Reconciling anthropogenic climate change and variability on decadal timescales: the challenge

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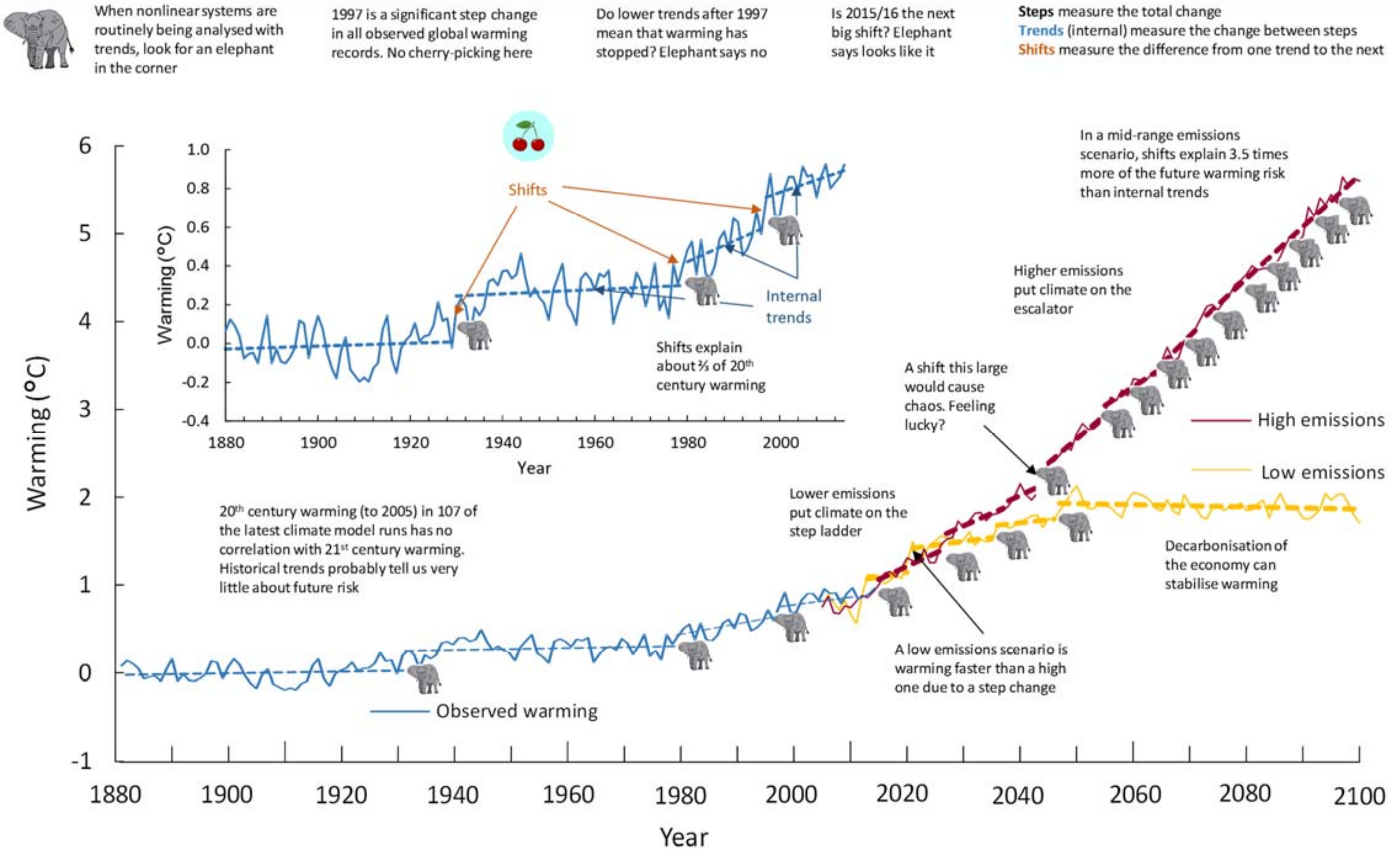

When nonlinear systems are routinely being analysed with trends, look for an elephant in the corner

1997 is a significant step change in all observed global warming records. No cherry-picking here

Do lower trends after 1997 mean that warming has stopped? Elephant says no

Is 2015/16 the next big shift? Elephant says looks like it

Steps measure the total change
Trends (internal) measure the change between steps
Shifts measure the difference from one trend to the next

Shifts explain about ⅔ of 20th century warming

20th century warming (to 2005) in 107 of the latest climate model runs has no correlation with 21st century warming. Historical trends probably tell us very little about future risk

In a mid-range emissions scenario, shifts explain 3.5 times more of the future warming risk than internal trends

Higher emissions put climate on the escalator

A shift this large would cause chaos. Feeling lucky?

