapted into the least squares model of curve fitting and the development of Gaussian statistics. This method has a long-standing status across science and economics (Stigler, 1986), and is fundamental to the measurement of climate.

The scientific reasoning of the time can be characterised as inductive inference based on a set of rational values (Gould, 1965;Baker, 1998). This is a normative view of a rational universe based on fixed principles originally articulated by Newton. It was later adapted and applied to a whole range of disciplines framed as "this is the way the world works", providing a logically valid explanation instead of exploring what nature actually says (Baker, 1998). The role of science was to uncover the absolute truth of the universe. The world, including human thought, was considered to conform to the laws of probability and logic (Chase et al., 1998) and the job of science was to identify evidence supporting this notion. Cognitive values, including simplicity, actualism and gradualism, were imposed to ensure valid inductive reasoning (Baker, 1998).

Wise (1993) describes how technologies and methods were developed by French scientists such as Lavoisier and Laplace to achieve balance and overcome disequilibrium. Chief amongst these was the calorimeter, linking the domains of chemistry and physical astronomy, which balanced heat in the same way that a mass balance equilibrates objects. These ideas of balance were expanded into national accounts and balance sheets, particularly by Lavoisier (Holmes, 1987). As Wise (1993) says *Measurements are not self-justifying. They employ particular sorts of instruments constructed for the purpose of attaching quantitative values to valued things.*

The notion of balance as rationality was given coherence between different areas of knowledge bridging the sciences, economics and society. Balance and order were also a foundation of what became uniformitarianism in the earth sciences (Baker, 1998) – originally linked to geology but eventually expanding to a whole range of earth-system processes. Through the calorimeter and similar developments, they also had a strong influence on the evolution of thermodynamics.

Two sets of methodologies developed during this period, one qualitative and the other quantitative, have had a lasting effect on the subsequent development of climatology. Uniformitarianism has influenced its descriptive (qualitative) aspect, whereas probability calculus in the form of least squares method of signal extraction dominates its analytic (quantitative) aspects. Both have gradualism at their core.

Qualitative methods: gradualism and uniformitarianism

Gradualism was introduced by Hutton as a cosmological approach to an ordered geological history of the earth, consistent with Newton's structure of the heavens (Baker, 1998;Palmer, 2003). Catastrophism, at times Biblical (early) and at times scientific (later), was the dominant view of geological change. These were value-based assumptions that posed God as an ordered regulator rather than as a catastrophic creator. Gradualism combined actualism – the view that present day processes were a guide to past events – with the assumption that change occurred at a constant rate (Palmer, 2003). These ideas were advanced by Lyell, whose geological doctrine of gradual change, proposed partly in opposition to the alternative theory of catastrophism (Lyell, 1830), became known as uniformitarianism (Baker, 1998). Lyell's insistence that rates of change did not divert from the observable, sidelined deductive speculation about the possibility of more extreme, or different events and processes that may have occurred in the past (LeGrand, 1988).

Gradualism as derived from Lyell's *Principles of Geology*, also underpinned Darwin's development of the theory of evolution (Mayr, 1991), Darwin arguing that gradualism was essential to his view of evolutionary adaptation (Gould, 1982). This view survived into the 20th century, only being widely challenged through the work of Gould (1965, 1982), addressing mass extinctions and evolutionary responses to these, and was eventually modified. Catastrophism survived throughout the 19th century, but was always subordinate to uniformitarianism, which was politicised in such a way that allowed its supporters to turn the debate into a science versus non-science argument, rather than a debate as to whether geological processes were constant or shaped by specific, often catastrophic, events (Palmer, 2003).

During this time, catastrophism survived by being linked to changes associated with ice ages, as developed by Agassiz, who was more concerned with interpreting nature than imposing the induced framework of "this is how the world works" (Baker, 1998). Palaeoclimatology therefore accepted the idea of rapid change more readily than other areas of earth science, especially after Milankovitch developed his theory of orbital cycles and their impact on climate (Milankovitch, 1920). This resulted in a wide ranging acceptance that earth systems exhibited rapid responses to gradual change in orbital forcing. A number of rapid changes within those cycles (Imbrie et al., 1992;Clark et al., 2002) and large discontinuities in the fossil record clearly show that rapid change is a feature of past climate. Instrumental or present day climatology did not take up these ideas so readily, so the acceptance of abrupt change has been largely restricted to climate processes operating on time scales longer than those of human affairs.

Gradualism remains an active cognitive value across the earth sciences including climatology, although actualism or presentism (where the present is used as a guide as to how processes worked in the past (Oreskes, 2013)) now dominates earth science methodologies (Marriner et al., 2010). Today, abrupt climate change, or neocatastrophism (Marriner et al., 2010), is largely reserved for large-scale changes such as basin-wide changes in ocean circulation, catastrophic ice-sheet break up, massive greenhouse gas out-gassing from permafrost or marine clathrates or nuclear/asteroid strike (Alley et al., 2003;Valdes, 2011). Anthropogenic climate change tends to be associated with the more traditional values of gradualism (Jones et al., 2013).

Likewise, gradualism persists in other disciplines that can be traced back to the French enlightenment, such as economics, which continues to combine gradualism with Newtonian cosmology (Solo, 1991;Rothschild, 2004;Nelson and Winter, 2009), whereas physics has moved well beyond it. However, all these systems show complex system behaviour, including non-linearity and feedbacks, showing that some disciplines have responded more quickly to theoretical developments than others.

Quantitative methods: statistics

The co-evolution of values and quantitative methods have also allowed gradualism to dominate the analysis and communication of future climate. The development and application of probability calculus by Laplace, Lagrange and others during the French enlightenment represented the balance of errors (Wise, 1993). The least-squares method of extracting signal from noise, published by Gauss in 1809, has been greatly enriched in the two centuries since, but the basic approach is largely unchanged since that time (Sorenson, 1970). Both probability calculus and least squares analysis are central to climate analysis and modelling today. Lagrange introduced techniques of variational calculus that were later developed into the Lagrangian mechanics of climate models. Gaussian statistics remain a staple method for understanding climate and climate change, although stochastic probability analysis methods are becoming more widely used (Ghil, 2012).

The next major methodological development was the signal-to-noise concept. This utilised Gaussian statistics in radio research in the 1920s and 1930s, extending to radar in the 1940s. Electronic signals were valuable information whereas electronic noise needed to be removed. This value-based way of sorting information into useful–useless has spread into science communication and pedagogy, where valued information is now referred to as the signal and poor information as noise (Pierce, 1980;Ziman, 1991;Norton and Suppe, 2001). This accentuated the value-laden aspect of the signal with respect to noise, which needs to be discarded.

