



Can public perceptions of Australian climate extremes be reconciled with the statistics of climate change?



Sophie C. Lewis*

Research School of Earth Sciences, The Australian National University, Canberra, ACT, Australia and ARC Centre of Excellence for Climate System Science, Australia

ARTICLE INFO

Article history:

Received 1 October 2015
 Received in revised form
 26 November 2015
 Accepted 30 November 2015
 Available online 2 December 2015

ABSTRACT

In this study alternative understandings of extreme climate events are examined by focusing on the consecutive spring record-breaking temperatures observed in Australia in 2013 and 2014. Aspects of these extremes have previously been investigated scientifically. However, widely held popular perceptions, such as those epitomised by the public statements of recent Australian Prime Minister Tony Abbott, refute the outcomes of these scientific analyses. Instead, these posit that new temperature records are purely an artefact of natural variability and the longer the period of observations available, the greater possibility of extreme events. Here, I characterise these understandings as alternative mental models of climate change and extremes, with one informed primarily by personal perceptions (The Natural Variability Concept), and the other (The Probabilistic Change Concept) informed by evidence of the physical climate system (i.e., high-quality observed temperatures and a suite of Coupled Model Intercomparison Project phase 5 (CMIP5) climate models). Using these tools, I demonstrate that observed temperature characteristics are irreconcilable with the personal perception-based understanding of extremes as artefacts only of natural climate variability. In addition to showing that the perception-based understanding of climate change and extremes adopted by Abbott (i.e., the Natural Variability Concept) is not fully consistent with the observed time series, I also show that it cannot be internally consistent. The use of these commonly employed statistical properties of temperature time series to examine directly elements of the perception-based conceptualisation of extremes provides insight into the communication of the scientific basis of extreme climate events. I suggest that further quantitative attribution statements are unlikely to explain such extremes more fully than information already available to the public. Directly addressing the misplaced foundational beliefs of the Natural Variability Concept, however, may help accurately communicate aspects of climate extremes more clearly to those open to learning from personal experiences.

© 2015 The Author. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

This study explores alternative understandings of extreme climate events by focusing on the example of the consecutive spring record-breaking temperatures experienced in Australia in 2013 and 2014. Over the period of late 2012 to 2015, Australia experienced well above average temperatures. The previous years of 2010–2011 were unusually cool and wet across Australia, in association with strong, consecutive La Niña events (Bureau of Meteorology, 2012). As these exceptional La Niña episodes subsided, sustained high temperatures across Australia were recorded. In 2013, for example, area-mean Australian temperature records were broken for the hottest day, week, month, season and year on record (Bureau of Meteorology, 2014). Temperature records were

broken on spatial scales ranging from individual locations through to State- and continent-wide area averages, and on timescales ranging from daily through to annual averages. Notably, a new spring temperature record was set in 2013 for Australia-wide area-average mean temperatures (T_{mean} ; Fig. 1) (Bureau of Meteorology, 2013), which was exceeded again in spring 2014. The 2013 and 2014 spring anomalies were the largest in a high-quality observational record extending back to 1910 (Jones et al., 2009; Trewin, 2012).

Specific aspects of these extreme Australian temperatures have been investigated previously. These studies have explored record temperatures from an attribution framework using climate models to quantify the change in likelihood of extreme temperatures that can be attributed to anthropogenic forcings, such as greenhouse gases (Lewis and Karoly, 2013; 2014). Such model-based attribution approaches provide just one perspective of observed record-breaking Australian temperatures. Personal perceptions of extremes, for example, often provide a differing perspective from

* Corresponding author.

E-mail address: sophie.lewis@anu.edu.au

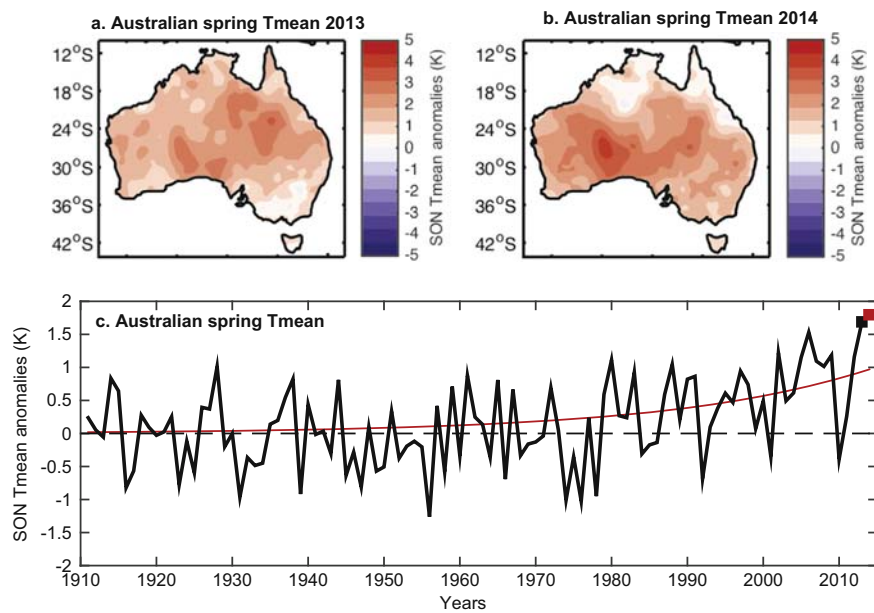


Fig. 1. Observed mean Australian spring (Spring–November; SON) temperature anomalies (K, relative to 1911–1940) for 2013 (a) and 2014 (b) and for the observed period 1910–2014 (c), with the record anomalies of 2013 (black) and 2014 (red) shown. Data are from AWAP (Jones et al., 2009).

scientific results. After an extreme climate event it is common for the public, media and research community to ask, what caused this event (Trenberth, 2012; Hulme, 2014)? Is it linked to global warming? Do recent record-breaking temperatures reveal aspects of climate change? Here I propose two simplified mental models widely used to address these questions and ultimately understand climate extremes. These mental models based on these alternative understandings, namely i) the Probabilistic Change Concept and ii) the Natural Variability Concept, which are outlined below.

1.1. Alternative understandings of extremes

The Probabilistic Change Concept refers to an understanding of climate extremes based around the quantification of the probability of occurrence. These approaches typically utilise data from climate models to determine the change in likelihood of a defined extreme event that can be attributed to a specific forcing. For example, the Lewis and Karoly (2013; 2014) analyses utilise data from global climate models that contributed detection and attribution experiments to phase five of the Coupled Model Inter-comparison Project (CMIP5) (Taylor et al., 2012) and demonstrate, for example, that anthropogenic influences substantially increase the risk of extreme spring temperatures occurring in Australia (Lewis and Karoly, 2014). The repeated spring records of 2013 and 2014 have also been investigated using these analysis tools showing such extremes are very unlikely to occur due to natural climate variations alone but have a significant chance of occurring under greenhouse gas forcing (Gallant and Lewis, submitted).