Lower emissions put climate on the step ladder

Decarbonisation of the economy can stabilise warming

A low emissions scenario is warming faster than a high one due to a step change

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Key words: decadal variability, climate change, regime change, nonlinear dynamics, detection and attribution, science communication, forecasting

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Cover image: Note – elephant's 2015/16 prediction made in 2015

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Abstract

Supporting papers exploring the relationship between anthropogenic climate change and variability on decadal timescales, conclude that gradually increasing radiative forcing interacts with internal variability, producing a series of nonlinear responses manifesting as shifts. For temperature, this produces a step-ladder like progression under low external forcing that becomes escalator-like under greater forcing. The dominant gradualist narrative of climate change, which communicated climate change as being a gradual process modulated by climate variability, is therefore considered to be obsolete. This paper summarises these findings and then goes on to explore their implications for methods of climate detection and attribution, prediction, adaptation, mitigation and communication. Currently, these methods depend heavily on linear methods based on least squares trend analysis, but if climate risks are to be characterised accurately, methods to detect climate shifts, to understand and attribute their causes, to characterise climate risks for adaptation and mitigation, and communicate these to the public, all need to be developed.

Introduction

The scientific literature contains two competing hypotheses that describe how anthropogenic climate change and natural variability interact on decadal timescales (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*).

Although the literature describes these hypotheses as both being plausible (Solomon et al., 2011;Kirtman et al., 2013), the methods used to analyse and communicate how the climate changes overwhelmingly self-select *H1* over *H2* (Jones et al., 2013;Jones, 2015a). These methods, based on least-squares trend analysis, treat the change in variables such temperature as being linear. Statistically, this is interpreted as a signal-to noise model where variations away from the trend are caused by the random noise of climate variability (North et al., 1995;Hegerl and Zwiers, 2011;Santer et al., 2011), where the signal is used to project likely future change and the noise is discarded. This forms the dominant scientific paradigm describing climate change over decadal timescales, which is communicated through the gradualist narrative. This narrative frames how climate-related risks are conceptualised, analysed and communicated (Jones et al., 2013;Jones, 2015a). Climate risks are being managed on the basis of there being smooth changes in mean variables over time, because the potential for abrupt changes, while being acknowledged, is regarded as being unpredictable.

There is mounting evidence that *H2* is true and that climate change does project onto modes of climate variability, producing shifts in climate. These include theoretical considerations (Ozawa et al., 2003;Ghil, 2012, 2014;Franzke et al., 2015), statistical analysis of nonlinear changes in observations and model output (Trenberth, 1990;Trenberth and Hurrell, 1994;Hare and Mantua, 2000;McFarlane et al., 2000;Mantua, 2004;Rodionov, 2006;Fischer et al., 2012;Jones, 2012;Jones et al., 2013;Chen et al., 2014;Jones and Ricketts, 2015a, b), and statistical methods for nonlinear attribution at the regional scale (Jones, 2012;Jones and Ricketts, 2015b). The main problem to date in detecting and attributing possible nonlinear signals has been the lack of a robust method for doing so (Rodionov, 2005;Reeves et al., 2007;Overland et al., 2008).

This leaves the theoretical and methodological aspects of climate change unreconciled (Jones, 2015b). Determining the more correct hypothesis is a high priority because of the substantial resources being invested in climate research programs and in developing climate services to provide end users with relevant and useful information (World Meteorological Organization, 2011;von Storch and Zwiers, 2013;WMO, 2014). This paper summarises issues raised in recent papers that characterise climate as a complex, nonlinear system (Jones, 2015a, b;Jones and Ricketts, 2015a, b). These cover theoretical, statistical, epistemological and historical considerations. This is followed by discussion of the implications for the characterisation of climate risks, covering detection, attribution, prediction, adaptation, mitigation and communication.

Key issues

The following key issues for why climate should be characterised as a nonlinear system are drawn from papers exploring theory (Jones, 2015a, b), statistics (Jones, 2012;Jones et al., 2013;Jones and Ricketts, 2015a, b) and history and philosophy (Jones, 2015b).