The signal-to-noise label was adopted by climatology in the 1970s, where a range of climate signals and their potential forcing mechanisms were being assessed for past and present climates (e.g., Chervin et al., 1974;Chervin and Schneider, 1976;Hasselmann, 1976). For many aspects of climate change, the signal to noise (Gaussian) model linearises forcing and response, reflecting the first law of thermodynamics and does so very successfully. For example, global temperature is linearised with forcing using the famous formula where $\delta t = \lambda \delta f$, where t is temperature, f is forcing and λ is a constant related to atmospheric feedback processes (Ramaswamy et al., 2001). This relationship forms the core of a small set of simple climate models that have been the mainstay of uncertainty management and projections provided by the IPCC over most of its history (Houghton et al., 1997). Such models are usually one or two dimensional and can only simulate the gradual signal of climate change, so are very good for analysing uncertainty at a given point in the future but not in how the climate changes over time.

Today, the signal to noise concept is highly prominent in climate change research, in detection and attribution studies, and in assessing long-term mean change for a range of variables via pattern scaling (IPCC-TGICA, 1999, 2007). Almost all predictive models of climate change extract the signal and discard the noise from climate model output using Gaussian or related methods. The signal to noise concept has therefore reinforced the value differential between signal and noise in climatology, bolstering the case for the prediction of mean change and the extraneous nature of random variability. By linearising the signal, methods and values emphasise H1 over H2.

Another factor influencing gradualistic or smooth change is the evolution of climate models from the earliest versions that were so simple that the signal was the only meaningful output. Since then, models have become more complex in their representation of processes and resolution, in many cases simulating realistic climate variability. However, while climate analyses now manage high resolution gridded data, they still have the Gaussian signal to noise model at their core. This evolutionary process has also allowed historical methods to survive by adapting rather than changing. In that time however, the evolution of climate theory has advanced from linear, additive models to complex, non-linear models (Lorenz, 1975;Hasselmann, 1976;Schneider, 2004).

Quantitative methods: forecasting

Forecasting and prediction are both highly valued by scientists and the general public (and for good reason). The history of weather forecasting is heavily value-laden because of its role in limiting loss, managing risk and providing comparative advantage. Successful methods within one related field are likely to be transferred to another if they share similar values and/or methods. For example, seamless links between weather and climate forecasting over a range of timescales are a key scientific target (Palmer et al., 2008;Hoskins, 2013). The Global Framework for Climate Services (World Meteorological Organization, 2011), reflects this: *Weather and climate research are closely intertwined; progress in our understanding of climate processes and their numerical representation is common to both. Seamless prediction (on timescales from a few hours to centuries) needs to be further developed and extended to aspects across multiple disciplines relevant to climate processes* (World Meteorological Organization, 2010).

This is a value-based statement but also needs to be methodologically and theoretically consistent, which is difficult to achieve. Solomon et al. (2011) state that *"Long experience in weather and climate forecasting has shown that forecasts are of little utility without a priori assessment of forecast skill and reliability"*. Although there is ample evidence that this assumption is appropriate for weather forecasting and for climate forecasting one season ahead (Kirtman et al., 2013), for climate forecasts greater than one year ahead, there is little evidence for its utility. The missing factor from this statement is that although skill and reliability can be calculated from models, the success of forecasts can only be measured through application.

The available evidence of the success of such techniques is quite contradictory, with stories of both success and failure in the limited number of cases where projections have been used and subsequent events have allowed some form of review to be undertaken (Power et al., 2005;Hulme et al., 2009;Jones, 2010a). For example, one project I was involved in, the Melbourne Water Climate Change Study (Howe et al., 2005), produced numerical estimates of change based on linearised methods and qualitative estimates of non-linear change. Policy changes were based on the numerical estimates, but subsequent events showed the qualitative prognosis to be more accurate and relevant (Jones, 2010a).

Alternatively, for south-west Western Australia, early indications from the relatively simple climate models of the time showed the region would dry (Pearman, 1988). Given the region had experience a prolonged dry period, major adaptations were put in place that turned out to be highly beneficial (Hennessy et al., 2007). Subsequent analyses shows that the observed rainfall change was step-like and permanent (Li et al., 2005;Vivès and Jones, 2005), so the success was as much due to those who championed that information and encouraged action, as to the information (Power et al., 2005).

Plans for decadal climate forecasting are to assess trends through climate model ensembles within and between different climate models (Collins et al., 2011;Solomon et al., 2011;Meehl et al., 2013). The climate research community is aware that longer term climate forecasts are both an initial conditions and a boundary issue, but has not fully investigated the effectiveness of different forecast types, such as trends and events, for users. The seamless nature of such forecasts as described above therefore should refer to the tools being used, but not the types of forecasts being produced, which are dominated by events on the weather timescale and trends at the climate timescale. This has been identified by the WMO (2014) who recognise the gap between how users value forecast information compared to its quality, which can be tested through hindcasts and similar methods. Even if the scientific community believes certain information is valuable, users may not.

Historically, the most useful forecasts have been for events, such as a coming storm or a potential El Niño. Less useful are forecasts of trends, which suffer the same issues as economic forecasts (Tilman et al., 2001), which are so general, they fail to identify where decisions are critical. For example, paraphrasing Wack (2002), most scenarios merely quantify alternative outcomes of obvious uncertainties (for example, global mean warming in 2080 may be 2°C or 4°C). Such scenarios, while useful for bounding uncertainties, are not overly helpful to decision makers.

If decadal climate forecasts and long-climate term projections continue to be dominated by the standard signal to noise model, then gradualism will dominate the nature of the change being contemplated (Jones et al., 2013). The current values embedded in climate science, as embodied in the use of the signal to noise model and forecasting techniques that generate and use gradual estimates of mean change, respectively, has a significant influence on adaptation policy and practice.

Reconciling theory, methods and values

Laudan's (1984) reticulated model of mutual adjustment and justification is built on the tripartite arrangement of theory, method and cognitive values shown in Figure 11. The methodological and theoretical narratives in that figure are unreconciled. Within the literature, this often occurs in the same paper or chapter where theory and methods are discussed. Both hypotheses are described as being possible (with neither judged as being more likely) then the methods that are in use and/or proposed overwhelmingly self-select H1 over H2.

This incommensurability requires some form of reconciliation between theory and methods, with the role of values being the mediating aspect. Says Kuhn (1977) "historically, value change is ordinarily a belated and largely unconscious concomitant of theory choice and the former's magnitude is regularly smaller than the latter's". That certainly seems to be the case here, where theories have changed significantly but some values (e.g., gradualism) have been retained as a core part of the climate change paradigm. This has hampered the development of methods that would better account for these changing theories.

There is little agreement over what values are most important to the conduct of science; and philosophically, the area is relatively undeveloped (Laudan, 2004;Douglas, 2013). Most emphasis has been on epistemic or truth values. Core epistemic values include internal consistency and empirical adequacy and are considered the minimal criteria for adequate science (Laudan, 2004;Douglas, 2013). Kuhn's (1977) slightly larger set is accuracy, consistency, scope, simplicity and fruitfulness. Laudan (2004) lists these as explaining the known facts, explaining different kind of facts in a consistent manner, explaining why rival theories were successful and outlining those theories' failings with respect to the new theory.