Such attribution studies using this fraction of attributable risk (FAR) framework (Stott et al., 2004) are considered useful for understanding the risks of future extreme temperatures and impacts, which has implications for adaptive decision-making (Stott et al., 2010). Through this Probabilistic Change understanding of extremes, record climate events potentially represent an important diagnostic of change in the climate system. A changing climate can lead to changes in the frequency, intensity, spatial extent, duration and timing of extremes, and furthermore, can result in unprecedented events (IPCC, 2012). An end member viewpoint of this model is Trenberth's (2012) statements that the "answer to the oft-asked question of whether an event is caused by climate

change is that it is the wrong question. All weather events are affected by climate change because the environment in which they occur is warmer and moister than it used to be."

Alternatively, in the second mental model of understanding (the Natural Variability Concept), climate extremes are considered artefacts of natural climate variability, and should not be linked to climate change. Under this conceptualisation, recent record-breaking is indicative of natural climate variability and the ever-greater length of observational record keeping available. The Natural Variability mental model based on a personal perspective of climate change and extreme climate events is a widely held understanding of extreme events, with many people understanding anthropogenic climate change as a future problem that does not currently impacts their locality (Myers et al., 2012). This understanding is readily demonstrated by public comments by the recent Australian Prime Minister Tony Abbott. During the record-breaking spring temperatures in Australia in 2013, Abbott said, "... the thing is that at some point in the future, every record will be broken, but that doesn't prove anything about climate change. It just proves that the longer the period of time, the more possibility of extreme events". Other public comments by Prime Minister Abbott about climate change and variability include that the argument behind human-caused climate change is "absolute crap", that "there doesn't appear to have been any appreciable warming since the late 1990s" and that the link between climate change and extreme Australian climate events is "complete hogwash" (Readfearn, 2014). Former Prime Minister Abbott's understandings of climate change and variability are not unique. Rather, these provide an encapsulation of a widely held view that the longer the period of time under consideration, the greater the possibility of extreme events. Abbott's comments are selected here for exploration as they demonstrate a widespread mental model of understanding and are capable of being highly influential.

These personal understandings of climate change arise from several causes. First, the manifestation of climate change in weather and climate is typically poorly understood (Trenberth, 2011). In general, people have difficulty perceiving changes in the physical climate system above the natural variability of local climate (Myers et al., 2012). Hansen et al., 2012 ask, "[h]ow can a person discern long-term climate change, given the notorious

variability of local weather and climate from day to day and year to year?" For example, local, short-term temperature abnormalities are sufficient to influence individual's beliefs about global warming (Li et al., 2011). Psychological perspectives reveal that the public's understanding of extreme is likely biased by learning that overemphasises the importance of the most recent experiences and events (Hertwig et al., 2004). Furthermore, the public understanding of climate change is affected by various factors in addition to the inherent difficulties in detecting and experiencing change. Complex psychological barriers can lead to systematic misconceptions (Weber and Stern, 2011; Hulme, 2014). Most pertinent for this current discussion, the lexicon of likelihood terms (likely, very likely etc.) used by climate scientists to communicate probabilities can be interpreted by the public as acknowledgement that scientists know less than they actually do (Somerville and Hassol, 2011). In combination, physical, psychological and social factors contribute to the chasm between public and scientific understandings of climate change and extreme climate events.

1.2. Approach of this study

These two outlined conceptualisations, or mental models of understanding, of climate extremes are rarely discussed together. Rather, scientists tend to produce quantitative understandings of extremes through attribution frameworks and present these as scientific answers to the 'extreme -weather blame question' (Hulme, 2014). Quantitative attribution statements are typically presented without engaging directly with the views of the Natural Variability Concept, which occur in parallel. These parallel conceptualisations of climate extremes provide the motivation for this study.

Here, I will explore these two differing conceptualisations of the changing likelihood of extreme events and their meaning for climatic change using the case study of recent extreme spring temperatures observed in Australia. I address the question of whether public perceptions of Australian climate extremes, characterising the Natural Variability Concept, can be reconciled with the statistics of climate change. To address this question, the Natural Variability Concept is explored using the same tools (observational datasets, together with model data provided by CMIP5) that are widely utilised to provide quantitative scientific attribution statements as a key component of the Probabilistic Change Concept and focusing the consecutive spring record-breaking temperatures experienced in Australia in 2013 and 2014. Ultimately, this exploration aims to offer insight into the clearer communication of scientific information around extreme climate events.

2. Statistical characteristics of temperature time series

Record-breaking climate extremes are typically analysed under the assumption that temperatures in a time series are independent and identically distributed (IID) random variables (Bassett, 1992). I first explore this IID assumption in the context of the Australian consecutive spring temperature records of 2013 and 2014. Next I explore whether the probability of these repeated spring record temperatures was influenced by anthropogenic climate change (the Probabilistic Change Concept) or are an artefact of natural climate variability and increased sequence length (the Natural Variability Concept). Following the approach of Bassett (1992), I investigate observed recent record-breaking using several possibilities to describe the characteristics of the temperature sequence, which are described as three Statistical Cases. It should be noted that these Cases are not necessarily mutually exclusive.

Statistical Case 1. Temperatures are independent and identically

distributed (IID)-In this Statistical Case, climatic variables are assumed to be independent and identically distributed, meaning they are stationary (Rahmstorf and Coumou, 2011). In this Case, the probability of a record is not dependent on the underlying distribution, it is simply given by $1/n$, where n is the number of previous data points in the series. A key characteristic of this Case is that new records are less likely later in a sequence of observations, compared with earlier in the sequence (Glick, 1978). Glick (1978) explains that the first observation must necessarily be the "record high". The second observation has equal probability of being smaller or larger than the first, and hence the probability is 50% that a second, independent observation will define a new record high value surpassing the first record. In summary of this Case, the probability of record-breaking decreases rapidly from the start of the series of observations, and hence records should fall less frequently. Furthermore, the temperature time series is stationary, with (i) constant mean, (ii) finite variance and (iii) the auto-correlation only depends on the relative position in the time series.

Statistical Case 2. Temperatures are not identically distributed (I)

-In this statistical Case, the IID assumption fails because the identically distributed assumption does not hold true for the sequence. In climate data, we can attribute nonstationarity of a variable time series to one of two principal causes, either a shifting mean value, and/or a changing shape of the probability distribution with time (Rahmstorf and Coumou, 2011). Recent observational studies highlight that for heat records, in particular, the assumption of stationarity fails and that the observed number of heat records is significantly higher than that expected in a stationary climate (Rahmstorf and Coumou, 2011). In Australia, for example, observational data indicates that new lower temperature records outnumber high temperature records in the early part of the observed period, but that high temperature records outnumber low temperature records in the modern period (Trewin and Vermont, 2010; Lewis and King, 2015). In this Case, the probability of a new record rises rapidly due to the increasing temperature trend, which must be a genuine feature of climate (Bassett, 1992).