Theoretical considerations include:

- The development of theory around Lorenzian attractors in the climate system (Lorenz, 1963, 1975), suggest that nonlinear 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 nonlinear 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 (e.g., Seidel and Lanzante, 2004).
- The statistical methods in use for measuring gradual change are two centuries old, are widely accepted and dependable. Many improvements have been made since but the basic principles and assumptions persist (Jones, 2015b). 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 (Jones and Ricketts, 2015a, b).
- Data limitations in investigating complex decadal variations involving ocean-atmosphere processes have meant that many climate variables lack reliable data extending back more than a few decades. As a result, stationary and nonstationary conditions have not been adequately determined for observed climate.
- When analysed using step change statistical methods, most climate variables demonstrate nonlinear behaviour (Jones, 2011a;Jones et al., 2013;Jones and Ricketts, 2015a, b).
- 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 three regions examined in 1968 (South-eastern Australia), in 1990 (Texas) (Jones, 2012;Jones and Ricketts, 2015b). Successive changes in observations and model output for South-eastern Australia show continued step changes in warming over the 21st century (Jones, 2012).
- Warming shows a step-ladder like progression in the 20th century and an escalator-like progression so steps and trends under high rates of forcing in the 21st century (Jones and Ricketts, 2015a).
- A number of step changes in zonal average, hemispheric and global temperature data coincide with regime changes in decadal modes of climate (Jones and Ricketts, 2015b). These change have in the past been linked to the modulation of gradual change by climate variability, but may in fact be externally forced change interacting with variability.

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 (Jones, 2015b).
- 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 (Baker, 1998;Baker, 2014).

- 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 (Jones, 2015b).
- The take-up of system complexity and nonlinear dynamics across the physical and social sciences has been patchy. In economics it is almost non-existent and in climatology, it is partial and incomplete (Jones, 2015b).

Historical and social considerations include:

- The evolution of climate modelling has proceeded from simple to complex models, therefore from simple to complex outputs (Weart, 2008). This process has 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, or Ockham's razor (Jones, 2015b).
- Strong cognitive values are invested in the signal to noise model used 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. Cognitive values attached to prediction adds to this investment, with the signal being predictable and noise assumed to be unpredictable (Jones, 2015b).
- 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 trend analysis in attributing climate change to observations and model output have therefore been relied upon (Santer et al., 2011;Cahill et al., 2015;Lewandowsky et al., 2015;Lewandowsky et al., 2016). Research on variable responses to forcing has probably been discouraged as a result (Jones, 2015b).

The evidence presented in these papers supports the alternative hypothesis H2 – that the gradual forcing of climate produces nonlinear, step-like changes in a wide range of climatic variables. This requires a re-examination of how climate risk is characterised.

Characterising climate risks under nonlinear change

The treatment of global climate as a complex and dynamic system, requires moving on from analytic methods based on gradualism, which was adopted by science as a cosmological value during the scientific enlightenment, later on becoming an explanatory value (Jones, 2015b). While other disciplines have moved away from gradualism, climatology has been slow to respond despite over fifty years having elapsed since the climate system was shown to be stochastic rather than deterministic (e.g., Lorenz, 1963, 1975;Hasselmann, 1976;Ghil, 2012). Even though a comprehensive theory of climate variability remains to be developed (Ghil, 2012), for the purposes of decision making, the treatment of climate as a simple linear system is no longer adequate.

Current methods of climate-related risk characterisation, analysis and communication do not treat shifts or abrupt changes as useful information. The only exception is where abrupt changes are treated as a nominated exception to the rule of change, a rule that is interpreted through trends. However, in a complex system, a trend can only describe how much a variable may change, not how it may change over time.

The analysis of shifts as useful information requires significant changes to current methods. These changes are surveyed in the following sections through these questions:

- Detection – how should a changing climate be measured?
- 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

Existing methods used to analyse climate change have a historical legacy, failing to keep up with the development of complex systems theory (Jones, 2015b). The recognition that climate change occurs in a series of shifts, or abrupt changes, with internal trends being less important (Jones, 2010;Jones, 2012;Jones and Ricketts, 2015a, b), 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. Detection of change points in a complex system is complicated, in part because data may not comply with the assumptions relied on in classical statistics (Bai and Perron, 2003;Beaulieu et al., 2012). As a result, the existing tools for detecting shifts or other types of statistical break points are considered less reliable than trend analysis, but if they are measuring the actual change, will actually be more reliable.

Detection of shifts can begin as a naïve activity, where initially, evidence for statistically significant step changes is sufficient. A shift into a new state, whatever the cause, will alter the pattern of existing hazards, so detection is an important first step. A step change in climate is analogous to an artificial inhomogeneity in a data set, so tests suitable for locating such inhomogeneities will also detect similar changes in observed data. Such data should be as clear as possible of artificial inhomogeneities to ensure false positives are minimised (so may already have been subject to such tests as part of the homogenisation process). Techniques to modify time series to remove ‘red’ noise in order to find underlying regime shifts (e.g., Rodionov, 2006) come under attribution rather than detection.

