An Initialized Attribution Method for Extreme Events on Subseasonal to Seasonal Time Scales

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ABSTRACT: When record-breaking climate and weather extremes occur, decision-makers and planners want to know whether they are random natural events with historical levels of reoccurrence or are reflective of an altered frequency or intensity as a result of climate change. This paper describes a method to attribute extreme weather and climate events to observed increases in atmospheric CO₂ using an initialized subseasonal to seasonal coupled global climate prediction system. Application of this method provides quantitative estimates of the contribution arising from increases in the level of atmospheric CO₂ to individual weather and climate extreme events. Using a coupled subseasonal to seasonal forecast system differs from other methods because it has the merit of being initialized with the observed conditions and subsequently reproducing the observed events and their mechanisms. This can aid understanding when the reforecasts with and without enhanced CO₂ are compared and communicated to a general audience. Atmosphere–ocean interactions are accounted for. To illustrate the method, we attribute the record Australian heat event of October 2015. We find that about half of the October 2015 Australia-wide, mean maximum temperatures (e.g., Lewis and Karoly 2013, 2014; Christidis et al. 2012) demonstrate a substantial anthropogenic influence on the likelihood of such extreme events that can be linked to anthropogenic forcing, such as increasing greenhouse gases (Lewis and Karoly 2013, 2014). This can be done using statistical analysis on observations and physical understanding alone (e.g., van Oldenborgh et al. 2012; Risser and Wehner 2017). However, climate models are used in many studies. Typically, parallel runs of a model are made with the current external anthropogenic climatic forcing and with forcing representative of the past. The change in probability of the occurrence of an extreme event as a result of the anthropogenic climate forcing is then estimated. This method was applied to the 2003 European heat wave (Stott et al. 2004; Christidis et al. 2012) and a robust conclusion was that summer heatwaves such as 2003 had at least quadrupled in their likelihood of occurring in the decade (1999–2008) as a result of anthropogenic climate change. The method has further been applied to floods in England in 2000 (Pall et al. 2011), and the 2010 Russian heatwave (Dole et al. 2011). Similar extreme event attribution for Australia has been carried out on various Australia-wide heat events using detection and attribution experiments from phase 5 of the Coupled Model Intercomparison (CMIP5) (Taylor et al. 2012). These studies demonstrate a substantial anthropogenic influence on the likelihood of occurrence of recently observed seasonal and annual mean maximum temperatures (e.g., Lewis and Karoly 2013, 2014; King et al. 2014; Perkins et al. 2014).

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1. Introduction

Extreme weather and climate events are of great concern to the public, emergency services, industry, finance sectors, and policy makers. While there is strong evidence linking global-scale warming to the increases in anthropogenic greenhouse gas emissions (Bindoff et al. 2013), there is increasing evidence that extreme heat and rainfall events are increasing as well. However, because of the smaller samples of extreme events, which by definition occur in the tails of distributions, it is more challenging to explain the possible links between human influences and individual extreme weather and climate events. Nonetheless, such information has proven to be immensely beneficial to raise awareness of climate change (Jézéquel et al. 2019), to inform risk management and adaptation planning (Huggel et al. 2015), to guide policy development, and to be used as evidence in litigation (Marjanac et al. 2017). Although the field of extreme event attribution is relatively new in climate research, over the last two decades much progress has been made in both science and methodologies for extreme event attribution (e.g., Hulme 2014; Stott et al. 2016).

