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Quantitative estimates of anthropogenic contributions to extreme national and State monthly, seasonal and annual average temperatures for Australia

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Extreme event attribution studies can provide valuable information for assessing the risks and costs of future climate change. However, the utility of such information for adaptive decision-making depends on reliable information being provided in a timely manner. Here, we present pre-computed Fraction of Attributable Risk (FAR) tables for various Australian temperature records, as an estimate of the change in likelihood of exceeding defined temperature thresholds that can be attributed to anthropogenic influences, such as long-lived greenhouse gases. Australian and State-based area-average mean, maximum and minimum temperature anomalies are considered. The likelihoods of extreme annual, seasonal and monthly temperatures occurring in a suite of Coupled Model Intercomparison Project phase 5 (CMIP5) simulations incorporating only natural forcings (solar and volcanic aerosols) are compared with the likelihoods from simulations including both natural and anthropogenic (greenhouse gases, aerosols and ozone) forcings. This approach provides a simple tool for the timely assessment of the contribution of anthropogenic factors to record-setting temperatures for different Australian regions. In the case when an existing national or State-wide temperature record is exceeded, the FAR 'look-up' data tables presented here provide an immediate source of information about the change in risk of such an event occurring that can be attributed to anthropogenic influences. In all regions, the FAR values demonstrate that the likelihood of warmer conditions on various timescales has increased due to anthropogenic forcings. The FAR values presented here will be most useful if updated to reflect future changes in anthropogenic forcings and using new record-setting temperature anomalies.

Introduction

Recent extreme climate events occurring in Australia have been investigated in the context of their underlying influences. Specifically, the record hot Australian summer of 2012–13 (Lewis and Karoly 2013a) and the heavy rainfall over eastern Australia in 2012 (King et al. 2013; Christidis et al. 2013b) have been examined in the terms of both anthropogenic and natural forcings, and the relative contribution of anthropogenic factors to the likelihood of these extremes occurring has then been estimated in a quantitative manner. Following from international studies that attempt to attribute extreme events to specific causes (e.g. Stott et al. 2004), these recent Australian-focused studies utilise a similar Fraction of Attributable Risk (FAR) approach (Stone and Allen 2005a; Pall et al. 2011), whereby the FAR value provides a quantification of the fraction of risk of a particular threshold being exceeded (i.e. an event) that can be attributed to a particular influence.

The calculation of FAR values for observed extreme events provides a valuable context for understanding event-specific case studies and can ultimately provide information applicable for developing adaptive strategies

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(Stott et al. 2012). However, the utility of such information for informing adaptive decision-making depends on reliable information being provided in a timely manner. While some comprehensive event-specific attribution studies have taken several years to complete (Pall et al. 2011), other studies have been able to provide general information on regional climate extremes prior to an event occurring by pre-computing a set of FAR values (Christidis et al. 2012). This pre-calculation involved a global anthropogenic fingerprint analysis, providing a global model response optimised by observations from which regionally relevant information was extracted. By adopting this approach of calculating in advance the change in likelihood of temperature thresholds being exceeded, for a range of defined thresholds, a real-time assessment of anthropogenic contributions to newly set temperature records was achievable. Under this framework, event attribution can provide a useful tool for helping to understand and manage the risks associated with climate change (Stott et al. 2012).

In this current study, we present pre-computed FAR tables for various existing Australian temperature records to the end of 2013, as an estimate of the change in likelihood of exceeding defined seasonal and monthly temperature thresholds that can be attributed to anthropogenic influences. In contrast to the optimised approach of Christidis et al. (2012), we utilise a suite of Coupled Model Intercomparison Project phase 5 (CMIP5) detection and attribution experiments (Taylor et al. 2012) and extend the approach of Lewis and Karoly (2013a) to consider anthropogenic influences on extreme annual, seasonal and monthly average mean (Tmean), maximum (Tmax) and minimum (Tmin) temperatures for various Australian regions. Focusing on area-average temperatures for Australia, as well as for the largest Australian State regions, we calculate FAR values based on thresholds (ΔT) defined by the highest recorded temperature anomaly in the observational record to the end of 2013. The major objective of this study is to present pre-computed FAR 'look-up tables' for use following newly set temperature records, which will serve as an immediate source of information about the change in likelihood of such Australian and State-wide temperature records being exceeded that can be attributed to anthropogenic forcings compared with natural climate variability alone.

Data and methods

This study extends the approach adopted by Lewis and Karoly (2013a), which examined changes in Australian area-average mean summer temperatures in observational and model sources. Here, we investigate Australian area-average (AUS) and State-wide area-average temperatures for Victoria (VIC), New South Wales (NSW), Queensland (QLD), the Northern Territory (NT), South Australia (SA) and Western Australia (WA). The Australian Capital Territory is included within the defined NSW region, while Tasmania is excluded from this analysis as it is poorly resolved by most global climate models. We investigate annual (January–December, ANN), seasonal (December–February, DJF; March–May, MAM; June–August, JJA; September–November, SON) and monthly average maximum, minimum and mean temperatures for each defined region. First, model-based data were regridded onto a common 1.5° latitude by 1.5° longitude horizontal grid and Australian and State region area-averages calculated using standard regions defined by the Bureau of Meteorology (henceforth, the Bureau), in order that temperatures derived from modelled and observational sources were comparable. In addition, model data also required that at least 75 per cent of each grid box was comprised of land surface in order to be included in area-average temperatures.

Observational data

We use observed Tmean, Tmax and Tmin values from the high-quality Australian Climate Observations Reference Network–Surface Air Temperature (ACORN-SAT) dataset, covering the period of 1910–2013 (Trewin 2013). ACORN-SAT is a homogenised temperature dataset derived from 112 stations across Australian and extending from 1910 to the present, with 60 locations having data for the full period and lower data coverage in the early part of the record. Overall, the ACORN-SAT dataset provides comprehensive coverage for Australia and is suitable for the analyses of long-term changes in mean temperatures, as well as changes in temperature extremes. Although there are other climate data products available for Australia, such as the Australian Water Availability Project (AWAP) analyses (Jones et al. 2009), we chose to use the ACORN-SAT data because of its rigorous quality control that is applied operationally to new observed data. In addition, AWAP data are best suited for high-resolution spatial analysis, rather than targeting broad-scale temporal changes, as these data have not been subject to temporal homogeneity adjustments (Fawcett et al. 2012). Nonetheless, there are generally only small differences between the two datasets in the later half of the record, although the AWAP analyses are generally slightly warmer in the earliest years of the observed record.

We use ACORN-SAT spatially averaged temperature data (Fawcett et al. 2012) provided by the Bureau (www.bom.gov.au/climate/change/acorn-sat/) and calculate observed Australian and State temperature anomalies relative to a 1911–1940 climatology. We use a standard 30-year period for calculating anomalies, selecting years 1911–1940 to demonstrate the change in temperatures over Australia in the observational record and to provide a common baseline with the model data (Lewis and Karoly 2013a).