Our preferred test 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). It detects step change in serially independent data and was originally designed to detect single steps. It has since been adapted into the multi-step bivariate test (Jones and Ricketts, 2015b;Ricketts, 2015) by automating the test and applying a predefined set of rules to improve its objectivity and make it more robust.

The advantage of the bivariate test, over most similar tests such as the Alexandersson (1986) and the STARS test (Rodionov, 2005;Rodionov, 2006), is that it works with a reference variable, allowing two types of analysis: testing paired variables and testing a variable against a standard reference. Paired variable tests are used to assess homogeneity and steps in one time series relative to another. The latter can be used to test whether variables are changing in or out of step with each other. A standard reference can be a high quality regional average data set, a set of serially independent random numbers after Vivès and Jones (2005), a set of random numbers containing a trend or other baseline reference time series as required to provide a null hypothesis. The bivariate test has worked successfully for a range of climate variables, including temperature, rainfall, ocean heat content, sea level, and a variety of climate-related indices (Jones, 2015c).

Further work in developing methods to detect nonlinear change is urgently required and to create a set of protocols around which such tests can be assessed. Measurement of the magnitude of a shift is problematic in time series with both steps and trends. One way to assess the importance of this problem is to undertake an inverse analysis, where specific levels of risk and risk appetite are identified and levels of change contributing to those are diagnosed.

Attribution

The attribution of shifts is less well developed than their detection. While existing methods of linear attribution successfully identify the contribution of external forcing over multiple decades, they are problematic on shorter timescales. Externally forced climate change and internal variability are difficult to separate, and the assumption of linearity is a convenient way to do this. 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 attribution method used in Jones (2012) and Jones and Ricketts (2015b) is a step and trend inverse model, a variation on a simple linear inverse model. Step changes in paired variables (e.g, maximum temperature and rainfall, minimum and maximum temperature) are used to identify baseline conditions under which stationarity exists. These relationships are then extended into the nonstationary period, subtracted from observations and the residuals used to estimate forced change. For temperature, they demonstrate clear shifts in both observations and model data. An advantage, is that this method does not 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.

Paired variables sometimes maintain stationarity across regime changes while at other times may become nonstationary. Shits that maintain stationarity represent regime changes occurring within a stable climate. These can be considered as part of internal climate variability. For example, a statistically significant shift between drought-dominated and flood-dominate regimes in eastern Australia in 1947/48 maintained relationships between maximum temperature and rainfall (Nicholls et al., 2004;Vivès and Jones, 2005), whereas a later shift in the early 1970s, attributed to global warming, did not (Jones, 2012). Of three regions tested using the inverse step and trend method, southern Australia experiences nonlinear change in 1968, and central England in 1988 and Texas in 1990, each of which can be attributed to global warming. However, using this method, central England also experienced a nonlinear shift in 1911 (Jones and Ricketts, 2015b). This earlier nonlinear response may not be due to anthropogenic forcing, but poor data, solar forcing or internal variability. Palaeoclimatic evidence and theory suggests that over time, multiple forcing elements will lead to nonlinear responses in hydrodynamic systems. Under natural conditions, these would be expected to be less frequent than changes under anthropogenic forcing.

Supporting evidence for regional warming to be initiated by an abrupt shift from stationarity to nonstationarity was provided by output from eleven climate models for south-eastern Australia (six independent 20th century simulations), which showed a stationary period ending in a step change in the late 20th century (Jones, 2012). The coincidence between the shift dates in local observations and shifts in mean temperature at zonal, hemispheric and global scale show the nonlinear nature of warming. These methods are suitable for in mid-latitude continental climates. Suitable methods for high latitude, tropical and marine climates need to be developed.

The potential for change proceeding via regime shifts offers an opportunity to use change points as markers. Characteristics such as storminess, rainfall intensity, extreme heat, ENSO characteristics and synoptic patterns often ‘switch’ at such times, and markers can make the statistical analysis of such characteristics more tractable. The linear analysis of less frequent extremes is difficult because of the long lead times in a changing climate required to extract a meaningful signal (IPCC, 2012). Using change points as markers will assist greatly with the attribution of extreme events and multivariate risk measures such as fire danger.

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 nonlinear manner. This suggests that work on the dynamic process and triggers of such changes can also assist in attribution (O'Kane et al., 2014;Franzke et al., 2015;Monselesan et al., 2015).