Extreme weather and climate event attribution seeks to answer whether anthropogenic climate change has altered the occurrence likelihood (e.g., Stott et al. 2016, and references therein) or the magnitude and duration of a specific extreme event (e.g., Magnusson et al. 2014). Several different methods of extreme event attribution have been developed, and new approaches are emerging. One popular approach is to assess how the probability of occurrence of an event has been altered by emissions (e.g., Stott et al. 2016). Given an event with a clear definition (magnitude and spatial/temporal extent), this method aims to quantify the change in the likelihood of such extreme events that can be linked to anthropogenic forcing, such as increasing greenhouse gases (Lewis and Karoly 2013, 2014). This can be done using statistical analysis on observations and physical understanding alone (e.g., van Oldenborgh et al. 2012; Risser and Wehner 2017). However, climate models are used in many studies. Typically, parallel runs of a model are made with the current external anthropogenic climatic forcing and with forcing representative of the past. The change in probability of the occurrence of an extreme event as a result of the anthropogenic climate forcing is then estimated. This method was applied to the 2003 European heat wave (Stott et al. 2004; Christidis et al. 2012) and a robust conclusion was that summer heatwaves such as 2003 had at least quadrupled in their likelihood of occurring in the decade (1999–2008) as a result of anthropogenic climate change. The method has further been applied to floods in England in 2000 (Pall et al. 2011), and the 2010 Russian heatwave (Dole et al. 2011). Similar extreme event attribution for Australia has been carried out on various Australia-wide heat events using detection and attribution experiments from phase 5 of the Coupled Model Intercomparison (CMIP5) (Taylor et al. 2012). These studies demonstrate a substantial anthropogenic influence on the likelihood of occurrence of recently observed seasonal and annual mean maximum temperatures (e.g., Lewis and Karoly 2013, 2014; King et al. 2014; Perkins et al. 2014).

Despite its wide use in climate change research, two limitations are often identified with this coupled climate model–based event attribution method. The first is that the likelihood

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DOI: 10.1175/JCLI-D-19-1021.1

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statement only conveys information about the general anthropogenic impact on one type of extreme event with no consideration of the specific circulation anomalies that accompany the event. Each extreme event arises under the combined influences of anthropogenic forcing and a specific circulation setup (e.g., Shepherd 2016). The second limitation is that the models that are used to produce the likelihood statement suffer from model biases, including model drift. These biases adversely affect the model’s ability in simulating extreme events with correct causes (Bellprat et al. 2019) and so hinder the attribution.

Several methods have been proposed aiming to address these limitations. One is to use Atmospheric Model Intercomparison Project (AMIP)-style simulations that may reduce model biases by prescribing sea surface temperature (SST). However, the simulated circulation anomalies do not necessarily correspond to the extreme event under investigation (Pall et al. 2011; Christidis et al. 2013).

An approach that accounts for the circulation patterns of the event in question is called the “storyline” approach (Shepherd 2016). For example, CMIP models that simulate a strengthened Arctic stratospheric vortex and stronger tropical intensification in response to historical anthropogenic forcing also simulate an enhanced decline in Mediterranean winter rainfall, equivalent to the response to several degrees of warming (Zappa and Shepherd 2017). Accounting for circulation changes makes the attribution statement more complex, but it can provide physical insight on why regional extremes occur and how anthropogenic climate change drives changes in the circulations and related regional extremes.

Initialized forecasts have also been used as tools for attribution, and the short simulation time limits the model biases that develop in free-running climate model simulations. Parallel runs with weather forecast models have been made with observed and hypothetical SSTs that have had an estimate of anthropogenically forced climate change removed (e.g., Magnusson et al. 2014) or with observed and similarly altered lateral boundary conditions (e.g., Pall et al. 2017). The attribution conclusions drawn from these types of experiments are conditioned on the state of the boundary conditions and on the specific atmospheric circulation anomalies leading to the event, thus fitting the description of the storyline approach described above.

Coupled seasonal forecast model simulations with altered levels of CO2 have also been assessed. For instance, Weaver et al. (2014) examined retrospective seasonal forecasts (hereafter reforecasts) with observed time-varying levels of CO2 over the last 50 years and found positive shifts in the probability density function of temperatures between the start and end of the time period. Such comparison can provide insight into how anthropogenic influences have changed the temperature distribution assessed with reduced SST biases, because the reforecasts were initialized with realistic ocean states and run for one to three seasons. However, low-frequency natural variability (e.g., the interdecadal Pacific oscillation) could interfere with the anthropogenic signal obtained using this method.