Fig.1. Probability density functions for Australian and State annual Tmean anomalies (relative to 1911–1940) for observations (dashed black) and historical simulations (red) over common years 1911–2005, estimated using a kernel density function. Where *h=0*, two-sided Kolmogorov-Smirnov tests indicate the distributions are statistically indistinguishable and could have been derived from the same data populations. In this case, FAR values are then calculated. In instances where *h=1*, the distributions are statistically different between modelled and observed, and hence FAR values are not reported.

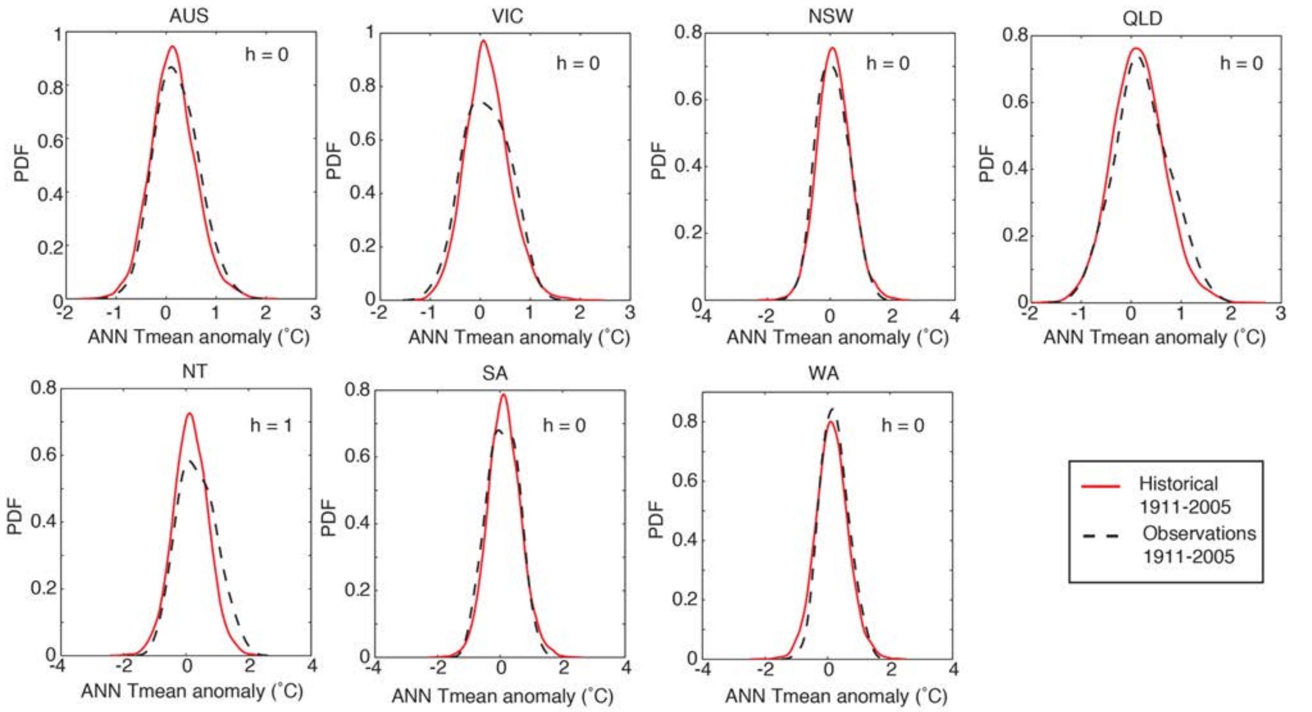
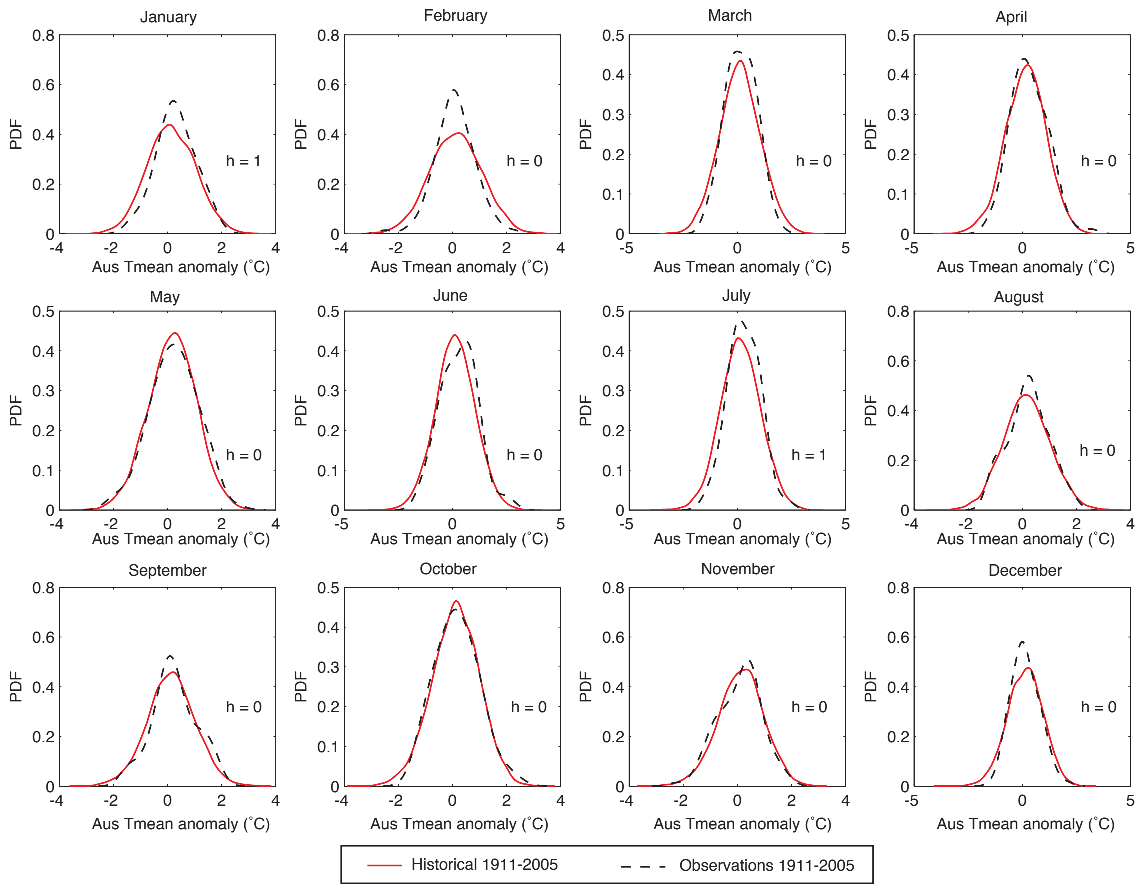


Fig. 2. As for Figure 1, but showing Tmean observed and historical distributions for Australia, for seasonal and monthly average temperatures.



Model data

We also utilise a suite of detection and attribution experiments provided for CMIP5 (Taylor et al. 2012). International modelling groups have contributed various standard model experiments to CMIP5 (Table 1) that can be used for the detection and attribution of observed climatic change. In the detection and attribution experiment suite, participating models simulate the climate of the twentieth century with subsets of known forcings, which allows the climatic response to individual forcings to be separated. Previous studies utilising output from these various CMIP5 simulations have detected and attributed various observed changes in the climate system over this period, including, for example, observed changes in global mean temperatures (Jones et al. 2013) and observed extreme climate events (Lewis and Karoly 2013a).