Prediction

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

The efficacy of scientific prediction measures 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. Because scientists value these abilities highly, those values are often conferred on model outputs produced for decision making. However, real-world prediction is more complex, its uncertainties are less bounded and it is subject to larger feedbacks, particularly if decisions made on the basis of new information can influence the outcomes (Risbey, 2004;Gerst et al., 2013). In such situations, scientific prediction is better thought of as providing decision support, rather than providing predictions that should be actioned directly (Hulme et al., 2009;Jones et al., 2014). Decision context is also important, meaning that end users may prefer different types of output.

The potential for nonlinear climate change significantly alters the balance between the prediction of mean trends and future events, such as step changes. 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 (Hurrell et al., 2009;Murphy et al., 2010;Meehl et al., 2013a). However, if temperature, rainfall and other variables can be expected to change rapidly, with the emphasis being when and not if, the emphasis of decadal prediction needs to change from trend to shift analysis. 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 ability to predict shifts in advance may be improved. However, some of the underpinning processes that may produce such instability at the regional scale are missing from the current generation of climate models (Risbey and O’Kane, 2011).

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 slow timescales within a genuinely nonlinear framework over the past decade have produced important results. Two aspects of climate forecasting that need to be confronted are:

1. There is little evidence that trends extracted from complex systems data provide useful decision support and much 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

To date, adaptation has been almost totally embedded within the gradualistic narrative (Jones et al., 2013). 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 these framings reinforce each other (and draw from similar origins in the scientific enlightenment). Because they underestimate risk, linear approximations of complex system behaviour 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 (Renn and Klinke, 2004;Renn, 2011;Jones et al., 2014). This would be the case anyway with gradually changing impacts plus exposure, but with nonlinear 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 (Carter et al., 2007;Dessai et al., 2009;Hulme, 2011;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 of regime changes may be possible (e.g., Sévellec and Fedorov, 2014;Monselesan et al., 2015). A better understanding of the nature of nonlinear change, and the conditions before a shift occurs may be diagnosable (Thompson and Sieber, 2011). Gathering the basic statistics of nonlinear 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, nonlinear change and how that may affect decision-making is a priority.

Mitigation

The influence of rapid, nonlinear 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;Oppenheimer et al., 2014). Damages can accelerate very quickly, particularly where other aspects of exposure are changing due to human activities (IPCC, 2012;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 nonlinear 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 (Feenstra et al., 1998;Jones et al., 2013;Burke et al., 2015a;Burke et al., 2015b;Lontzek et al., 2015). The potential benefits of managing those changes through risk mitigation is also more valuable because of the attendant uncertainty and risk (Lontzek et al., 2015). 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 shifts 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 supports this narrative, describing a trend gradually emerging from the noise as incremental climate change proceeds.

In recent years, 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;Lewandowsky et al., 2015):

- 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 interpreted by those opposing the science, as scientists misdiagnosing observations (Stott et al., 2010;Hansen et al., 2012;Boykoff, 2014). 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 over the previous period are engaged in a type of exceptionalism, where they are analysing why temperatures have not increased at the 'expected' rate (e.g., Trenberth and Fasullo, 2013;England et al., 2014;Watanabe et al., 2014). These papers have been interpreted as seepage, where it is argued that by using terms such as hiatus and pause, this work gives legitimacy to the opposing narratives listed above (Lewandowsky et al., 2015;Lewandowsky et al., 2016). Using trend analysis

Lewandowsky et al. (2016) identify this period as a routine fluctuation. However, by focussing on the trend as the right scientific position, this stance takes a method-as-theory position where linear analytical methods provide a proxy framing for anthropogenic climate change (Jones, 2015b). Both sides of this debate are framing the trend as the orthodox representation of the in/correct position and deviations away from this as a kind of exceptionalism.

Framing climate change through the language of complex system behaviour and explaining climate change as an episodic step and trend process turns the standard statistical narrative 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 relates more easily to climate to peoples' experience of weather and extremes, which are experienced as event-driven changes. It allows the narrative of the chaos butterfly of Lorenz to extend over multiple timescales, from short-term 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 comprehensive theory of climate variability over time and space.

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). This type of framing will move away from predictable cause and effect explanations to those describing systemic connection and response.

An important aspect of recasting the gradualist 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 (Jones, 2015b).

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 from the viewpoint of scientist versus decision makers 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, 2011b). 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 (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's (1996) sand piles, where a system absorbs added inputs (grains of sand or incremental radiative forcing), then periodically cascades when a threshold for instability is reached. For climate, this instability reflects preferred modes of climate variability on interannual to decadal time scales (and potentially longer). It also accelerates 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 (Meehl et al., 2013b;Trenberth, 2015). 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 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 nonlinear 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.

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