Methods go beyond the straightforward assessments of whether a theory is, or is not, true. Laudan (2004) says "we expect our theories to do much work for us", identifying a group of cognitive values not involved with theory-making, but relating to the general conduct of science, particularly to its application. Such values include rationality, dispassion, and self-restraint (Brysse et al., 2013). Values that have been successful in the past, tend to be maintained – as seen above, values move from being epistemic to being methodological, relating to the conduct and application of science. They also promote conservatism and a certain reluctance to change.

Balance and gradualism were two values associated with the scientific enlightenment. At the time, these were epistemic values and theories were developed to be consistent with such values. The graduation of science to a multistep process of hypothesis, testing and evaluation has meant that these values are no longer epistemic but remain attached to methods. The disjunct in Figure 11 occurs because theory and methods no longer share the same values. Science has no formal methods for reconciling these. Each broad disciplinary area has its own set of values utilised by a community of scientific practice that contain a number of historical and sociological influences. Also influencing climatology are the styles of system complexity and simulation. For these to be fully utilised, they need to be better reconciled with the longer standing styles including experiment, statistics and evolution.

Cognitive values relating to the conduct and application of science extend beyond theory validation to application and communication. Prediction is central to scientific application. In the case of climatology, the two legacy values, balance and gradualism, dominate long-standing methodologies, whereas climatological theory is weighing up the opposing forces of chaos and equilibrium in a system that has clear nonlinearities, shifts and regime changes. While, balance in the form of understanding mean change and signal behaviour remains useful, gradualism clearly does not.

Efforts to determine whether H1 or H2 is more likely have so far proven inconclusive (Solomon et al., 2011;Christensen et al., 2013), leading to an impasse that limits the application of theories of non-linearity between forcing and response. For example, in defining internally and externally forced variability in near-term climate change in the IPCC Fifth Assessment Report, both are treated as linearly additive with the following caveat: *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). In practice, the predominant method being used is ensemble averaging and the development of probabilities around the mean. Levels of model skill in back-casting, particularly when models are initialised with historical conditions are providing a level of success, so reinforce the status quo view of gradual climate change independent of variability.

The question not being asked is: if H2 is possible and internal climate variability is interacting with external forcing, what is the best way to analyse and communicate those changes? Part IV addresses this challenge.

Part IV Challenge

The gradualist narrative defines the dominant paradigm of anthropogenic climate change. This narrative selects by default the hypothesis that human-induced climate change is gradual, proceeding independently of climate variability (H1) over the hypothesis that the two interact, producing non-linear behaviour by projecting changes onto modes of climate variability (H2).

Several lines of evidence provide strong evidence that climate change is, in fact, projecting onto modes of climate variability. These include theoretical considerations, statistical analysis of non-linear changes in observations and model output, and statistical methods for attribution at the regional scale. An assessment of the historical epistemology of climate-related science shows that the reasons for the self-selection of H1 over H2 are largely to do with methods and values that date back to the scientific enlightenment. The evolution of these methods and values have failed to keep up with changes in theory occurring over the same period.

The climate literature clearly shows that non-linear responses to gradual forcing on the decadal scale is widely considered to be one of two alternative hypotheses (Kirtman et al., 2013). Furthermore, a preference for one over the other is rarely given, suggesting that conclusive evidence has been hard to find. However, the methods and practice in analysing and applying climate data and model output almost entirely self-select the gradual change over the non-linear hypothesis.

Theoretical considerations include:

- The development of theory around Lorenzian attractors in the climate system, suggest that non-linear regime changes are a normal aspect of atmosphere-ocean interactions and can potentially be influenced by external forcing (Palmer, 1993;Corti et al., 1999;Palmer, 1999;Slingo and Palmer, 2011). This raises the question as to why externally-forced change is overwhelmingly considered to be gradual, rather than combining with such non-linear behaviour.
- Under the second law of thermodynamics, the greater entropy production required because of increased external forcing might be expected to accelerate the rate of regime changes as the system attempts to dissipate that energy and return to a stable state (Ozawa et al., 2003;Kleidon and Lorenz, 2005). Consistent with this, Slingo and Palmer (2011) ask “whether anthropogenic climate change due to increasing greenhouse gases constitutes a strong enough forcing to lead to a population of new regimes”.

Statistical considerations include:

- Statistical analyses in the literature have so far failed to identify a clear preference for one hypothesis over another (Seidel and Lanzante, 2004).
- The statistical methods in use for measuring gradual change are two centuries old and widely accepted and dependable. Many improvements have been made over that time but the basic principles and methodologies persist. The methods for analysing step changes are much newer and less reliable, with the risk of false positives in non-stationary data being an ongoing issue.
- Data limitations in investigating complex decadal variations involving ocean-atmosphere processes have meant that many climate variables lack long-term data reaching back more than a few decades.
- When analysed using statistics that analyse step-like changes in time series, most climate variables demonstrate non-linear behaviour. Global temperature and rainfall output from one region from climate models show similar behaviour.
- Regional continental temperatures in observations and models show a period of stationarity during the first half of the 20th century. Anthropogenic regional warming commences with a step change in the two regions examined in 1968 (South-eastern Australia) and 1990 (Texas). Successive changes in observations and model output for SEA show continued step changes in warming.
- A number of step changes in zonal average, hemispheric and global temperature data coincide with regime changes in decadal modes of climate. This has been linked in the past to modulation of gradual change by climate variability, but here shows signs of being abrupt.

- When influences such as ENSO, volcanic forcing and solar output are removed from global mean surface and satellite temperatures using the Foster and Rahmstorf (2011) model, step changes become more coherent between records and more statistically significant.

Epistemological considerations include:

- The statistical methods used in climate analysis have their roots in the scientific enlightenment, so act as foundational methods for the consideration and analysis of climatological data. Such foundational methods are rarely questioned and tend only to be overturned as part of a paradigmatic upheaval.
- The process of gradual change underpinning the gradualist narrative was originally a cosmological value associated with Newtonian mechanics and science by induction that have evolved into methodological and explanatory values after science by induction was made redundant in the 19th century.
- The success of linear statistics in explaining climate change at the first order level describing the evolution of the climate system at the multi-decadal–century timescale under external forcing, reinforcing gradualism as an explanatory value.
- The take-up of system complexity and non-linear dynamics across the earth and physical sciences has been patchy and in economics is almost non-existent. In climatology it is partial and incomplete.

Historical and social considerations include:

- The evolution of climate modelling has proceeded from simple to complex models, therefore from simple to complex time series. This process has also governed the simplicity of methods, because a linear response to forcing has served well as a first approximation of change in many climate variables, especially temperature. This fits well in to the scientific value of parsimony of methods.
- The strong values invested in the signal to noise model for assessing a variable under change. The value of the signal is emphasised as the component of greatest interest and the noise component of the least interest. The value of prediction adds to this investment, with the signal being predictable and noise assumed to be unpredictable.
- Climate science has been in defensive mode because of attacks from interests that range from the preservation of specific ideological world views to a more basic financial interest in preserving the existing dependence on fossil fuels (Oreskes and Conway, 2010;Hoffman, 2012). Arguments supporting the integrity of simple climatological trends in attributing climate change to observations and model output have therefore been relied upon. Research on variable responses to forcing has probably been discouraged as a result.