For the CMIP5 models included, we first use all available data from the historical experiment, simulating the climate of 1850 to 2005 with both anthropogenic (well-mixed greenhouse gases, tropospheric aerosols and ozone) and natural forcings (volcanic and solar) imposed. For the historical experiment, observed time-varying atmospheric concentrations of CO_2, CH_4, N_2O, O_3 and halocarbons were applied. In addition, time-varying total solar irradiance was applied from Lean (2009) and stratospheric volcanic aerosols were implemented from the Sato et al. (1993) monthly mean optical depth data source. While each of the historical detection and attribution simulations utilised here follows the protocols described by Taylor et al. (2012), each of the climate forcings stipulated by CMIP5 was implemented differently for each model. For example, several of the models analysed here also incorporate variable land use changes over the historical periods as an additional anthropogenic forcing. We first consider historical model years 1911 to 2005 and compare the simulated temperature anomalies with those observed over this common period as an evaluation of model performance.

Within the CMIP5 framework, there are several future projection experiments forced with differing specified atmospheric composition changes, known as representative concentration pathways (RCPs). In this study, we utilise the RCP8.5 experiment that provides a high emissions scenario in which the radiative forcing increases throughout the 21st century before reaching 8.5 W/m^2 at the end of the century. We use the high emissions scenario as this is considered most representative of global CO_2 emissions occurring from 2005 to present (Peters et al. 2012) and we consider only model years for the period 2006–2020, which is centered on the present. Finally, we use simulations for the historicalNat experiment over the period 1850–2005, with only time-varying solar and volcanic aerosols imposed. We calculate Tmean, Tmax and Tmin anomalies for the historical, historicalNat and RCP 8.5 experiments, relative to a 1911–1940 climatology, in accordance with how the observational data was processed. We compare temperature anomalies from the anthropogenically-forced RCP8.5 simulations to those calculated from the historicalNat experiment forced only with changing solar irradiance and volcanic aerosols. In total, 450 RCP 8.5 and 5572 historicalNat model years were analysed.

Table 1. Summary of CMIP5 model experiments analysed, major forcings imposed, model years analysed and climatology used to calculate temperature anomalies (modified from Lewis and Karoly 2013a).

Experiment	*Major forcings*	*Years Analysed*	*Baseline*
historical	Anthropogenic (greenhouse gases, aerosols, ozone) and natural (solar, volcanics)	1911–2005	1911–1940
RCP8.5	Anthropogenic (greenhouse gases, aerosols,ozone scenarios) and natural (solar)	2006–2020	1911–1940
historical-Nat	Solar, volcanics	1850–2005	1911–1940

Evaluation of model data

Model data analysed here were derived from eleven climate models (Table 2) participating in CMIP5 (Taylor et al. 2012). Models were selected for inclusion in this analysis using similar criteria to those employed by Lewis and Karoly (2013a). That is, models were included where data were available for all utilised experiments on the Australian node of the Earth System Grid (ESG) and also based on their assessed skill in capturing observed variability of Australian annual temperatures. First, time series of 80-year length were synthesised by bootstrap resampling 2000 times observed Australian area-average mean temperatures over the period of 1911–2005 and a distribution of possible observed interannual standard deviations of Australian temperatures was obtained. This bootstrap resampling procedure was then applied to available historical simulations and a skill score determined for each model, as a measure of the common area between the modelled and observed distributions of interannual standard deviations of Australian temperatures (Perkins et al. 2007). This score provides a simple and robust measure of the relative similarity of the model and observed distributions, allowing comparison across the entire PDF, rather than using weightings defined by other statistical tests that are sensitive in specific parts of the distribution. CMIP5 models were excluded from further analysis as physically unrealistic in instances where the skill score was below a threshold of 0.5, which reflects that the excluded models do not capture well the observed variations in Australian average annual mean temperatures. In total,

Table 2. List of CMIP5 climate models and ensembles used in this study. Further details of individual models can be found from the Program for Climate Model Diagnosis and Intercomparison (PCMDI).

Model	*historical*	*RCP8.5*	*historicalNat*
ACCESS1-3	r1i1p1, r2i1p1, r3i1p1	r1i1p1	r1i1p1, r2i1p1, r3i1p1
bcc-csm1-1	r1i1p1, r2i1p1, r3i1p1	r1i1p1	r1i1p1
CCSM4	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1	r1i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1	r1i1p1, r2i1p1, r4i1p1, r6i1p1
CNRM-CM5	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1, r7i1p1, r8i1p1, r9i1p1, r10i1p1	r1i1p1, r4i1p1, r6i1p1	r1i1p1, r2i1p1, r4i1p1, r5i1p1, r8i1p1
CSIRO-Mk3-6-0	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1, r7i1p1, r8i1p1, r9i1p1, r10i1p1	r1i1p1, r2i1p1, r4i1p1, r6i1p1, r10i1p1	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1
FGOALS-g2	r1i1p1 r2i1p1 r3i1p1	r1i1p1	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, r2i1p1, r3i1p1	r1i1p1, r1i1p3, r2i1p1, r2i1p3, r3i1p1, r3i1p3, r4i1p1, r4i1p3, r5i1p1
HadGEM2-ES	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1	r1i1p1, r2i1p1, r3i1p1, r4i1p1	r1i1p1, r2i1p1, r3i1p1, r4i1p1
IPSL-CM5A-LR	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1	r1i1p1, r2i1p1, r3i1p1, r4i1p1	r1i1p1, r2i1p1, r3i1p1
MIROC5	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1	r1i1p1	
NorESM1-M	r1i1p1, r2i1p1, r3i1p1	r1i1p1	r1i1p1

five participating models were determined to be unsuitable for this analysis due to their representation of Australian temperature variability, relative to that observed. We now include a greater number of models than used in the previous Lewis and Karoly (2013a) assessment of model skill, as further model experiments have been made available through the ESG portal.

In addition, Fraction of Attributable Risk values for each region (Australia and States), period (annual, seasonal and monthly) and temperature variable (Tmean, Tmax and Tmin) are presented only in instances where the distributions of simulated area-average temperatures are found to be statistically indistinguishable from those observed. In each case, for the purpose of evaluating the temperature distribution from the historical simulations, we estimate the distributions using a kernel density function and compare to the relevant observed distribution over the common years 1911–2005 using a two-sided Kolmogorov-Smirnov test (see Fig. 1 for an annual Tmean example and Fig. 2 for seasonal and monthly examples). The FAR values were then calculated only in instances where the simulated temperature distribution is significantly indistinguishable from that observed (at the five per cent level). In general, the observed distributions are best matched by the historical simulations for Tmean, rather than for Tmin and Tmax. The comparatively better representation of Tmean variability, relative to Tmax and Tmin, in CMIP5 simulations of the historical period has been noted previously (Lewis and Karoly 2013b; Lindvall and Svensson 2014). In particular, for the global land surface, an increase in the frequency of high Tmax values, compared with observations and a decreased frequency of low Tmax values has been generally noted in these studies. There is also an underestimate of the frequency of low Tmin values in the CMIP5 simulations, relative to observations. Finally, we find here that the observed temperature anomalies are best represented in the historical simulations when longer temporal averages, such as annual or seasonal averages, rather than monthly averages are considered, and similarly when larger spatial areas are examined.