Here we present a method for extreme event attribution that can provide a description of the attributed change in the event’s magnitude and dynamic structure. Our method was originally developed to understand the features of a specific extreme heat event (Wang et al. 2016), and has subsequently been used to examine hot and cold temperature extremes (Hope et al. 2016; Grose et al. 2018), wet and dry extremes (Hope et al. 2018; Grose et al. 2020), and extreme fire weather (Hope et al. 2019). Here we present the method in more detail, to serve as a reference for future studies and inspiration for further testing of this framework using other models.

The method uses a subseasonal to seasonal (S2S) prediction system based on a global coupled dynamical model (see section 3) that is run twice: one time where reforecasts of a specific event are initialized from a climate state in the factual world, and the other where the mean state of the ocean, atmosphere, and land initial conditions are replaced with an estimate of the mean state from a counterfactual world with “low CO2” (~1960s in this case). In both reforecasts, the initial anomalies from the respective mean state remain the same. The reforecasts of the event can then be compared, and the differences between the two forecast ensembles can be attributed to the introduced change in the initial states. Here the “factual” world and the “counterfactual” world will be indicated as the HighCO2 and LowCO2 world, respectively. The full method is detailed in the following sections, including an example application to a record hot month across Australia that occurred in October 2015.

The key differences of our method from other methods and its advantages include the following:

1) Because this is built upon an operational prediction system, extensive model evaluation has already been done across many real-world events.
2) Forecasts and reforecasts are limited to short lead times (~1 month), which limits the growth of model biases. Furthermore, if the event can be well forecast then there is more confidence that the response of that event to anthropogenic forcing can be more faithfully captured.
3) The global coupled model removes the need to estimate counterfactual boundary conditions at the edges of the domain (e.g., Magnusson et al. 2014; Massey et al. 2015) in studies using regional models. Furthermore, ocean–atmosphere coupling is included, which can be important, for instance for events influenced by El Niño–Southern Oscillation (ENSO).
4) There is no interference arising from decadal variability on the attribution, because the mean state difference is free from the effect of decadal variations as the same reference years (2000–14 in this study) are used for both the HighCO2 and the LowCO2 world reforecasts; see section 5b).
5) Analysis of the influence of CO2 on a forecast event can be made prior to the event, which has many implications, as detailed below.

Some limitations include the following:

1) Computational costs of running a global coupled system can be high, and/or resolution might be lower than regional models, which might limit the type of event considered (see section 6).
2) A primary assumption is that the “synoptics” of a particular event that have occurred in the present climate could have occurred in the counterfactual climate. It is possible that the specific weather pattern that resulted in the extreme event in the present climate may have never occurred in the pre-anthropogenically forced climate and so estimates of the changes in the event may be underdone.

In recent years there have been efforts to develop near real-time event attribution, for example by the organization World Weather Attribution (https://www.worldweatherattribution.org/), that employ a suite of methods to each event, often in collaboration with local climate experts (e.g., Kew et al. 2019). The method described here could be included in such a suite of methods and could also be applied in an operational agency to inform frontline operational meteorologists and climatologists on the influence of CO2 on the event prior to its occurrence.

The datasets are described in section 2. A description of the S2S prediction system used for our method is given in section 3. The detailed procedure of deriving LowCO2 world initial conditions and its application to the extreme heat event are given in sections 4 and 5. A summary and discussion are given in section 6.

2. Datasets

The datasets used in describing the October 2015 Australian extreme heat event and its associated large-scale circulation patterns are given in this section. Datasets and initialization for the Predictive Ocean Atmosphere Model for Australia (POAMA) prediction system (Cottrill et al. 2013; Hudson et al. 2013), which was the operational coupled model S2S prediction system at the Australian Bureau of Meteorology during 2008–18, is given in section 3.