Statistical Case 3. Temperatures are not independent (ID)-In this statistical Case, the IID assumption fails because the assumption of independence does not hold true. In this Case, successive temperatures in the sequence may be correlated. This can be understood in a climate context by a variety of physical mechanisms that could plausibly influence year-to-year changes in climate (Bassett, 1992). For example, mechanisms that would cause auto-correlated variables include thermal feedbacks between the ocean and atmosphere, and sunspot or volcanic activity. These climatic mechanisms do not necessarily imply a change in long-term mean climate. In this first example, oceans dissipate heat slowly warm years are more likely one followed again by warm years. In this Case, the probability of a new record depends not only on the current record value, but also on when that record was set. The probability of a new record is higher if the previous record was recently set, than if it was broken in the distant past due to auto-correlation.

3. Exploring record-breaking in observations and models

I now focus on exploring the recently observed repeated record-breaking spring temperatures in Australia in 2013 and 2014 using these Statistical Cases. Spring temperatures are explored in detail because of both the recently observed records occurring during this season in Australia and the explicit public discussion of these records. However, additional seasonal analyses are provided in the Supplementary Material and these show statistical characteristics consistent with spring temperatures. Furthermore, this

analysis strictly focuses on the probability of record-breaking extremes, although further insights could be obtained from investigating the relative of news records using extreme-value approaches in future analysis.

The spring example is investigated using several available datasets. First, the observed temperature time series is examined following the approach of Gallant and Lewis [submitted] using spring Tmean values calculated from the Australian Water Availability Project (AWAP) gridded climate dataset (Jones et al., 2009). The characteristics of the observed Australian September–November (SON) Tmean time series are explored further using CMIP5 detection and attribution experiments. Data were analysed from two standard CMIP5 experiments in order to assess the influence of climate change on record-breaking. Record-breaking is evaluated in the CMIP5 historical experiment, which simulates the climate of 1850–2005 with time-evolving forcing imposed (well mixed greenhouse gases, tropospheric aerosols and ozone, volcanic aerosols and solar irradiance). Record-breaking is next assessed in the CMIP5 historicalNat experiment, where only natural climate forcings (volcanic aerosols and solar irradiance) only are imposed. The same ensemble of models is used here as Gallant and Lewis [submitted], providing an ensemble of 9 participating models that capture well observed variability in Australian spring temperatures.

Australian SON Tmean anomalies for the historical and historicalNat experiments, and observations were calculated relative the 1911–1940 climatology. In total, 65 historical realisations and 36 historicalNat realisations were utilised (Table 1). First, model data were regridded onto a 1.5° latitude by 1.5° longitude horizontal grid and a requirement imposed that at least 75 per cent of each grid box was comprised of land surface in order to be included in area-average temperature calculations. It should be emphasised that the model simulations analysed here conclude in the year 2005, while the observational record is investigated through to 2014, and hence are not directly comparable to the historical (natural and anthropogenically forced) experiment.

Statistical Case 1. Temperatures are independent and identically distributed (IID)—First, the probability of record-breaking is assessed. If the temperature sequence is accurately described by this Case and is IID, the probability of record-breaking decreases rapidly from the beginning of observations (Bassett, 1992). In the time series of observed Australian spring temperatures, the rate of record-breaking increases significantly in the later part of the record, with the highest rate of record-breaking occurring in the most recent decades (Fig. 2a). The evolution of the rate of record-breaking throughout the observed sequence is substantially different when detrended data are considered. In this instance, the warming signal through the time series has been removed using a quadratic fit, which is most suitable for Australian mean temperatures post-1910 (Fawcett et al., 2012) (see Fig. 1a). In the

observational time series with the warming signal subtracted, the rate of record-breaking follows what would be qualitatively expected in temperatures that are independent and identically distributed; that is, the probability of record-breaking decreases from the start of series.

There are also substantial differences in the average rate of record-breaking between the variously forced CMIP5 experiments (Fig. 2b), which were explored comprehensively by Gallant and Lewis [submitted]. In the current study, the lowest average rate of record-breaking per decade occurs in the historicalNat experiment, and the highest in the historical experiment. There is a wider range of the rate record-breaking in the observed temperature series, with the highest decadal rate occurring in the period after the historical and historicalNat experiments cease. There is also a lower rate of record-breaking in the historical experiment after the warming signal has been removed, which is consistent with the impact of warming on record-breaking rates in the observed sequence. The differences in the rate of record-breaking through the observed sequence, and the differences between the historical and historicalNat experiments, suggest that Australian spring temperatures are not consistent with *Statistical Case 1* and rather that the temperature are not identically distributed and/or not independent. These possibilities are now examined.

Statistical Case 2. Temperatures are not identically distributed (I)-I now assess the stationarity of the spring temperature time series. If we suppose that the assumption of IID failed because the data are not identically distributed, then the time series is nonstationary. In this case, we can expect the observed number of heat records to be significantly higher than that expected in a stationary climate. The nonstationarity of a time series can be caused by a shifting mean value—a trend in the series—that results in increasing probability of new temperature records through time. In the observational record of Australian spring temperatures, the rate of record-breaking is associated with an increasing trend in the temperature time series approximated as 0.09 K/decade (Fig. 3). For simplicity, the trend is estimated using Sen's Kendall slope non-parametric method (Sen, 1968) and the statistical significance of trends assessed using a t-test at the 5 per cent level. Although a quadratic fit is used to detrend the time series data, a linear assumption is made here as an approximation of the average increase in temperature through the sequence for ready comparison of the various datasets.

The multi-model mean trend in the historical simulation from 1911–2005 is calculated as 0.05 K/decade, while no statistically significant trend was determined for the historicalNat simulation. The trend in both the observations and historical temperature time series is also evident when the mean temperature value is examined for each decade (Fig. 4). The multi-model mean value for the historicalNat simulations does not change appreciably

Table 1
List of CMIP5 climate models and ensembles used. Further details of individual models can be found from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) (modified from Lewis and Karoly, 2014).