Fraction of Attributable Risk

In this study, the Fraction of Attributable Risk is an expression of the fraction of risk of a particular temperature threshold being exceeded that can be attributed to anthropogenic influences. The FAR value (Stone and Allen 2005b) is calculated as

$$FAR = 1 - \frac{P_{NAT}}{P_{ALL}}, \quad ...(1)$$

where P_{NAT} denotes the probability of an event occurring in a natural reference state (historicalNat) with natural internal and externally forced (solar and volcanic) climate variations and P_{ALL} under a parallel forced state (RCP 8.5 experiment) with both natural and anthropogenic forcings (changes in anthropogenic greenhouse gases and aerosols). The FAR values were calculated by comparing the probability of event occurrence in each experiment using all the relevant model simulations, as determined by the number of times the

Table 3. The Fraction of Attributable rRisk of extreme Australian (AUS) area-average temperatures exceeding the record (ΔT) for Tmean, Tmax and Tmin in the observational record to 2013. Conservative estimates of the FAR values are reported here, which are exceeded by 90 per cent of the values in the bootstrapped FAR distributions, calculated as the difference in probabilities between the RCP8.5 simulations (model years 2006–2020) and the historicalNat simulations (model years 1850–2005). Values are presented only in instances where the simulated temperature distributions are statistically similar to those observed. The maximum observed temperature (K) in the observational record (from 1910–2013) is given, together with the observed anomaly (relative to 1911–1940 climatology) used as a threshold for calculating FAR values. Also, the average frequency of exceeding the observed record (as of 2013) in the RCP8.5 and historicalNat experiments are shown in years. FAR values are shown in bold where they indicate at least a tripling of risk of extreme temperatures that is attributable to anthropogenic forcings.

	Tmean				*Tmax*				*Tmin*			
AUS	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*His-toricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*His-toricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*His-toricalNat frequency*
ANN	23/1.5	**1**	1-in-7	0-in-5572	30.1/1.7	**0.98**	1-in-8	1-in-356				
DJF	28.6/1.5	**0.96**	1-in-3	1-in-75	35.7/1.7	**0.87**	1-in-4	1-in-27	21.7/1.4	**0.98**	1-in-3	1-in-152
MAM	23.6/2	**0.95**	1-in-11	1-in-718	30.6/2.4	**0.86**	1-in-12	1-in-133				
JJA	16.6/1.7	**0.96**	1-in-8	1-in-195	23.4/2	**0.92**	1-in-9	1-in-681				
SON	24.1/1.8	**0.96**	1-in-8	1-in-567	31.8/2.2	**0.94**	1-in-14	1-in-201	16.5/1.7	**0.99**	1-in-5	1-in-1895
JAN					36.9/2.6	**0.79**	1-in-9	1-in-44	23/2.3	**0.96**	1-in-11	1-in-201
FEB	29.3/2.2	**0.92**	1-in-7	1-in-95	36.3/2.4	**0.73**	1-in-7	1-in-27	22.4/2	**0.94**	1-in-5	1-in-106
MAR	27.3/1.9	**0.87**	1-in-6	1-in-43	34.5/2.5	**0.74**	1-in-8	1-in-39	20.2/1.6	**0.88**	1-in-3	1-in-30
APR	24.9/3.2	**0.86**	1-in-71	1-in-1698	31.8/3.4	**0.78**	1-in-41	1-in-274				
MAY	20.3/2.5	**0.96**	1-in-17	1-in-446	26.5/2.3	**0.9**	1-in-7	1-in-69				
JUN	17.6/2.7	**0.94**	1-in-33	1-in-450	23.4/2.5	**0.9**	1-in-13	1-in-135	11.6/2.9	**0.93**	1-in-30	1-in-401
JUL					22.9/2.3	**0.91**	1-in-9	1-in-196				
AUG	18.6/2.8	**0.87**	1-in-50	1-in-396	26.3/3.4	**0.95**	1-in-74	1-in-1482				
SEP	22/3	**0.89**	1-in-36	1-in-1350	30/3.5	**0.94**	1-in-42	1-in-704				
OCT	24.9/2.5	**0.95**	1-in-14	1-in-310	32.7/2.8	**0.85**	1-in-19	1-in-137	17.1/2.1	**0.97**	1-in-7	1-in-238
NOV	27.3/2.1	**0.94**	1-in-9	1-in-157	34.6/2.3	**0.83**	1-in-8	1-in-51	20/2	**0.97**	1-in-11	1-in-451
DEC	29/2.1	**0.94**	1-in-7	1-in-123	36.5/2.6	**0.84**	1-in-11	1-in-94	22.5/2.6	**0.98**	1-in-35	1-in-778

Table 4. As for Table 3 but showing FAR values for Western Australian (WA) area-average temperature anomalies.

	Tmean				*Tmax*				*Tmin*			
WA	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*
ANN	23.5/1.3	**0.99**	1-in-3	1-in-477	30.4/1.4	**0.94**	1-in-3	1-in-52	16.9/1.7	**1**	1-in-8	0-in-5572
DJF	29.6/1.7	**0.95**	1-in-4	1-in-69								
MAM	25.2/2.6	**0.94**	1-in-18	1-in-1268	31.8/2.5	**0.77**	1-in-10	1-in-69	18.6/2.6	**1**	1-in-23	0-in-5572
JJA	17.2/1.8	**0.96**	1-in-6	1-in-168	23.9/1.9	**0.87**	1-in-6	1-in-174	11.2/2.2	**0.99**	1-in-13	1-in-2032
SON	24.6/2.1	**0.97**	1-in-8	1-in-786	32.1/2.2	**0.93**	1-in-7	1-in-106	17.1/2	**1**	1-in-8	0-in-5572
JAN												
FEB									23.2/2.3	**0.86**	1-in-8	1-in-57
MAR	28.6/2.3	**0.82**	1-in-6	1-in-31	35.8/2.7	0.56	1-in-7	1-in-22	21.8/2.1	**0.77**	1-in-6	1-in-27
APR									19/2.8			
MAY	21.5/3	**0.86**	1-in-24	1-in-305	28.2/3.2	**0.82**	1-in-16	1-in-145	15.4/3.1	**0.93**	1-in-22	1-in-2067
JUN	18/2.6	**0.91**	1-in-12	1-in-140	23.8/2.2	**0.85**	1-in-6	1-in-41	12.3/3	**0.96**	1-in-22	1-in-575
JUL	16.8/2.1	**0.87**	1-in-7	1-in-56	23.6/2.5	**0.86**	1-in-9	1-in-102				
AUG	18.5/2.3	**0.87**	1-in-7	1-in-75					11.6/2.3	**0.94**	1-in-8	1-in-195
SEP	21.7/2.3	**0.85**	1-in-8	1-in-52	29.4/2.4	**0.89**	1-in-6	1-in-61	14.1/2.3	**0.95**	1-in-8	1-in-155
OCT	25.2/2.8	**0.84**	1-in-16	1-in-255	33/3.1	**0.87**	1-in-20	1-in-120	17.7/2.5	**0.95**	1-in-9	1-in-444
NOV	27.9/2.3	**0.93**	1-in-7	1-in-101	35.5/2.5	**0.84**	1-in-9	1-in-62	20.5/2.2	**0.97**	1-in-7	1-in-213
DEC	30.4/2.8	**0.93**	1-in-25	1-in-357					23/2.7	**0.96**	1-in-25	1-in-2078

Table 5. As for Table 3 but showing FAR values for South Australian (SA) area-average temperature anomalies.