The evidence presented in this paper supports the alternative hypothesis H2 – that the gradual forcing of climate produces non-linear, step-like changes in a wide range of climatic variables. Such a proposition should be testable, in terms of tracking where energy, especially heat, is moving within the climate system.

Proposed physical mechanism for non-linear atmospheric change

One widely-held assumption about climate models is that they do not readily simulate rapid change (Valdes, 2011). This is partly due to a lack of precision concerning the language of rapid or abrupt change and of time scales upon which such changes are anticipated to occur. Much of the discussion in the literature concerns major dislocations that would be readily detectable (e.g., Oppenheimer et al., 2014). These are linked to known feedbacks related to albedo change, ice sheet instability, ocean overturning and so on. Less attention has been given to non-linear thermodynamic behaviour within the climate system and how that would affect phenomena such as warming, wetting or drying, although this is changing (e.g., Arias et al., 2012;Coats et al., 2015;Jacques-Coper and Garreaud, 2015). Yet here, step changes have been measured in regional temperature and rainfall for SEA and in every mean global warming time series so far analysed (over 200 simulations).

Most of the extra energy produced by increased greenhouse gases in the atmosphere goes into the ocean: 93% from 1971–2010 (Rhein et al., 2013). A lesser amount is involved in the ice-melt process and the smallest amount ends up in the atmosphere (Bindoff et al., 2007;Trenberth et al., 2009;Trenberth et al., 2014). The atmosphere holds as much heat as the top 3.2 m of ocean (Bureau of Meteorology, 2003). When the added energy from external forcing, including heat, is transferred around the climate system, it will do so via gradual or abrupt means, or a combination of both. The pathways by which heat moves through the climate system should therefore be detectable.

For the atmosphere to warm gradually as opposed to abruptly, heat flows would have follow specific pathways. For gradual warming to occur, the two most plausible processes are:

1. The atmosphere heats up gradually *in situ*. Variability is mediated by varying amounts of additional heat emitted from the ocean, perhaps sometimes mediated by additional heat take-up by the ocean during cool phases as part of decadal variability.
2. Where the ocean absorbs almost all the available energy and releases it gradually into the atmosphere. This rate is mediated by shallow and deep ocean overturning rates, prevailing wind regimes affecting mixing and similar phenomena.

In both cases, the ocean plays an influencing role, which sees the atmosphere as a more active participant in the first process and being almost totally passive in the second.

For the first process to be operating, the atmosphere should be warming gradually at the surface and/or at higher altitudes, but neither surface temperatures over land nor satellite temperatures show signs of a clear trend (Figures 8 and 9). Instead, both show step changes and insignificant trends in the intervals between such changes. As shown in Figure 3, there is little trend in either land-based or ocean temperatures between significant shifts, although their relative timing varies. For the second process to be operating, the atmosphere should be warming gradually at the surface, especially over the ocean.

The presence of an initial stationary state in both Australian and continental US regional climates that is ended by a step change in warming, is consistent with the climate remaining in a thermodynamically stable state until it reaches a critical point, at which a regime change to a new state will offer greater stability.

For non-linear warming of the atmosphere to occur, the most plausible explanation is for heat to be emitted from the ocean to the atmosphere in relatively brief episodes, punctuated by periods of relative stability. This is consistent with the evidence presented in this paper. Given the low thermal capacity of the atmosphere and the limited spatial scale of step changes (except for 1997–98) this could be achieved by brief but intense periods of regional upwelling, and the larger changes by upwelling from several sources linked by teleconnections or large-scales areas such as the eastern Pacific Ocean. A pause in ocean heat uptake may be an alternative explanation. Given current data limitations with respect to upward sensible heat flux from the ocean, no sign clear of such heat flux for other dates has been obtained from ocean basin average data. Further investigation of observations, models and re-analyses is warranted.

The proposed pathway for warming and accompanying climate change on decadal timescales is that energy trapped by additional greenhouse gases in the atmosphere are by and large absorbed by the ocean, with little or no in situ warming of the atmosphere. An exception is the heat absorbed by melting ice, which serves to cool the immediate surrounds. Net absorption of energy by the land surface can be largely discounted because it is small and is retained for long periods of time. In a metastable climate, heat energy in the ocean will build up until it reaches critical levels and the ocean will do some work.

Energy may then be mixed into the deep ocean at different rates and/or released into the atmosphere. The evidence presented so far indicates that energy is being released at different times in different regions and may impact on regions extending from sub continental scale up to hemispheric and global scales. Deep ocean and surface processes may be teleconnected, which could also potentially modulate the size and frequency of step changes in surface variables. However, the rate of entropy production within the atmosphere will vary depending on which system-wide processes predominate at any particularly time, suggesting a two-way interaction between natural variability and greenhouse-gas induced change.

This paper presents limited evidence of gradual warming in the climate system, either in the atmosphere or the oceans. The first law of thermodynamics, stipulates that if the internal energy of a system changes, it will seek a new state of thermodynamic equilibrium. In the absence of large-scale feedbacks and accompanying tipping points, this can be represented as a gradual change over decades to centuries but is at best, a first order approximation rather than a true representation of how climate changes.

Under the second law of thermodynamics, the process of transferring heat from the equator to the poles is known to take place within a background of non-linear processes taking place on annual and longer timescales, involving significant regime changes at multi-decadal timescales (Ozawa et al., 2003;Ghil, 2012). Given that these processes are now widely recognised as being non-linear and episodic, the simplest explanation for situations when the internal energy balance has changed is for those changes to act on the existing processes, rather than independently of them.

Smooth curves of change have long been communicated at the simplest explanation for a stochastic process. However, for dynamic systems such as climate, the simplest statistical explanation may not be the simplest theoretical explanation. Nor may those explanations be the most useful for decision making on human time scales.

Characterising climate risks under non-linear change

The observational evidence and theoretical considerations presented in this paper supports H2 rather than H1: anthropogenic climate change interacts with climate variability rather than acting independently of it. It does so by projecting change onto the principal modes of climate variability (e.g., Corti et al., 1999) so that warming proceeds in manner that resembles the regime changes seen in decadal climate, producing step-like changes within periods of relative stability.

This conclusion treats global climate as a complex and dynamic system, and signals a move away from gradualism, which was adopted by science as a cosmological value during the scientific enlightenment, later on becoming an explanatory value. Other disciplines have moved away from gradualism as theory has shown that such assumptions are unsustainable. However, climatology has been slow to respond, despite over fifty years having elapsed since the climate system was shown to be stochastic rather than deterministic over interannual to decadal timescales and perhaps longer (e.g., Ghil, 2012). A comprehensive theory of climate variability remains to be developed (Ghil, 2012).