Model	historical	historicalNat
ACCESS1-3	r1i1p1, r2i1p1, r3i1p1	r1i1p1, r2i1p1, r3i1p1
bcc-csm1-1	r1i1p1, r2i1p1, r3i1p1	r1i1p1
CCSM4	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1	r1i1p1, r2i1p1, r4i1p1, r6i1p1
CNRM-CM5	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1, r7i1p1, r8i1p1, r9i1p1, r10i1p1	r1i1p1, r2i1p1, r4i1p1, r5i1p1, r8i1p1
CSIRO-Mk3-6-0	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1, r7i1p1, r8i1p1, r9i1p1, r10i1p1	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1
FGOALS-g2	r1i1p1 r2i1p1 r3i1p1	r1i1p1, r2i1p1, r3i1p1
GISS-E2-R	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1, r1i1p2, r2i1p2, r3i1p2, r4i1p2, r5i1p2, r6i1p2, r1i1p3, r2i1p3, r3i1p3, r4i1p3, r5i1p3, r6i1p3	r1i1p1, r1i1p3, r2i1p1, r2i1p3, r3i1p1, r3i1p3, r4i1p1, r4i1p3, r5i1p1
HadGEM2-ES	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1	r1i1p1, r2i1p1, r3i1p1, r4i1p1
IPSL-CM5A-LR	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1	r1i1p1, r2i1p1, r3i1p1
NorESM1-M	r1i1p1, r2i1p1, r3i1p1	r1i1p1

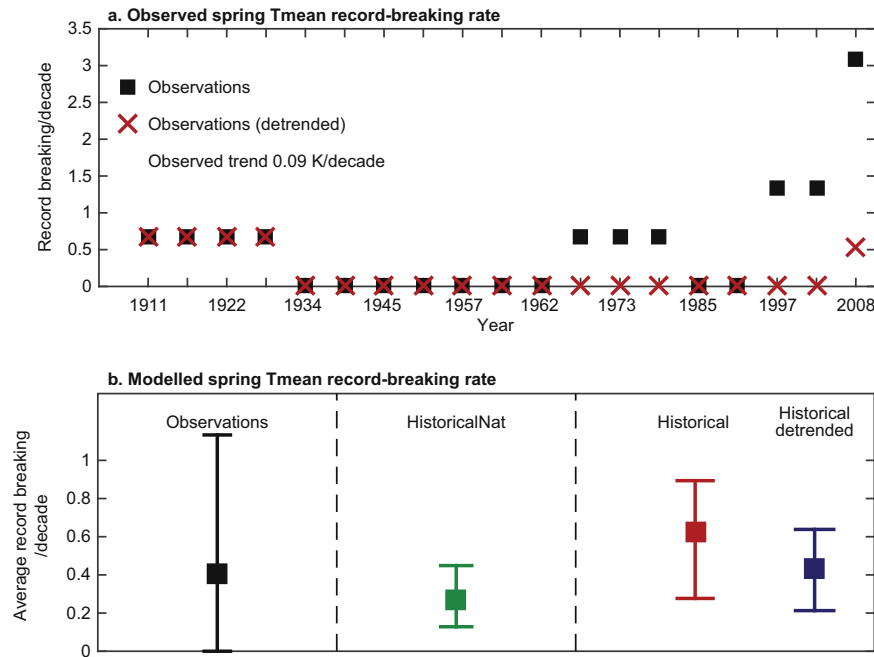


Fig. 2. (a) Average rate of record-breaking of observed mean Australian spring temperature anomalies (K) per decade and for the detrended observed mean Australian spring temperatures, where the warming signal has been removed using a quadratic fit (Fawcett et al., 2012). (b) Comparison of the average decadal rate of record-breaking for observations (black), the historicalNat (green) and historical (blue) simulations. Record breaking for nonlinearly detrended historical time series is also shown. Squares represent the average record-breaking rate for all decades in the observations and the multi-model average decadal rate for the historical and historicalNat simulations, and the ranges indicate the 10th and 90th percentile values.

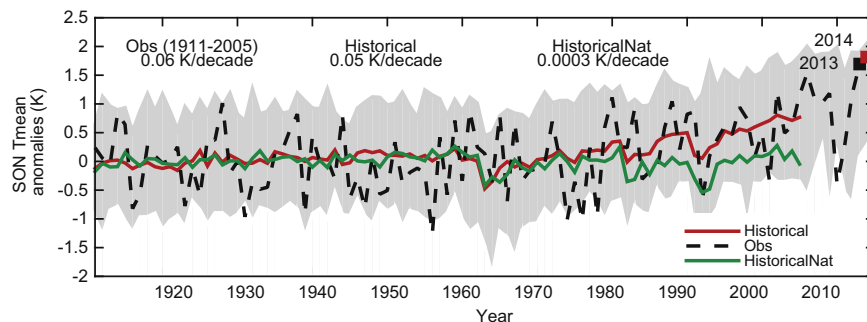


Fig. 3. Australian SON Tmean anomalies (K, relative to 1911–1940) for observations (1911–2014, dashed black), historicalNat (1911–2005, green) and the historical (1911–2005, red) multi-model mean. The grey plume indicates the 5th–95th simulated range of spring temperatures across the historical model ensemble members. The trends are shown, as calculated using Sen's Kendall slope non-parametric method (Sen, 1968). The historicalNat trend is not statistically significant at the 5 per cent level.

throughout the sequence for successive decades. However, the mean value increases throughout the observed time series and through the historical time series, as calculated using the multi-model ensemble mean. The trend in the observed Australian spring temperature and those simulated in the historical experiment appear to invalidate the assumptions of *Statistical Case 1* and indicate that the temperatures are not identically distributed. These time series are nonstationary (with varying mean value) and the probability of new temperature records increases, rather than decreases, through the sequence.

Statistical Case 3. Temperatures are not independent (ID)—I now assess the correlation of successive temperatures in the observed time series. If the assumption of IDD fails because the assumption of independence does not hold, the sequence is auto-correlated, which will result in an increase the probability of a new record if a record was recently set. The auto-correlation of the detrended observed temperature time series is considered for various lagged values (Fig. 5). When monthly temperatures are considered, there is no statistically significant auto-correlation beyond lag-6. Inter-

annual variability was also investigated for serial correlation, and when average observed spring temperatures are examined there is no statistically significant auto-correlation even for lag-1. This is also reflected in the multi-model mean detrended historical and historicalNat time series. Significant auto-correlation is persistent for a great number of lags when observed and simulated data are considered that has an underlying trend of increasing temperatures. In this case, positive correlations make future record breaking more likely if a record was recently broken. However, this is related to the determined trend and hence the assumption of independence holds for the spring records under consideration here.