	Tmean				*Tmax*				*Tmin*			
SA	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat frequency*
ANN	21.1/1.7	**1**	1-in-8	0-in-5572	28.6/1.9	**0.99**	1-in-9	1-in-662	13.4/1.5	**1**	1-in-5	0-in-5572
DJF	28.9/3	**0.99**	1-in-23	1-in-2976	36.7/2.9	**0.93**	1-in-19	1-in-174	21/3	**0.98**	1-in-34	1-in-1700
MAM	21.4/2.2	**0.95**	1-in-9	1-in-184	29.3/2.9	**0.9**	1-in-16	1-in-340	14.4/2.3	**0.97**	1-in-10	1-in-344
JJA	14/1.7	**0.87**	1-in-8	1-in-60	20.6/1.8	**0.88**	1-in-6	1-in-49	7.5/1.8	**0.96**	1-in-7	1-in-178
SON	21.9/2.1	**0.87**	1-in-8	1-in-140	30.1/2.6	**0.88**	1-in-14	1-in-150	13.5/1.6	**0.95**	1-in-4	1-in-78
JAN	30.8/4.4	**0.94**	1-in-64	1-in-1433	39/4.7	**0.89**	1-in-81	1-in-475	23.3/4.9	**0.95**	1-in-84	1-in-1224
FEB	29.2/3	**0.83**	1-in-7	1-in-39	37.3/3.1	**0.71**	1-in-6	1-in-22	22.2/3.8	**0.9**	1-in-14	1-in-142
MAR	26.3/2.7	**0.83**	1-in-7	1-in-42					19.3/3.4	**0.88**	1-in-13	1-in-110
APR	23/4	**0.84**	1-in-48	1-in-402	30.9/4.8	**0.83**	1-in-41	1-in-251	15.2/3.3	**0.86**	1-in-17	1-in-129
MAY	17.8/2.6	**0.83**	1-in-10	1-in-63	24.3/2.5	**0.77**	1-in-6	1-in-25	11.6/3.1	**0.87**	1-in-15	1-in-197
JUN	16/4	**0.84**	1-in-242	1-in-2576	22.3/4.1	**0.77**	1-in-66	1-in-639	9.7/4	**0.92**	1-in-154	1-in-1925
JUL	13.9/2.3	**0.78**	1-in-10	1-in-50	20.8/2.8	**0.88**	1-in-8	1-in-72	7.4/2.2	**0.87**	1-in-8	1-in-64
AUG					24.4/4.1	**0.88**	1-in-38	1-in-995	8.5/2.3	**0.86**	1-in-9	1-in-74
SEP	20.5/4.3	**0.81**	1-in-88	1-in-3026	29.1/5.1	**0.96**	1-in-158	1-in-3950	12/3.5	**0.88**	1-in-56	1-in-1065
OCT	22.3/2.4	**0.82**	1-in-6	1-in-35	30.9/3	**0.85**	1-in-8	1-in-55	14.1/2	**0.83**	1-in-4	1-in-24
NOV	26.4/3.4	**0.82**	1-in-31	1-in-357	34.4/3.5	**0.85**	1-in-20	1-in-198	19.4/4.1	**0.83**	1-in-79	1-in-2655
DEC	27.6/2.3	**0.89**	1-in-5	1-in-44	36.3/3.1	**0.87**	1-in-10	1-in-71	19.9/2.5	**0.9**	1-in-6	1-in-70

Table 6. As for Table 3 but showing FAR values for Northern Territory (NT) area-average temperature anomalies.

NT	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat frequency*
ANN									20.1/2	**1**	1-in-17	0-in-5572
DJF									24.6/1.4	**0.95**	1-in-3	1-in-68
MAM	26.8/2.3	**0.89**	1-in-12	1-in-182					20.7/2.4	**0.95**	1-in-13	1-in-365
JJA	21.2/2.7	**0.93**	1-in-44	1-in-1313					14.5/3.1	**0.96**	1-in-46	1-in-987
SON	28.6/2.3	**0.94**	1-in-26	1-in-424					21.8/2.7	**1**	1-in-31	0-in-5572
JAN	32/2.6	**0.77**	1-in-8	1-in-34					25.2/1.7	**0.82**	1-in-4	1-in-24
FEB	31.6/2.7	**0.76**	1-in-9	1-in-42	38.7/3.6	0.45	1-in-14	1-in-25	25/2.3	**0.84**	1-in-7	1-in-99
MAR	29.9/2.4	**0.77**	1-in-6	1-in-26	37/3.2	0.49	1-in-8	1-in-23	23.3/1.9	**0.83**	1-in-5	1-in-28
APR	28.3/3.5	**0.76**	1-in-38	1-in-384	35.1/3.8	0.64	1-in-25	1-in-70				
MAY	24.5/3.3	**0.91**	1-in-29	1-in-384	30.7/3.2	**0.71**	1-in-10	1-in-63	18.4/3.5	**0.83**	1-in-25	1-in-148
JUN	22.2/4	**0.9**	1-in-73	1-in-645					15.6/3.7	**0.81**	1-in-19	1-in-95
JUL	20.6/3.1	**0.77**	1-in-24	1-in-105	27.7/3.3	**0.83**	1-in-21	1-in-228	14.3/3.8	**0.81**	1-in-40	1-in-214
AUG	23.2/3.7	**0.77**	1-in-104	1-in-436	31.6/4.4	**0.9**	1-in-218	1-in-2092	15.3/3.4	**0.83**	1-in-21	1-in-172
SEP					35.3/4.4	**0.75**	1-in-202	1-in-720	18.9/3.7	**0.89**	1-in-46	1-in-2142
OCT	29.7/2.9	**0.87**	1-in-28	1-in-243	37.1/3.2	**0.83**	1-in-22	1-in-133	22.9/3.1	**0.94**	1-in-17	1-in-302
NOV	31.9/2.9	**0.8**	1-in-66	1-in-268					25.4/3.1	**1**	1-in-61	0-in-5572
DEC	31.9/2.1	**0.8**	1-in-6	1-in-31	38.9/3	0.55	1-in-19	1-in-66	25.3/1.6	**0.92**	1-in-3	1-in-52

Table 7. As for Table 3 but showing FAR values for Queensland (QLD) area-average temperature anomalies.