One reason for the emphasis on interpreting climate change via simple trends, is the defensive position that climatology has taken as part of the science wars, where attacks on climate science have in part, used variations in observed temperature to maintain that climate change is either not happening or is less of a concern than concluded in scientific assessments of future risk (Mooney, 2006;Oreskes and Conway, 2010;Mann, 2013).

This is especially relevant for the so-called hiatus in global mean air temperature (GMT) that began 1997–98. Because climate change has been communicated as a gradual trend (even though mediated by climate variability) one major opposing argument is that if warming deviates from gradual increases in greenhouses gases, then the scientific consensus behind anthropogenic climate change is under threat. As has occurred with tobacco, organised opposition to well-established scientific findings has focused on any perceived uncertainty to sow doubt (Oreskes and Conway, 2010). Such opposition focuses on perceived weak points in the scientific evidence: for example, the relationship between global mean air temperature and rising greenhouse gases (mainly CO_2). This has discouraged exploration into non-linear responses of climate to gradual forcing. Whereas, the evidence presented in this paper is that such 'hiatus' periods are a normal feature of climate behaviour, which is in fact what the models show.

Figure 12 shows a global warming simulation with step changes and intervening trends as diagnosed by the bivariate test (MRI medium resolution model A2 run 5 from the CMIP3 archive). It contains a 'hiatus' period from 1995–2015, which contains a non-significant trend of -0.4°C per century. Figure 12 also shows the typical step-ladder form of change in the 20th century, changing into an escalator for of change in the 21st century. Step changes are in the vicinity of 0.1–0.2°C in the early part of the record and 0.4–0.5°C in the latter part.

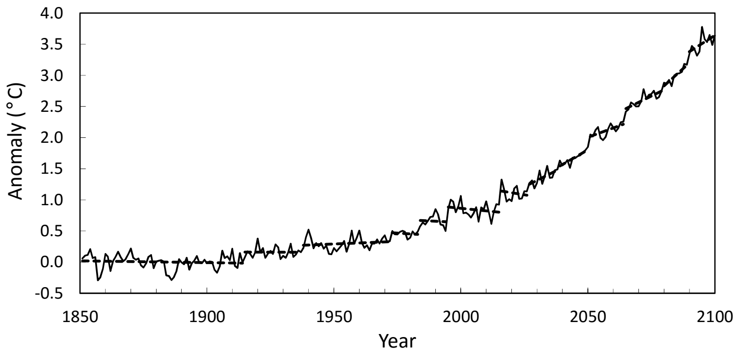


Figure 12. Global mean warming anomalies showing step changes and intervening trends as diagnosed by the bivariate test (MRI medium resolution model A2 run 5 from the CMIP3 archive).

The importance of reconciling climate variability and change for decision-making should not be understated. The differences between gradualism and punctuated change when characterising and managing climate risks are important for all areas such as:

- Detection – how and how much is climate changing?
- Attribution – what are the causes of observed changes?
- Prediction – what is the balance between prescriptive and diagnostic techniques for managing climate risks?
- Adaptation – what current and future changes may require an adaptive response?
- Mitigation – what aspects of climate change can be considered safe, tolerable or dangerous?
- Communication – how is climate change framed using explanatory values?

Detection

The detection of non-linear change in climate time series is much more difficult than straightforward trend analysis. However, the recognition that climate change occurs in a series of steps, or abrupt changes, perhaps often associated with regime changes in decadal climate variability, requires a very different toolkit to standard climatological tools. Trend analysis remains relevant and works well as a first approximation, but the detailed detection of how the climate changes requires new approaches.

None of the existing tools for detecting shifts or break points are as reliable as trend analysis. This is partly due to the long history of trend analysis with its dos and don'ts, but is also due to the more complex data environment needing to be managed (It is the same data but is being managed in a different way). For example, the presence of red noise is problematic, leading to a higher likelihood of false positives (Rodionov, 2006). Most tests are sensitive to sample length and also to perturbations near the ends and beginnings of time series and need to be managed for these weaknesses (Vivès and Jones, 2005).

The bivariate test is preferred here, having been used over the last 25 years by the author for a range of purposes including detection of inhomogeneities in observed climate data, regime changes in Australian rainfall and for detecting step changes in a wide range of observed and simulated climate data (Jones, 1995;Vivès and Jones, 2005;Kirono and Jones, 2007;Jones, 2010b;Jones, 2012;Jones et al., 2013). Randomised data is used as a reference to detect significant step changes using the null hypothesis except when climate stationarity is being tested. The test has been applied to detect multiple breaks in time series by using a moving window technique to identify major breaks, then testing individual breaks by hand to determine a stable solution with the minimum number of step changes $p<0.01$. The STARS test (Rodionov, 2005;Rodionov, 2006), tuned to artificially generated data, is used as a back-up.

Almost all breakpoint tests are sensitive to the autocorrelation contained in trending data and the bivariate and STARS tests are no exception. The bivariate test is further buttressed by undertaking randomisation tests, by shuffling data either side of a nominated breakpoint. If the shuffled data shows similar statistics, in particular by robustly nominating the year of change, then the step change is considered genuine. If the year of change is indeterminate then the time series is subject to a trend or short-term acceleration.

This problem becomes especially relevant when dealing with time series averaged over large areas that may integrate numerous local step changes. Such data are not serially independent, exhibiting red noise, therefore step changes are over-estimated in terms of significance. This is certainly the case for 20th century sea level rise, which can be contrasted with local tide gauge measurements that show definite step and trend behaviour. The global average shows no distinct steps when subject to the moving window test and totally fails the randomisation test. Therefore, it contains no or limited and obscured step changes. However, local tide gauge records show distinct shifts that pass the randomisation test.

A further consideration is whether to treat data by whitening to remove the effects of auto-correlation. This may help to identify regime changes, but if risk is being assessed, those exposed to such changes will be more sensitive to when the numbers change, and less sensitive to the underlying cause. Detection is therefore about when time series change affecting the incidence of important variables such as climate extremes. Attribution however, can provide useful information about the likely persistence of such changes.

The weakness of all of these tests is that they cannot detect changes for some time after they have occurred. For annual data, this may be almost a decade or more, which may be shortened by using de-seasonalised monthly data. This requires understanding the causal process better, so that non-linear changes can be detected instrumentally while it is occurring. Potentially, this requires detecting large amounts of heat upwelling from the ocean into the atmosphere.

The knowledge that south-east Australia is now experiencing maximum daily exceedances above 35°C that were projected for 2030 and fire danger weather projected for 2050, and that both have been subject to abrupt changes (Jones et al., 2013), suggests that the diagnosis of changing climate risks under non-linear change should be a priority.