4. Reconciling increased rates of record-breaking with popular perceptions

In summary, examination of observed Australian spring temperatures over the period of 1911–2014 using the defined

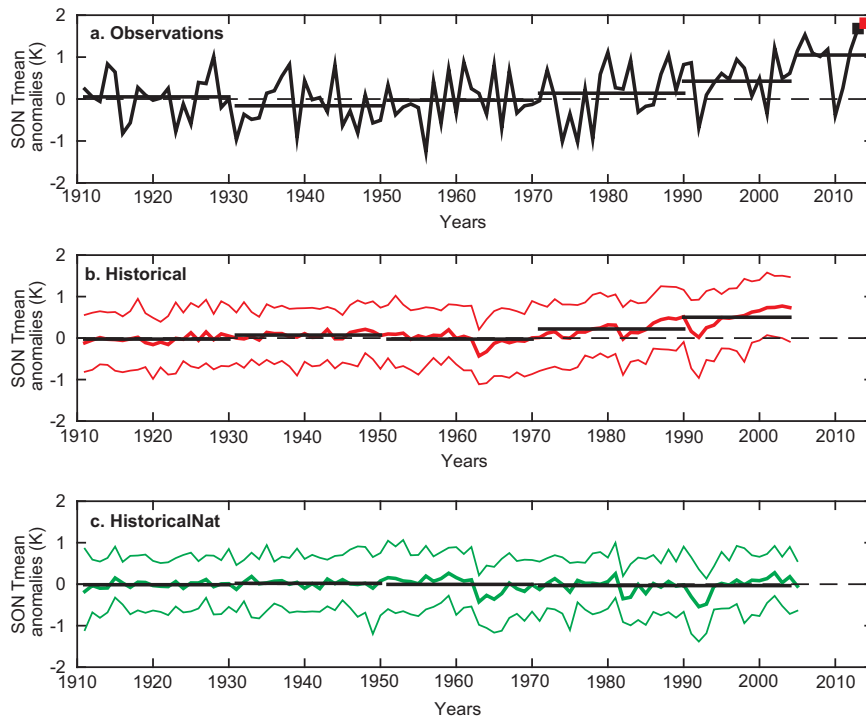


Fig. 4. Mean Australian spring temperature anomalies (K, relative to 1911–1940) for observations (a, black), the historical multi-model mean (b, red) and historicalNat multi-model mean (c, green). The ensemble 10th and 90th percentile ranges are shown for the historical and historicalNat experiments. The horizontal black lines indicate the mean temperature over that period.

Statistical Cases reveals several key points:

- The probability of record-breaking increases, rather than decreases, in the later part of the observed sequence of Australian spring temperatures.
 - Hence the observed sequence of Australian spring temperatures is not identically distributed *and* independent.
- The observed sequence of Australian spring temperatures has a statistically significant trend estimated at 0.09 K/decade on average over the time series.
 - Hence the observed sequence of Australian spring temperatures is not considered identically distributed.
- The observed sequence of Australian spring temperatures is not significantly positively correlated with values in previous years.
 - Hence the observed sequence of Australian spring temperatures is considered independent.

A parallel analysis of CMIP5 simulated Australian spring temperatures over the period of 1911–2005 identifies significant differences in the characteristics of the temperature time series in the natural-only forced simulations (historicalNat) and the simulations including natural and anthropogenic simulations (historical):

- The probability of record-breaking is greater in the historical experiment than in the historicalNat.
- The sequence of Australian spring temperatures in the historical multi-model ensemble has a statistically significant trend of 0.06 K/decade. There is no statistically significant trend in the historicalNat simulation.

Overall, record-breaking temperatures are more likely in later years in the observations and in the historical simulation, compared with the historicalNat. Furthermore, this increasing probability of record-breaking is likely largely due to an increasing temperature trend that differentiates the experiments.

Can these statistical characteristics of the observed physical

climate system be reconciled with the Natural Variability Concept that is formed around personal understandings of climate change and extreme climate events? I now consider particular aspects of this widely held personal conceptualisation of extremes, as demonstrated by specific statements made by Prime Tony Abbott. On October 30 2013, Prime Minister Abbott stated, “... the thing is that at some point in the future, every record will be broken, but that doesn’t prove anything about climate change. It just proves that the longer the period of time, the more possibility of extreme events”. A statistical interpretation of this statement is that the sequence of observed temperatures fails to satisfy the assumption of being identically distributed and independent. If the assumption of IID were the case, then the “possibility” of an extreme would be less likely in 2013, and in 2014, than in the early part of the observed sequence. The assumptions of *Statistical Case 1* can fail (and hence the probability of record-breaking increases later in the sequence) because temperatures are not identically distributed and/or because temperatures are not independent.

Under *Statistical Case 2*, the sequence of temperatures is non-stationary and exhibits a trend in temperatures and/or a changing shape of the probability distribution with time (Rahmstorf and Coumou, 2011). In this case, the rate of record-breaking increases later in the sequence of temperatures and “the longer the period of time, the more possibility of extreme events.” As this necessarily requires the time series to be nonstationary, I also explore the consistency of this with other aspects of the Natural Variability Concept. In October 2009 Prime Minister Abbott stated that the argument behind human-caused climate change was “absolute crap.” Later in December 2009, Abbott stated that “there doesn’t appear to have been any appreciable warming since the late 1990s” and in July 2007 that “there may even have been a slight decrease in global temperatures (the measurement data differs on this point) over the past decade”. That is, in these statements Abbott rejected that an increasing trend in temperatures has occurred in the sequence of observations in recent years. Hence, these particular statements by Prime Minister Abbott are in