	Tmean				*Tmax*				*Tmin*			
QLD	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat frequency*
ANN	24.4/1.6	**0.98**	1-in-7	1-in-446	31.4/1.7	**0.95**	1-in-7	1-in-151				
DJF	30.6/2.4	**0.94**	1-in-17	1-in-198	36.9/2.5	**0.8**	1-in-11	1-in-47	24.2/2.3	**0.98**	1-in-13	1-in-585
MAM	24.9/2.1	**0.92**	1-in-10	1-in-143	31.3/2	**0.76**	1-in-6	1-in-27				
JJA	18.8/2.4	**0.93**	1-in-28	1-in-986	26/2.5	**0.77**	1-in-40	1-in-643	12.4/3	**0.92**	1-in-47	1-in-526
SON	26.1/2.1	**0.96**	1-in-12	1-in-291	34/2.5	**0.89**	1-in-18	1-in-168	18.9/2.3	**0.94**	1-in-16	1-in-895
JAN	30.7/2.3	**0.78**	1-in-6	1-in-26	37.6/3	0.49	1-in-9	1-in-17	25/2.7	**0.92**	1-in-13	1-in-161
FEB	30.6/2.8	**0.77**	1-in-14	1-in-87	37.3/3.6	0.48	1-in-17	1-in-52	24.1/2.3	**0.89**	1-in-7	1-in-59
MAR	28.4/2.2	**0.84**	1-in-7	1-in-45	35.1/2.8	**0.71**	1-in-8	1-in-30	22.1/2.1	**0.85**	1-in-6	1-in-40
APR	25.8/2.8	**0.83**	1-in-24	1-in-186	32.4/2.8	**0.72**	1-in-12	1-in-55				
MAY	22.4/3.1	**0.88**	1-in-34	1-in-464	28.7/2.7	**0.77**	1-in-10	1-in-63				
JUN	19.5/3	**0.9**	1-in-22	1-in-228	25.8/2.7	**0.81**	1-in-16	1-in-83	13.7/3.8	**0.79**	1-in-43	1-in-200
JUL					25.3/2.8	**0.81**	1-in-19	1-in-161	12.5/4	**0.79**	1-in-63	1-in-1005
AUG	20.9/3.7	**0.84**	1-in-153	1-in-754	29.2/4.4	**0.88**	1-in-411	1-in-3452	12.7/3.1	**0.89**	1-in-16	1-in-149
SEP	24.2/3.5	**0.85**	1-in-55	1-in-862	32.8/4.2	**0.9**	1-in-98	1-in-1019	17.1/4	**0.89**	1-in-33	1-in-1037
OCT	27.4/2.9	**0.87**	1-in-36	1-in-278	35.1/3	**0.83**	1-in-17	1-in-100	19.7/2.9	**0.85**	1-in-17	1-in-117
NOV	28.9/2	**0.82**	1-in-7	1-in-38	36.3/2.4	**0.78**	1-in-6	1-in-26	21.7/1.9	**0.87**	1-in-8	1-in-72
DEC	30.7/2.5	**0.77**	1-in-14	1-in-57	37.8/3	**0.71**	1-in-17	1-in-50	23.6/2	**0.89**	1-in-7	1-in-59

Table 8. As for Table 3 but showing FAR values for New South Wales (NSW) area-average temperature anomalies.

	Tmean				*Tmax*				*Tmin*			
NSW	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*His-toricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat fre-quency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat fre-quency*
ANN	18.7/1.5	**0.99**	1-in-5	1-in-756					11.9/1.6	**0.96**	1-in-6	1-in-152
DJF	26.6/2.5	**0.98**	1-in-10	1-in-323	34.2/2.6	**0.87**	1-in-12	1-in-70	19.4/2.7	**0.87**	1-in-12	1-in-70
MAM	19.3/2	**0.95**	1-in-7	1-in-150					13.6/3	**0.85**	1-in-7	1-in-75
JJA	11.7/1.7	**0.94**	1-in-10	1-in-155	18.2/2.2	**0.91**	1-in-14	1-in-282	6/1.8	**0.91**	1-in-14	1-in-282
SON	19.7/2.3	**0.94**	1-in-16	1-in-297	27.3/2.6	**0.84**	1-in-15	1-in-94	12.5/2.5	**0.84**	1-in-15	1-in-94
JAN	28.7/4.1	**0.91**	1-in-50	1-in-372	36.3/4.1	**0.7**	1-in-40	1-in-102	21.4/4.3	**0.7**	1-in-40	1-in-102
FEB	27.2/2.8	**0.83**	1-in-6	1-in-34					20.2/3.2	0.66	1-in-9	1-in-27
MAR	24.1/2.4	**0.8**	1-in-6	1-in-27					17.5/2.8	0.66	1-in-18	1-in-77
APR	20.8/3.7	**0.79**	1-in-75	1-in-436	28.2/4.4	**0.78**	1-in-61	1-in-1971	13.5/3.2	**0.78**	1-in-61	1-in-1971
MAY	15.5/2.5	**0.88**	1-in-12	1-in-111	21.5/2.2	**0.82**	1-in-5	1-in-31	10.5/3.7	**0.82**	1-in-5	1-in-31
JUN					19.5/3.9				8.1/3.9	**0.82**	1-in-412	1-in-1757
JUL	11.5/2.1	**0.8**	1-in-12	1-in-69	17.6/2.6	**0.91**	1-in-13	1-in-138	6.4/2.7	**0.91**	1-in-13	1-in-138
AUG	13.2/2.4	**0.82**	1-in-13	1-in-95	21.3/4.1	**0.91**	1-in-70	1-in-777	7.2/2.7	**0.91**	1-in-70	1-in-777
SEP	17.2/3.4	**0.83**	1-in-64	1-in-277					9.7/2.9	**0.71**	1-in-63	1-in-199
OCT	19.8/2.3	**0.77**	1-in-6	1-in-29					12.4/2.3	**0.68**	1-in-9	1-in-30
NOV	25.3/4.5	**0.78**	1-in-229	1-in-1083					18.1/5	**0.69**	1-in-39	1-in-709
DEC	25.7/2.5	**0.84**	1-in-6	1-in-40	33.5/2.7	0.64	1-in-7	1-in-19	18.7/2.8	0.64	1-in-7	1-in-19

Table 9. As for Table 3 but showing FAR values for Victorian (VIC) area-average temperature anomalies.