Attribution

The attribution of rapid change is less well developed than its detection. One major finding in Jones (2012), expanded upon here, is that regional climate in both observations and models shows a period of stationarity that ends abruptly with a step change in minimum temperature. This is shown here for south-eastern Australia and Texas, although the general technique applies for other regions in Australia and mainland USA. All eleven climate models tested for south-eastern Australia (six independent 20th century simulations) also showed a stationary period ending in a step change, revealing it to be a consistent feature of observed and simulated climate. Given the presence of step changes in temperature for all regions of the globe, it is reasonable to assume an abrupt end to stationarity as a general feature of climate change.

The presence of a stationary period and subsequent step changes in warming suggests that the climate system is buffered to small perturbations but, over time, a build-up in internal energy can lead to an abrupt change to a new state. These changes show similar timing with known shifts in decadal regimes, suggesting that climate change is projecting onto modes of natural climate variability as proposed by Corti et al. (1999). Under this model, the heat produced by gradual radiative forcing will be absorbed into the climate system until it responds in a non-linear manner.

The knowledge of how to attribute stationarity and non-nonstationarity using non-linear methods is only partial. Tmax/P and Tmax/Tmin indicators can be used over mid-latitude continental areas but for other regions such as the tropics the oceans and the poles, other means will have to be selected. Long records of high quality observed data are required for such exercise, but models and perhaps also reanalysis data may provide further evidence in regions where data are lacking.

While existing methods of linear attribution will continue to work as they have in the past, methods for attributing non-linear change have in the past, proven to be very difficult. The available statistical methods are less reliable than those derived from linear best fit analysis, with a greater chance of false positives and/or negatives. However, the event-based nature of non-linear change can potentially assist in establishing a more robust set of baseline conditions from which change may be measured. If change is gradual, then a signal may be entrained into any method developed from observations whereas if it is abrupt, then the task is to look for a signal that is distinct. This may assist greatly with the attribution of extreme events and multivariate risk measures such as fire danger.

Solomon et al. (2011) state that all five methods they examine: analysis of means and variance (ANOVA), optimal fingerprinting, signal to noise maximisation via empirical orthogonal functions, linear inverse models and initialised hindcasts conflate natural and forced decadal variability. The method of attribution used in this paper is a step and trend inverse model. Step changes are used to identify baseline conditions under which linearity exists. This is used to infer the rate and magnitude of change, which is quasi-episodic. An advantage of inverse models is do not necessarily require climate models to represent the null hypothesis, as is the case for most other methods. The separation of stationarity from non-stationarity in both observations and models allows a comparison of like with like, rather than relying on a model to represent the null case.

Under this step and trend model, attribution remains a statistical problem. However as the physical pathway that heat is following becomes better understood, attribution can be physical in terms of identifying particular processes of change. Therefore, episodic changes on a decadal timescale offer a greater potential for physical attribution than gradual change, which relies on diffuse processes within the climate system.

Finally, non-linear warming substantially alters many of the climate change probabilities usually calculated using trend analysis. For example, the limited number of step changes in any time series divides it into a series of distinct regimes, each containing an internal trend. If the target temperature time series is considered as a random walk, then the likelihood of a trend of a given length can be assessed by analysing the probabilities associated with a moving window through that time series. With a step and trend analysis, the samples of a trend period with no shift in it is much lower. Using such analysis, the recent ‘pause’ or ‘hiatus’ in global warming since 1997–98 moves from being rare to rather more typical, but needs a large number of sample time series to calculate reliable statistics.

On the other hand, step changes can alter extreme events substantially. Knowing that a shift has occurred makes locating the start and end dates of particular regimes known, therefore changes in extremes or related variables can be assessed. For example Jones et al. (2013) calculated days of extreme heat and high fire danger pre and post 1997 for Victoria, Australia, based on shift dates in temperature and related data, attributing most of those changes to anthropogenic climate change.

Prediction

Neils Bohr is often linked to the following quote, possibly coined from a traditional Danish saying: “prediction is difficult, especially of the future.” This nicely sums up the distinction between scientific prediction, where a theory or model will forecast some kind of outcome conditional on a set of assumptions; and future prediction, which predicts an event or outcome in the real world.

The ability of a model to predict an outcome subject to its inputs and assumptions, or to predict the outcome of an experiment to test a stated hypothesis, are two major scientific tasks, so scientific prediction is highly valued. The model’s output uncertainties can be considered as scientific uncertainties. However, real-world prediction is subject to the added complexities of the context within which such are predictions are made. The real world is more complex, its uncertainties are less bounded, contain more feedbacks and have the confounding effects of human behaviour, particularly if decisions made on the basis of new information can influence the outcomes.

In such situations, scientific prediction is better thought of as providing decision support, rather than predictions (Hulme et al., 2009;Jones et al., 2014). If the climate is likely to change rapidly in an unpredictable way on decadal time scales the question that needs to be asked is “which information offers the best decision support in a given set of circumstances?”

The current major thrust of decadal forecasting is to assess mean ensemble trends from a specific date; the ability of models to do so being evaluated through hindcasts. However, if temperature, rainfall and other variables can be expected to change rapidly, with the emphasis being when – not if, the emphasis of decadal prediction may need to change from producing future trends, to investigating the statistics of potential future shifts. For example, if the thermodynamic states of ocean basins primed to shift were better known, or the signs of rapid transport of heat from the oceans to atmosphere could be understood in both models and observations, the ambition to provide a seamless transition between weather and climate forecasting stated by the World Meteorological Organization (2010) may become more possible.

However, the products being produced currently are not seamless. Weather forecasting is event-based, whereas climate forecasting is trend-based. This is largely due to the long-standing emphasis on the statistics of signal to noise and the underlying gradualist model of change, rather than a theoretical understanding of how the climate works.

A complete theory that blends forced change and variability across the time scales of interest is required but remains in the future (Ghil, 2012). However, Ghil (2012) concludes that studies of the interaction between fast and low timescales within a genuinely non-linear framework over the past decade have produced important results. From the results shown in this paper, prediction at the decadal scale should be event-based rather than trend-based.

Two aspects of climate forecasting that need to be confronted are:

1. There is little evidence that trends extracted from complex system interactions provide useful decision support and some evidence to the contrary (this evidence supports the development and use of scenarios), and
2. People and systems impacted by a changing climate will be far more affected by changes in extremes rather than means; step changes can lead to significant changes in the frequency and magnitude of those extremes.

Adaptation

As detailed by Jones et al. (2013), adaptation has been almost totally embedded within the gradualistic narrative. For example, the following statements are typical:

- Within limits, the impacts of gradual climate change should be manageable. www.pc.gov.au
- Therefore, climate change adaptation can be understood as: (a) adapting to gradual changes in average temperature, sea level and precipitation. www.prevention.web
- Gradual climate change allows for a gradual shift in the mix of crops and to alternative farming systems. www.ers.usda.gov

The effect of the gradualistic narrative on adaptation has been extensively critiqued by Jones et al. (2013). In particular, they compared the gradualistic framings of climate change and conventional economics, pointing out that they reinforce each other (and draw from similar origins in the scientific enlightenment). Because they both underestimate risk, they promote complacency.