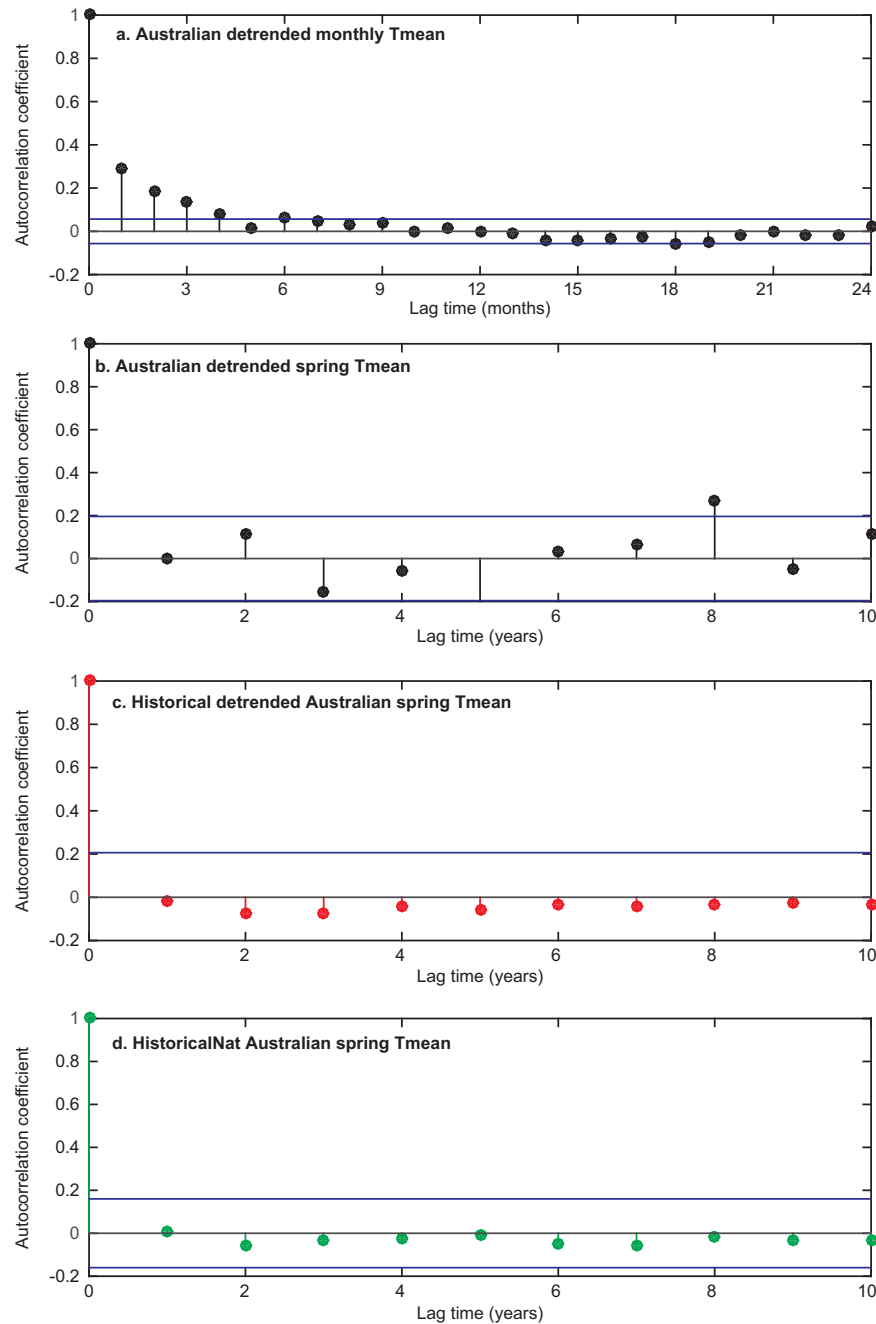


Fig. 5. Auto correlations of (a) observed monthly mean Australian spring temperature anomalies for lags 0–24 months, and spring Tmean anomalies for observations (b), multi-model mean for historical (c) and historicalNat (d) for lags 0–10 years. All data are nonlinearly detrended.

apparent contradiction in terms of explaining the increase in record-breaking in the later part of the observational record. If climate change is “absolute crap” and “there doesn’t appear to have been any appreciable warming” then the probability of recent record breaking should be *lower* with an increasing length of temperature time series.

There are several physical climate mechanisms by which it remains possible to maintain the Natural Variability Concept and to acknowledge recent increases have occurred in the rate of record-breaking. Prime Minister Abbott concluded in October 2013 that the link between extremes (in this case bushfires) and climate change was “complete hogwash” and that “I’m not one of those people who runs around and says every time there’s a fire or a flood, that proves climate change is getting worse. Australia has had fires and floods since the beginning of time. We’ve had much

bigger floods and fires than the ones we’ve recently experienced. You can hardly say they were the result of anthropic [sic] global warming.” Hence, to hold an internally consistent viewpoint within the Natural Variability Concept, the increase in the rate of record-breaking requires either a change in the shape of the temperature probability distribution with time that can be attributed to natural climate mechanisms, or requires that record-breaking rates have increased because temperatures are auto-correlated due to natural physical climate mechanisms such as thermal feedbacks between the ocean and atmosphere, sunspots and volcanic activity (Bassett, 1992).

These possible mechanisms can also be explored using the tools that inform the Probabilistic Change Concept of understanding climate change and extremes and are used to make quantitative attribution statements. First, I investigate the

possibility that record-breaking rates for Australian spring temperatures have increased because of nonstationarity in the sequence derived from a change in the shape of the temperature probability distribution. There are several possibilities for changes in the shape of distributions, including an increase in variability and a change in symmetry (IPCC, 2012). An increase in variability would result in increase in the frequency of record-breaking for both hot and cold extremes, which has not been observed. Australian temperatures have not been observed as becoming more variable generally. Rather, in observations of Australian temperatures, low temperature records outnumber high temperature records in the early part of the period, and high temperature records outnumber low temperature records in the later part of the period (Trewin and Vermont, 2010). Globally, observed monthly heat records occurring more than three times more frequently than expected in a stationary climate (Rahmstorf and Coumou, 2011). Hence, any change in the shape of the probability distribution of temperature that led to increased record-breaking rate would require a complex change in symmetry whereby the hot tail of the distribution is solely affected and is driven by natural climatic processes. Alternatively, the increased rate of record-breaking in observed temperatures could be auto-correlated and hence the probability of extreme temperatures relates to recent extreme temperatures. However, this is not support by analysis of the observational dataset (Fig. 5).

Two possibilities remain. First, the Natural Variability Concept can be both internally consistent and potentially consistent with some aspects of the recent observed time series if we acknowledge that the probability hot Australian spring temperature record-breaking has increased in recent decades. However, this would again require a complex change in the hot tail of the temperature distribution that is driven (at least predominantly) by natural climatic processes. Second, the Natural Variability Concept is neither internally consistent, nor consistent with the observed time series. The analysis conducted here supports this second statement with several lines of evidence that demonstrate that the observed sequence of Australian average spring temperatures demonstrates a statistically significant trend of increasing temperatures (average 0.09 K increase per decade) and an increase in the rate of record-breaking in the later part of the sequence (Fig. 2).

What caused this observed trend? Comparison of observed Australian spring temperatures over the period of analysis shows that the observed warming is best captured by CMIP5 experiments that include both natural and anthropogenic (Fig. 4). The rate of record breaking (Fig. 2) and trend (Fig. 3) determined for the observed temperature sequence is consistent with that simulated for the historical, but inconsistent with simulations that incorporated only natural climates forcings. The finding of increased probability of hot records and a warming trend has previously been made and attributed to anthropogenic forcings in a formal sense. For Australia, Karoly and Braganza (2005) found that a significant contribution to the observed warming during the second half of the twentieth century resulted from increasing atmospheric greenhouse gases. In terms of event attribution, the record spring temperatures observed Australia-wide in 2013, there is a 50-fold increase in risk of hot spring temperatures in Australia that can be attributed to anthropogenic forcings (Lewis and Karoly, 2014). Further, a detailed analysis of Australian spring temperatures using observations and climate model simulations shows that conditions similar to those in 2013 and 2014 have occurred previously with the regional and large-scale inter-annual processes associated with these extreme temperatures observed in the past (Gallant and Lewis, submitted). However, without an anthropogenically-driven warming trend, the 2013 and 2014 anomalies were unlikely to have been record-breaking, and can be attributed in this sense to background warming.