	Tmean				*Tmax*				*Tmin*			
VIC	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*HistoricalNat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat frequency*	*Threshold (°C)*	*FAR*	*RCP8.5 frequency*	*Historical-Nat frequency*
ANN	15.3/1.5	**1**	1-in-7	0-in-5572	21.3/1.6	**0.96**	1-in-6	1-in-172	9.3/1.4	**0.99**	1-in-5	1-in-1034
DJF	21.9/2.6	**0.96**	1-in-15	1-in-283	29.2/2.9	**0.87**	1-in-12	1-in-79	14.7/2.4	**0.99**	1-in-12	1-in-733
MAM	16.2/2	**0.96**	1-in-10	1-in-884	21.9/2	**0.86**	1-in-5	1-in-54	11.1/2.7	**0.98**	1-in-32	1-in-3477
JJA	9.7/1.2	**0.96**	1-in-5	1-in-133	14.3/1.4	**0.9**	1-in-5	1-in-117	5.6/1.7	**0.94**	1-in-10	1-in-186
SON									9.1/1.8	**0.95**	1-in-9	1-in-369
JAN	23.5/4.1	**0.96**	1-in-32	1-in-511					16/3.8	**0.95**	1-in-33	1-in-345
FEB	23.5/3.4	**0.88**	1-in-11	1-in-92	31.1/3.9	**0.78**	1-in-11	1-in-49	16/3.2	**0.9**	1-in-9	1-in-93
MAR	20.6/2.9	**0.8**	1-in-13	1-in-61	28.8/4.4	**0.78**	1-in-25	1-in-192	14.6/3.5	**0.9**	1-in-34	1-in-337
APR	16.9/3.2	**0.79**	1-in-29	1-in-354	23.8/4.3	**0.88**	1-in-32	1-in-316	11/2.9	**0.91**	1-in-19	1-in-297
MAY	13.4/2.6	**0.92**	1-in-33	1-in-529	18.4/2.7	**0.88**	1-in-12	1-in-100	9.1/3.1	**0.89**	1-in-61	1-in-406
JUN									7.7/3.5	**0.85**	1-in-67	1-in-458
JUL	10/2.1	**0.86**	1-in-33	1-in-248	14.5/2.2	**0.83**	1-in-16	1-in-97	5.5/2	**0.8**	1-in-10	1-in-52
AUG	10.6/1.7	**0.89**	1-in-8	1-in-87					5.7/1.6	**0.77**	1-in-7	1-in-32
SEP									8/2.5	**0.77**	1-in-34	1-in-369
OCT									9.2/1.9	**0.83**	1-in-7	1-in-42
NOV	20.6/4.7	**1**	1-in-274	0-in-5572					13.5/4.3	**1**	1-in-82	0-in-5572
DEC	20.6/2.2	**0.85**	1-in-5	1-in-33	28.1/2.9	**0.8**	1-in-6	1-in-33	14/2.5	**0.88**	1-in-9	1-in-74

defined threshold was exceeded, relative to the total sample size. For each area-averaged temperature variable, only a single FAR is obtained from the multi-model temperature distributions for each experiment, so an assessment of uncertainty associated with the FAR estimates was obtained by bootstrap resampling modelled temperature distributions. Each PDF was bootstrap resampled 1000 times (using in each iteration sub-samples of all years from only 50 per cent of available model simulations indicated in Table 2) and a distribution of possible FAR values was calculated. This calculated distribution of 1000 FAR values represents the uncertainty associated with using different models. Conservative estimates of the FAR values are reported here, which are exceeded by 90 per cent of the values in the bootstrapped FAR distributions. We provide very likely (90 per cent) FAR values for each annual, seasonal and monthly Tmean, Tmax and Tmin values for Australia, VIC, NSW, QLD, NT, SA and WA. In addition, FAR values are calculated based on threshold defined by the current highest temperature (ΔT) in the observational record for 1910–2013, as well as in three 0.1 K increments exceeding the current ACORN-SAT record (e.g. $\Delta T+0.1$, $\Delta T+0.2$, $\Delta T+0.3$). We calculate FAR values for a range of thresholds to test the sensitivity of FAR calculations to the defined events, although for simplicity we discuss these but do not provide these in the FAR data look-up tables.

FAR data tables

We present pre-computed FAR values for each region in a separate data table (Tables 3–9), where the FAR value indicates the (very likely) change in risk of each threshold being exceeded between the RCP 8.5 experiment (years 2006–2020) and the historicalNat experiment (1850–2005). The pre-computed FAR values are useful in the instance of new record-breaking temperatures across Australia and enable a near real-time assessment of the anthropogenic impact on observed Australian and State temperatures. In the case where an existing State- or Australia-wide temperature record observed from 1910–2013 is exceeded, the FAR value listed in the relevant FAR data table provides an estimate of the fraction of such a risk that can be attributed to anthropogenic influences. In these data tables, we also present changes in the simulated average return periods of such events due to anthropogenic forcings. The frequency of events was calculated using the P_{NAT} values for historicalNat experiment and P_{ALL} for the RCP 8.5 experiment.

Influence of anthropogenic factors on future temperature records

The FAR values presented here collectively demonstrate how recent observed Australian temperature anomalies have been influenced by anthropogenic forcings. For Australian area-average temperature anomalies, for all thresholds and time periods considered, there is at least a tripling of the likelihood of exceeding current record temperatures that can be attributed to anthropogenic factors. We find that FAR values are generally higher when larger spatial regions are considered, which may reflect the greater natural variability occurring at smaller spatial scales (Stott et al. 2004; Hegerl et al. 2004). That is, it is less likely for an extreme temperature threshold to be broken over a large spatial area as a result of natural variability, without a forced response, than for a smaller spatial area. Nonetheless, the FAR values for the State-based area average temperature anomalies indicate a clear shift to warmer temperatures due to anthropogenic forcing. In no case do we find an analysed temperature threshold less likely to occur in the RCP 8.5 anthropogenically-forced simulations than in the natural-only historicalNat simulations. Similarly, the FAR values tend to be higher for the longer temporal periods analysed, such as annual or seasonal, rather than monthly averages.

In general, the FAR values tend to increase incrementally when calculated for higher thresholds. Because the FAR is calculated from the ratio of the tail areas of two different distributions which are themselves estimated from finite sample data, such monotonicity is only likely, not guaranteed. Christidis et al. (2012) also investigated changes in regional temperature occurrences using multiple thresholds and found that FAR values saturated to unity for higher temperatures. While that study considered thresholds increasing from zero by multiples of the standard deviation, we calculate FAR values based on absolute temperature thresholds and hence do not cover as large a range of climatic variability. Nonetheless, we do find several instances where FAR value is calculated as equal to one, indicating that such temperature thresholds do not occur in the historicalNat simulations, which exclude anthropogenic influences. For example, when considering the record-breaking annual average Australia-wide Tmean anomalies observed in 2013 using the same approach as utilised here, Lewis and Karoly (2014) find it virtually impossible to reach such a temperature record due to forced natural climate variability alone in these standard CMIP5 model simulations.

Furthermore, the FAR values calculated for minimum temperatures are generally higher than the corresponding values calculated for maximum temperatures. A relatively stronger increase over land in daily minimum temperatures compared with daily maximum temperatures is a notable feature of recent climatic change (Karl et al. 1993, Vose et al. 2005), as minimum temperatures relate to longwave radiative fluxes, while maximum temperatures are determined largely by shortwave radiative fluxes. As such, the higher Tmin FAR values computed here may reflect this comparatively stronger increase in minimum, rather than maximum, land-based temperatures due to anthropogenic climate change. The disparity in magnitude between the Tmin and Tmax FAR values is also most notable for the annual and seasonal average temperatures.