The prospect of step changes in climate raises three main issues for adaptation:

1. Rapid changes in impacts. Step changes in warming and associated variables will lead to rapid changes in extremes associated with the direction of change. Warming in ocean regions will be magnified on land. For example, the increase of 0.8°C in maximum temperature in south-eastern Australia resulted in the number of days above 35°C increasing from 8–12 per year in the Melbourne region, the number projected for 2030 (Jones et al., 2013). Such changes would lead to critical thresholds being exceeded after a change with potentially serious impacts that would lead to significant damage and loss if they occur unanticipated.
2. Changes in the nature of climate information. The utility of calculating and communicating mean trends is limited, except as a long-term (multi-decadal) approximation. Instead of gradual change, periodic shifts in means can be anticipated, although trend-like behaviour may increase with accelerated warming. Probabilistic projections therefore become much less useful for decision making with the window of years to decades, shifting the emphasis to qualities such as resilience and robustness. The framing of climate information moves from prescriptive: "how climate will change", to diagnostic: "how will climate change?"
3. Systemic risk. The potential for rapid change and threshold exceedance, and interactions between climate risk and other risks moves the agenda from adapting to individual impacts to managing systemic risk. This would be the case anyway with gradually changing impacts plus exposure, but with non-linear changes, or shocks to the system, becomes much more important.

The preparation and communication of climate information has moved from top-down climate impact assessments, towards making it relevant to a wide range of decision-making contexts where climate is only one factor that needs to be considered (Jones et al., 2014). The potential for shifts and shocks in these different contexts, such as testing their potential to exacerbate systemic risks, needs to be assessed.

Prediction may be possible. A better understanding of the nature of non-linear change, and the conditions before a shift occurs may be diagnosable (Thompson and Sieber, 2011). Gathering the basic statistics of non-linear changes under a wide range of forcings will assist in planning adaptation. The bottom line is that the prediction of trends over decadal time scales may not be useful if the climate does not behave in a trend-like fashion. A better understanding of how climate changes over decadal timescales taking into account the process of rapid, non-linear change and how that may affect decision-making is a priority.

Mitigation

The influence of rapid, non-linear change on mitigation highlights the risks of climate impacts. Rapid change has the potential to cross thresholds more rapidly than incremental change as larger shocks are delivered to natural and human systems. For example, impacts such as coral bleaching severity and extent, droughts and floods, storm severity, warming extremes and severe fire weather are all phenomena that could change very quickly. The crossing of tipping points becomes more likely with larger shocks (Lenton et al., 2008). Damages can accelerate very quickly, particularly where other aspects of exposure are changing due to human activities (Jones et al., 2013).

The potential for large, global risks such as the break-up of ice sheets or the acceleration of ice melt on land, such as in Tibet, raising the risk of glacial lake outbreak, are risks that may affect large regions or the globe (Oppenheimer et al., 2014). If gradual forcing results in a step-like approach to climate change, then the proverbial straw that breaks the camel's back could come at any time with global consequences. The most recent step change in Arctic regions of 1°C in 2006, was followed by rapid thinning and loss of arctic sea-ice, so polar impacts are vulnerable to amplified non-linear change compared to elsewhere (Cohen et al., 2014;Jun et al., 2014).

The economics of loss and damage suggest that potential losses are higher than for smooth changes (Jones et al., 2013). The potential benefits of managing those changes through risk mitigation is also more valuable because of the attendant uncertainty and risk. This raises the stakes for mitigation and increases the benefits of avoiding damage, especially if tipping points and/or cascading risks are avoided by not meeting additional step changes in climate.

Communication

The communication of climate change has been normalised around the gradualist paradigm and associated narrative (Jones et al., 2013). Under increasing forcing, this narrative describes gradual trends in climate as business as usual and deviations from this as the influence of climate variability. Classical statistics support this narrative, describing a trend gradually emerging from the noise as incremental climate change proceeds.

This has been challenged by a range of opposing narratives, which are distinguished by having no compelling scientifically-justified evidence to back them up. They include (Poortinga et al., 2011;Washington and Cook, 2013):

- Observational data have been manipulated by scientists.
- It hasn't warmed since 1998.
- We are recovering from the Little Ice Age, so any observed warming is a bounce back.
- Climate change is occurring but it's less than projected by the IPCC so there is little to be concerned about.
- The lack of recent observed warming is not reproduced in climate models.

Any statistically-based scientific finding can be undermined by those who oppose that finding; publicly if they have access to media and wield political and public influence (Boykoff, 2013). This opposition is not unique to climate change (Oreskes and Conway, 2010;Dunlap and McCright, 2011) and requires continual refutation of the same talking points, the major disadvantage being that clarification generally takes longer to relay than sound bites of denial (Moser, 2010;Boykoff, 2013). This is not a criticism of how trend statistics are communicated, but concerns the need to change the focus of communication when scientific findings change (e.g., Hawkins et al., 2014). For example, for quite some time it was widely concluded that single-event attribution was not possible, but now it is for a range of weather events including heat waves, droughts and intense rainfall (Peterson et al., 2013;Zwiers et al., 2013;Herring et al., 2014).

The strong emphasis on trend analysis in communicating climate change has allowed any perceived deviation from a trend to be criticised as scientists misdiagnosing observations (Stott et al., 2010;Hansen et al., 2012). Large deviations therefore need to be explained by some form of climate behaviour that can be interpreted as an aspect of climate variability. Many of the recent papers assessing reduced rates of mean global warming since 1997–98 are engaged in a type of exceptionalism, where they are analysing why temperatures have not increased at the expected rate (Trenberth and Fasullo, 2013;England et al., 2014;Watanabe et al., 2014).

This is a maturing conversation where climate change and variability are being interpreted in a more considered way than simple trend statistics (Hawkins et al., 2014). When about 90% of the resulting heat is going into the ocean and ocean heat content is rising (Trenberth et al., 2014), global warming has, of course, not stopped. However, opposing lobbies are continuing to argue that it has by ignoring the steep increase in 1997–98, staying on the plateau and ignoring the heat in other the 99% of the system (Trenberth and Fasullo, 2013).

Most analyses examining the plateauing of air temperature continue to interpret climate change in the mode of H1, where changes in the rate of oceanic contributions to global warming are moderated by increased deep-ocean mixing (e.g., Trenberth and Fasullo, 2013) and surface cooling identified in the eastern Pacific Ocean (Kosaka and Xie, 2013;England et al., 2014). The recent reduction in warming rates is contrasted to an acceleration between the mid-1970s and 1997–98 and related to the modulation of atmospheric warming by decadal climate variability through phases in the Pacific Decadal Oscillation (Kosaka and Xie, 2013;Trenberth and Fasullo, 2013;England et al., 2014;Watanabe et al., 2014). The period 1976–1998, where the Pacific Decadal Oscillation was in a positive phase has been linked with an accelerated warming trend, but in the analyses presented here suggest that period exhibited two step changes in 1978–79 and 1987. This period involves two shifts that easily turn up as trends.