5. Insights for communicating climate extremes

5.1. Summary of findings

Extremes of weather and climate have been the focus of previous research, which has investigated the occurrence of extreme climate events and their link to climate change from either primarily a scientific (IPCC, 2012) or a social scientific perspective (Weber and Stern, 2011; Myers et al., 2012). The first category of studies have provided quantitative estimates of the influence of anthropogenic forcings on mean climate and extreme climate events as answers to the ‘extreme -weather blame question’ (Hulme, 2014). Here, I have described this as a ‘Probabilistic Change Concept’ of broadly understanding climate change and extremes, which centres on formalised attribution approaches that quantify the change in likelihood of extreme temperatures that can be linked to anthropogenic forcings, such as greenhouse gases (Lewis and Karoly, 2013; 2014).

Public comments about extreme temperatures in Australia over the period of 2012–2014 provide an example of an alternative understanding of climate change and extreme climate events, which I term the ‘Natural Variability Concept.’ In this second model of understanding, climate extremes are typically considered artefacts of natural climate variability, and should not be linked to climate change. Under this Concept, recent record-breaking is indicative only of the ever-greater length of observational record keeping available. The two models co-exist in parallel, with scientific attribution statements produced as part of the Probabilistic Change Concept, without engaging with the views central to the Natural Variability Concept. In this study, the Natural Variability Concept was explored with the model and observational tools used to inform scientific studies as part of the Probabilistic Change Concept. Specifically, I have examined one example of an understanding of climate change and extremes through this lens, using the case study of consecutive Australia-wide spring record-breaking temperatures of 2013 and 2014 (Gallant and Lewis, submitted), and the influential public statements made by then Australian Prime Minister Tony Abbott, including “... the thing is that at some point in the future, every record will be broken, but that doesn't prove anything about climate change. It just proves that the longer the period of time, the more possibility of extreme events”.

Conversely, analysis in this study of recent record-breaking spring temperatures in Australia demonstrates that we cannot reconcile the Natural Variability Concept with evidence of the physical climate system, provided by AWAP observations (Jones et al., 2009) and CMIP5 climate models (Taylor et al., 2012). That is, the probability of record-breaking increases later in the observed sequence of temperatures, due to an anthropogenic-warming trend. In addition, it is difficult to argue with these datasets that the Natural Variability Concept can be internally consistent; if climate change is “absolute crap”, then statistically we should expect fewer, rather than more, records to be broken later in the sequence of observed temperatures. It should however, be noted, that I have taken a subset of representative quotes by Prime Minister Abbott to constitute a simplified mental model of climate change, and Mr Abbott has provided many opinions of the physical science behind climate change in addition to the small selection of quotes used here. In addition, I have focused on the probability of record-breaking in the observational temperature record and the impact of the anthropogenic warming trend on the rate of record-breaking. Natural variability remains an important factor in the climate system, its variability and extreme climate events (Trenberth, 2011), and hence we can expect records to be still broken through time even in a climate with natural forcings only as the sequence length increases (Trenberth, 2012). Nonetheless, the rate of record-breaking should decrease in a stationary climate.

5.2. Implications for communicating climate extremes

The statistical basis used for the analysis of observed and modelled Australian spring temperatures conducted here is not new. However, the test of differing mental models of understanding extremes represents a novel approach of confronting personal experiential-based understandings of climate extremes with observation and model-derived statistics typically used exclusively in the quantitative-based Probabilistic Change Concept. This approach provides direct refutation of the validity of the Natural Variability Concept. In addition, the use of these commonly employed statistical properties of time series to explore these two Concepts provides further insight into the communication of the scientific basis of extreme climate events.

Extreme climate events have been described as “moments of teachable science” because of the opportunity they may present for providing experiential evidence of climate change (Kerr, 2013). The scientific validity of such moments have been discussed previously (Hulme, 2014), with suggestions made that these may represent a risky strategy for scientists given the limited evidence for significant anthropogenic influences in some extremes (Kerr, 2013). The broader public value of these moments has been explored by Myers et al. (2012), whose study questioned whether observable climate impacts create opportunities for people to develop greater certainty around global warming, or whether perceptions are primarily shaped by prior belief. This study determined that extremes do create teachable moments, albeit only in some circumstances. That is, both cognitive processes took place in survey respondents, with experiential learning (through perceptions) occurring amongst people who are poorly engaged with climate change issues, and the reinforcement of beliefs (or motivated reasoning) occurring in those already highly engaged in such issues. This American focused study noted that 75% of adults have low levels of engagement and are hence more open to experiential learning based on personal perceptions.

The current paradigm for the communication of the scientific analysis of extremes (the Probabilistic Change Concept described here) essentially has several aims. It aims to affirm the beliefs of those positively engage with climate science information, to dispute the beliefs of those highly engaged with, but sceptical of, climate science information and to reinforce possible experiential learning in those poorly engaged with said issues. However, the value of extremes as teaching moments for those open to experiential learning (such as Myers et al.'s (2012) majority of poorly engaged adults) is intrinsically limited if perceived extremes are viewed by some members of the public as purely artefacts of natural climate variability. In this case, direct experience may simple reinforce scientifically spurious beliefs.

Hence this current study demonstrates that this fundamental misconception must be addressed before such moments can become “teachable”. This supports the ideas that the simple occurrence and scientific analysis of extremes is not sufficient, but requires trusted communication to turn the observable impacts of climate change into learning opportunities (Myers et al., 2012). In this present case study focusing on Australia, further quantitative attribution statements will not explain such extremes to the public more fully than information already available. This point should be emphasised given that commonly used scientific terms with precise meanings, such as ‘likely’, ‘very likely’ and ‘virtually certain’, can be misinterpreted by the public as indicating that scientists know less than they actually do (Somerville and Hassol, 2011). Directly addressing the misplaced foundational beliefs of the Natural Variability Concept, however, may explain extremes more clearly to those open to direct personal experiences. Such findings do not suggest that existing or future attribution studies are of limited scientific usage, but rather that these are not in themselves

sufficient to communicate with a suite of mental models of climate extremes held by a range of people.