Application of pre-computed FAR values

The pre-computed FAR values presented here provide useful 'look-up tables' for understanding in real-time the relative contributions of anthropogenic actors and natural variability to new record-breaking area-average Australian and State temperatures. These FAR values are most useful when recognised as providing general information about the impacts of anthropogenic forcings on the likelihood of extreme Australian temperatures occurring. As the FAR values were calculated based on the distribution of temperature anomalies simulated in the anthropogenically-forced RPC8.5 experiment for model years 2006–2020, with the model data centered on the year 2013, the pre-calculated FAR values may have limited utility in providing information about record-breaking temperatures that occur beyond this period. In particular, as the CMIP5 RCP8.5 experiment is forced by an emissions scenario that may eventually diverge from actual emissions, the FAR values may become less applicable to record-breaking events occurring thereafter. Indeed, the FAR values presented here will be most useful if updated in the future to reflect changes in anthropogenic forcings and also using newly observed record-setting temperature anomalies.

A previous analysis of the record 2012–2013 summer temperature for Australia demonstrated that the change in likelihood of this event due to anthropogenic forcings could be accurately estimated by using the observational record and modelled mean temperature changes for 2006–2020 (Lewis and Karoly 2013a). Using this simplified approach, an assessment of event risk can potentially occur in near-real time. We test this simplistic additional approach of Lewis and Karoly (2013a) for estimating FAR values for seasonal and monthly temperatures for the various Australian States. In many cases, however, using projected changes in temperature due to anthropogenic forcings from the multi-model mean from the RCP 8.5 experiment does not accurately reproduce the pre-computed FAR values. In particular, the simplified approach generally overestimates FAR values for the smaller, State regions and shorter, monthly time periods considered, compared with calculating FAR values by investigating event likelihoods in the natural-only and anthropogenically forced experiments. As such, near-real time assessment of FAR values for State-based, monthly temperatures are likely to be more accurate when determined from pre-calculating FAR values, rather than basing FAR calculations on the temperature distribution of the observational record and projected mean warming trends as used by Lewis and Karoly (2013a).

The results presented here are derived from a multi-model dataset with a limited set of models. Although we assess temperature anomalies derived from multiple realisations from 11 climate models in this analysis and hence include a large number of model years, the utility of the attribution results necessarily depends on ability of the utilised models to accurately capture both forced climatic responses and unforced variability. The validity of the calculated FAR values depends on the observed temperatures being simulated accurately and deficiencies in modelled Tmin and Tmax trends in CMIP5 models, relative to those observed, have been noted in various global regions (Lewis and Karoly 2013b). In this study, Tmin and Tmax trends over Australia were simulated accurately, relative to observations, compared with other regions such as North America and mid-latitude Asia. Nonetheless, discrepancies in observed and simulated Tmax and Tmin trends would result in uncertainties in computed FAR values. While we first select the CMIP5 models that best represent observed Australian temperature variability over the historical period prior to calculating FAR values, any errors in the variability characteristics of the models will necessarily influence the computed FAR values (Stott et al. 2004).

In addition, systematic modelling and forcing uncertainties may result in subsequent errors in the quantification of the FAR values presented here. We calculate FAR values using a suite of CMIP5 global climate models (GCMs) and compare anthropogenically forced simulations with natural-only forced simulations. As such, the computed FAR values are indicative of the anthropogenic climate change signal and provide general information about changes in risk of extreme Australian and State-wide temperatures. Alternatively, Christidis et al. (Christidis et al. 2012) calculated the contribution of anthropogenic forcings to FAR estimates for regional temperature changes derived from ensembles of simulations with atmospheric GCMs conditioned by prescribed sea-surface temperatures (SSTs). In that approach, the calculated risk combines not only the influence of the anthropogenic climate change signal, but also the specific SST patterns associated with the event being considered. It may be useful in future studies to explore the sensitivity of the calculated FAR values for Australia–wide and State-wide extreme temperatures to the experimental design, with the use of another, distinct event attribution model dataset such as that used by Christidis et al. (2012). Nonetheless, the range of uncertainty in the FAR values is generally low and the use of 11 CMIP5 models likely reduces the model dependence of the FAR calculations presented here.

Concluding remarks

In this study, we present pre-computed Fraction of Attributable Risk tables for various Australian temperature records, as an estimate of the change in likelihood of exceeding defined temperature thresholds that can be attributed to anthropogenic influences, such as long-lived greenhouse gases. For Australian and State-based (WA, SA, NT, QLD, NSW and VIC) area-average mean, maximum and minimum temperature anomalies, we compare the likelihood of extreme annual, seasonal and monthly temperatures occurring in a suite of CMIP5 simulations incorporating only natural forcings with simulations including both natural and anthropogenic forcings. We also calculate FAR values for a range of thresholds, defined by the current maximum value (*ΔT*) in the observational data from 1910–2013, and by multiple increments of 0.1 K exceeding the current ACORN-SAT observed record (*ΔT+0.1*, *ΔT+0.2*).

Our methodology provides a simple tool for the timely assessment of the contribution of anthropogenic factors on record-setting temperatures for Australian regions. In the case when an existing Australia- or State-wide temperature record is exceeded, the FAR 'look-up' data tables provide an immediate source of information about the change in risk of such an event occurring that can be attributed to anthropogenic influences. In all regions, the FAR values demonstrate that the likelihood of new record temperatures on various timescales has increased markedly due to anthropogenic forcings. This increase in risk is clearest for the longer temporal (annual and seasonal) and spatial (Australia-wide) scales considered. The FAR values generally reflect the shift to warmer conditions observed over the historical period, with Australian annual-average mean temperatures having increased by ~0.9 K since 1910 (Bureau of Meteorology 2012). Previous Australian seasonal-scale temperature attribution studies have determined that the increased likelihood of recent record-breaking Australian temperatures can be explained simply by this underlying mean warming trend. Furthermore, in some cases, the FAR value is calculated as equal to one, reflecting that in these cases, it is impossible to reach such a temperature record due to forced natural climate variability alone in these model simulations.

The FAR data tables provide general information on regional- to continental-scale temperature changes. These data are not applicable on finer spatial or temporal scales, such as, for example, daily temperature records set for particular cities. Also, the FAR values are most relevant for understanding newly observed record-breaking temperatures occurring in the near future, as the FAR values were calculated based on the distribution of temperature anomalies in the anthropogenically forced RPC 8.5 experiment only for model years 2006–2020. Beyond this period, the FAR values will most useful if updated to reflect changes in anthropogenic forcings and using new record-setting temperature anomalies.

Overall, event attribution can be considered a valuable service that links climate monitoring and prediction services. Rapid, scientifically robust attribution-related responses are invariably requested following an extreme event, and these provide information about the risks and associated costs of climate change impacts (Stott et al. 2012). There are pilot versions of such near real-time attribution services being implemented into current operational frameworks to deliver event-specific information (Christidis et al. 2013a). In this approach, together with a standard seasonal forecasting service, a parallel forecast is conducted as an estimate of the 'natural' world without perturbation from anthropogenic greenhouse gases and in association, these forecasts can be utilised for event attribution. While the approaches will help provide valuable, event-specific information, the implementation of such a system requires regularly updated and validated ensembles of simulations, and as such requires ongoing computational and analytical commitments. Any future investment in an operational event attribution service for Australian extreme events would therefore provide valuable information that is complementary to the generalised, pre-computed attribution 'look up' tables presented in our current study.

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