Explaining climate change as an episodic step and trend process in the mode of H2 turns the standard explanation on its head. Step changes following by relatively stable periods would become a description of normal climate behaviour, instead of smooth trends being modulated by climate variability. This requires a more complex explanation statistically, but in a sense becomes simpler because it is actually easier to relate climate to peoples' experience of weather and extremes, which are experienced as abrupt changes. It allows the narrative of the chaos butterfly to operate over multiple timescales, extending from weather events through to long-term phenomena such Heinrich Events and glacial–interglacial transitions. This is consistent with the proposition by Ghil (2012) that theoretical advances proposed by Lorenz (1963) and Hasselmann (1976; 1979) could contribute to a complete theory of climate variability over time and space.

With the conclusion that climate change is an episodic rather than a gradual process, the prevailing narrative of how climate changes needs to be recast to better reflect that nature of the changes being observed, those being anticipated and the consequent framing of risk communication (Jones et al., 2013). In particular, it will mark a significant move away from predictable cause and effect to system complexity and systemic response.

An important aspect of recasting that narrative is not to say that science is wrong, but to emphasise the need to reconcile outstanding problems without in any way invalidating established theory. The changes being proposed are not to the underpinning theory but affect the attendant methods and values used to analyse data and communicate findings. Instead of those methods self-selecting H1, recasting the narrative from gradualism to punctuated change promotes H2 over and above H1. It is more about moving methods beyond a historical and conservative legacy.

Changing the climate change narrative also provides the opportunity to separate the communication of scientific findings from risk communication as much as is feasible. Two major reasons for doing so are that:

1. The probative (proof) values of science and risk are different, and
2. The values at risk are different. The risk of the science being right or wrong should be kept distinct (point 1) from the consequences of a set of calculated risks and potential responses to those risks.

With respect to probative values, the conventional burden of proof for statistical methods attributing change to external drivers is 95% (a one in 20 chance that a data sample is random) whereas for a risk to be worth assessing, scientific plausibility (<<1% event likelihood) is all that is required if the consequences of that event are of sufficient concern (Jones, 2011). Using the probative values of science to filter information to be used in a risk assessment, can bias the results of that assessment. To assess decision-making needs, all scientifically plausible cases need to be on the table, not just those selected by a particular form of heuristic.

Communicating risk in the second sense will require scientists to go beyond what the science says is proven and communicate all plausible aspects of risk while being quite open about the attendant uncertainties. This is the approach advocated by a number of key scientists and science communicators (Climate Change Science Program, 2009;Moser, 2010;Young, 2014), including the late Stephen Schneider (2001, 2004).

Conclusions and next steps

Kuhn's definition of a paradigm as "scientific achievements that, for a time, provide model problems and solutions for a community of practitioners" (Kuhn, 1996) helps to identify gradualism as a governing value that shapes how climate change is analysed and interpreted. Gradualism informs the bulk of the quantitative methods that describe problems and address solutions for climate change.

However, when analysed for steps and trends, limited signs of gradual change can be found in a wide range of climate time series. Records of surface and satellite air temperature, rainfall, sea surface temperature, tide gauge measurements and ocean heat content show complex system behaviour similar to Bak (1996) sand piles, where a system absorbs added inputs (grains of sand or incremental radiative forcing), then periodically cascades when instability is reached. In the climate system, this instability seems to reflect preferred modes of climate variability on interannual to decadal time scales (and potentially longer). It also appears to accelerate in frequency and magnitude as forcing increases.

The presence of similar patterns in climate model output suggests that this behaviour is an emergent property of the climate system. The acceleration of step changes with increasing radiative forcing is clear in analyses of mean global warming. This suggests that the physical pathways that heat energy takes within the climate system can be tracked and that the nature of these changes can be better understood.

A better understanding of this behaviour may also help define the relationship between the boundary conditions limits of prediction, which broadly map onto the first law of thermodynamics, and the initial conditions limits to prediction, which broadly map onto the second law of thermodynamics (Lorenz, 1975;Hasselmann, 2002;Ozawa et al., 2003;Ghil, 2012). The linear process of converting radiative forcing into heat, becomes an entropic process once that heat enters the ocean and is entrained into ocean-atmosphere processes transporting heat from the low latitudes to the poles (Ozawa et al., 2003).

To date, variability at longer than interannual scales has largely been considered a random process. As a result, decadal prediction has focussed on trend analysis with the assumption that variability will mediate the rate of change depending on the balance between deep-ocean mixing and the gradual release of heat into the atmosphere. However, an episodic pathway where warming is dominated by step changes rather than gradual trends, suggests that the potential for rapid shifts in climate needs to be factored into decision making (Jones et al., 2013).

The epistemological history of science reaching back to the enlightenment suggests that gradualism was applied as a cosmological value to a range of natural phenomena in the 18th century. It has been particularly influential on physics, the earth sciences, biological evolution and economics. Gradualism later became a methodological value attached to the earth sciences, including climatology. Its dominance to the present day has hampered the development and take up of new methods addressing the development of theories of non-linear behaviour in the climate system.

The main epistemological lesson for science, and especially climatology, is to become more reflexive with respect to theory, methods and values in terms of recognising and understanding the sociological aspects of science than is currently the case. This paper supports Laudan's (1984) assertion that the Kuhnian notion of paradigm overturning is not a holistic revolution but is more likely to be a reticulated process of reconciling theory, methods and values.

The history of scientific styles has also been addressed and two further styles affecting earth systems science are proposed, namely system complexity and simulation. System complexity is different to adaptation as a style in that it takes on the idea of networks, feedbacks and non-linear response in addition to adaptation (such systems are admittedly self-adapting). Simulation is different to experimentation in that it develops mathematical models that visualise a wide range of phenomena that can involve the users of the output in a process that extends beyond standard experimentation in a controlled system.

The characterisation of climate risk changes substantially as to whether change is characterised as being gradual or episodic, moving its main approach from a largely predictive mode to much more diagnostic characterisation. The development of robust statistics characterising change needs to be developed and tested in a wide range of social and ecological systems, in order to understand how the impacts of step changes may play out. The potential for predictability in such systems also need to be understood through a range of statistical and process-related investigations.

The next steps for this project are to expand the analysis into a fully-automated and objective technique that can analyse gridded data sets and gain a better understanding of how warming events evolve by tracing heat energy within the climate system. Goals are to use this understanding to identify potential shifts in real time, understand the evolution of the ocean-atmosphere to subcritical states and contribute to the theoretical understanding of how the system behaves.

The evidence presented in this paper provides a compelling case for H2 – that climate variability and change interact, to be preferred over H1 – that they proceed independently. Even if only partially correct, an understanding that climate change and variability interact on decadal timescales should change that way the climate change is assessed, analysed, communicated and applied in decision making.

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