As a caveat, I note that the two Concepts defined here are simplifications of complex suites of mental models and do not encompass the range and diversity of understandings about climate change and extremes. An individual's personal view of climate change is shaped by a variety of physical, psychological and social factors (Weber and Stern, 2011). This study has attempted to confront the perception-based views the Natural Variability Concept with the analytical tools that are used as part of the scientific-based Probabilistic Change Concept, rather than allowing both Concepts to remain separate and disengaged. This does not, however, suggest that understandings developed under the Natural Variability Concept can be readily changed by simply viewing this conceptualisation as a deficit of knowledge. For example, former Prime Minister Abbott said in July 2009 that he was “...hugely unconvinced by the so-called settled science on climate change”. Hence, this mismatch between an individual's perceptions of the climate change and extremes, and the physical evidence of the observed and modelled climate system, is undoubtedly complex and cannot be resolved simply with a singular approach.

Acknowledgements

This research was supported by the ARC Centre of Excellence for Climate System Science (grant CE 110001028), an ARC DECRA (DE160100092) and the NCI National Facility. We thank the Bureau of Meteorology, the Bureau of Rural Sciences, and CSIRO for providing AWAP data. We acknowledge the WCRP's Working Group on Coupled Modelling, which is responsible for CMIP. The U.S. Department of Energy's PCMDI provides CMIP5 coordinating support.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at <http://dx.doi.org/10.1016/j.wace.2015.11.008>.

References

- Bassett Jr, G.W., 1992. Breaking recent global temperature records. *Clim. Chang* 21 (3), 303–315.
- Bureau of Meteorology, 2012. Exceptional Heavy Rainfall Across Southeast Australia. Special Climate Statement 39.
- Bureau of Meteorology, 2013. Extreme Heat in January 2013. Special Climate Statement 43, 1–19.
- Bureau of Meteorology, 2014. The Report of Annual Climate Report 2013, 1–19.
- Fawcett, R.J.B., B.C. Trewin, K. Braganza, R.J. Smalley, B. Jovanovic, and D.A. Jones (2012), *On the sensitivity of Australian temperature trends and variability to analysis methods and observation networks-CAWCR Technical Report No. 050*, edited by K. A. Day.
- Glick, N., 1978. Breaking records and breaking boards. *Am. Math. Mon.*, 2–26.
- Hansen, J., Sato, M., Ruedy, R., 2012. Perception of climate change. *Proc. Natl. Acad. Sci.* 109 (37), E2415–E2423. <http://dx.doi.org/10.1073/pnas.1205276109>.
- Hertwig, R., G. Barron, E.U. Weber, and I. Erev (2004), Decisions from experience and the effect of rare events in risky choice, *Psychol. Sci.* <http://dx.doi.org/10.1111/j.0956-7976.2004.00715.x>.
- Hulme, M. (2014), Attributing weather extremes to “climate change”: A review, *Prog. Phys. Geogr.* <http://dx.doi.org/10.1177/0309133314538644>.
- IPCC, 2012. Summary for Policymakers. In: Field, C.B., et al. (Eds.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, pp. 1–19.
- Jones, D.A., Wang, W., Fawcett, R., 2009. High-quality spatial climate data-sets for Australia. *Aust. Meteorol. Ocean. J.* 58 (4), 233.
- Karoly, D.J., Braganza, K., 2005. A new approach to detection of anthropogenic temperature changes in the Australian region. *Meteorol. Atmos. Phys.* 89 (1–4), 57–67. <http://dx.doi.org/10.1007/s00703-005-0121-3>.
- Kerr, R., 2013. In the hot seat. *Science* 342, 688–689.
- Lewis, S.C., and A.D. King (2015), Dramatically increased rate of observed hot

- record-breaking in recent Australian temperatures. *Geophys. Res. Lett.*, <http://dx.doi.org/10.1002/2015GL065793>
- Lewis, S.C., and D.J. Karoly (2013), Anthropogenic contributions to Australia's record summer temperatures of 2013. *Geophys. Res. Lett.* <http://dx.doi.org/10.1002/grl.50673>.
- Lewis, S.C., Karoly, D.J., 2014. The Role of Anthropogenic Forcing in the Record 2013 Australia-Wide Annual and Spring Temperatures [in "Explaining Extremes of 2013 from a Climate Perspective"]. *Bull. Am. Meteorol. Soc.* 95 (9), S31–S34.
- Li, Y., E.J. Johnson, and L. Zaval (2011), Local warming daily temperature change influences belief in global warming. *Psychol. Sci.*, <http://dx.doi.org/10.1177/0956797611400913>
- Myers, T.A., E.W. Maibach, C. Roser-Renouf, K. Akerlof, and A.A. Leiserowitz (2012), The relationship between personal experience and belief in the reality of global warming. *Nature Clim. Change* <http://dx.doi.org/10.1038/NCLIMATE1754>.
- Rahmstorf, S., Coumou, D., 2011. Increase of extreme events in a warming world. *Proc. Natl. Acad. Sci.* 108 (44), 17905–17909. <http://dx.doi.org/10.1073/pnas.1101766108>.
- Readfearn, G., 2014. What does Australian prime minister TonyAbbott really think about climate change? *The Guard.* 16 (June), 1–4.
- Sen, P.K., 1968. Estimates of the regression coefficient based on kendall's tau. *J. Am. Stat. Assoc.* 63 (324), 1379–1389.
- Somerville, R., and S.J. Hassol (2011), Communicating the science of climate change, *Phys. Today.*
- Stott, P.A., Stone, D.A., Allen, M.R., 2004. Human contribution to the European heatwave of 2003. *Nature* 432 (7017), 610–614. <http://dx.doi.org/10.1038/nature03089>.
- Stott, P.A., N.P. Gillett, G.C. Hegerl, D.J. Karoly, D.A. Stone, X. Zhang, and F. Zwiers (2010), Detection and attribution of climate change: a regional perspective, *WIREs Clim. Change* <http://dx.doi.org/10.1002/wcc.34>.
- Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* 93 (4), 485. <http://dx.doi.org/10.1175/BAMS-D-11-00094.1>.
- Trenberth, K.E., 2011. Attribution of climate variations and trends to human influences and natural variability. *WIREs Clim. Change* 2 (6), 925–930. <http://dx.doi.org/10.1002/wcc.142>.
- Trenberth, K.E., 2012. Framing the way to relate climate extremes to climate change. *Clim. Chang* 115 (2), 283–290. <http://dx.doi.org/10.1007/s10584-012-0441-5>.
- Trewin, B. (2012), A daily homogenized temperature data set for Australia, *Int. J. Climatol.* <http://dx.doi.org/10.1002/joc.3530>.
- Trewin, B., Vermont, H., 2010. Changes in the frequency of record temperatures in Australia, 1957–2009. *Aust. Meteorol. Ocean. J.* 60, 113–119.
- Weber, E.U., Stern, P.C., 2011. Public understanding of climate change in the United States. *Am. Psychol.* 66 (4), 315–328. <http://dx.doi.org/10.1037/a0023253>.