We use daily maximum temperature (T_{max}) averaged over Australia, denoted by T_{max}, as an indicator of extreme heat severity; T_{max} is a common index for monitoring heat extremes (e.g., Lewis and Karoly 2013). The observed Australian-mean October-mean T_{max} time series used in Fig. 1 is from the Bureau of Meteorology Australian Climate Observations Reference Network (ACORN)-SAT dataset (Trewin 2012). For most of our other diagnostics, we use T_{max} from the Australian Water Availability Project (AWAP) analyses (Jones et al. 2009). The AWAP analyses are an optimum interpolation of available station observations across Australia and are provided on a ~5 km × 5 km grid. Here we use the monthly mean daily T_{max}. Global SST is from NOAA optimum interpolation SST, version 2 (OIH2) (Reynolds et al. 2007). Global mean sea level pressure (MSLP) and pressure level winds are taken from the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis (ERA-Interim, herein ERA-I; Dee et al. 2011). Two soil moisture datasets are used. One is from the Atmosphere–Land Initialization (ALI), which provides the atmosphere and land initial conditions for the POAMA model (described in the next section; Hudson et al. 2011) and the other from the AWAP analyses (Raupach et al. 2009). The AWAP soil moisture analyses is based on a simplified water balance model that covers Australia and is available on the same grid as the AWAP T_{max} analyses. We use the upper-layer soil moisture (top 1 m) as this layer responds to forcing on S2S time scales (Raupach et al. 2009).

Prior to analysis, these observational datasets were regridded to the POAMA model grid scale (~250 km). Anomalies are defined as deviations from the 2000–14 reference period mean. This choice of the recent 15 years as a reference period is based on 1) the observed CO2 level in this period is substantially different from that in earlier climatology periods so that the CO2 impact over the last 50 years on extreme events can be assessed, and 2) the influence of natural variability on extreme events can be approximately established using data within the reference period.

Indices of some modes of climate variability that are known to be important for Australian climate are also used. ENSO is represented by Niño-3.4 (SST average over 5°N–5°S, 170°–120°W), and the Indian Ocean dipole is represented by the Dipole Mode Index (DMI; the SST difference between the western pole (10°S–10°N, 50°–70°E) and the eastern pole (10°S–0°, 90°–110°E); Saji et al. 1999). The southern annular mode (SAM) is monitored by the difference of the normalized zonal-mean MSLP anomalies at 40° and 65°S, following the definition of Gong and Wang (1999).

3. S2S prediction system POAMA

The atmospheric component of POAMA is the BoM’s Atmospheric Model version 3 (BAM3; Colman et al. 2005), which has ~250 km horizontal resolution on 17 vertical levels. The land surface component in BAM3 is a simple bucket model for soil moisture with a field capacity of 150 mm (Manabe and Holloway 1975) and has three active soil layers for temperature. The ocean component of POAMA is the Australian Community Ocean Model version 2 (ACOM2; Schiller et al. 2002), which is based on the GFDL Modular Ocean Model (MOM2; Pacanowski 1996) and has a zonal resolution of 2° longitude and a telescoping meridional
resolution of 0.5° equatorward of 8° latitude, gradually increasing to 1.5° near the poles. ACOM2 has 25 vertical levels, with 12 levels in the top 185 m and a maximum depth of 5 km.

Initial conditions for atmosphere, land, and ocean used by POAMA are generated from an atmosphere–land surface initialization scheme, named ALI (Hudson et al. 2011) and an ocean data assimilation scheme, named PEODAS (POAMA Ensemble Ocean Data Assimilation System; Yin et al. 2011). Importantly, PEODAS, which assimilates available in situ temperature and salinity observations with an ensemble Kalman filter, provides reanalyses of the ocean back to 1960. Perturbed initial conditions are provided for forecasts using a coupled breeding technique; these are required to sample forecast uncertainty due to sensitivity to initial condition errors (Hudson et al. 2013). Sea ice and ozone are set to climatological values.

CO₂ values are specified depending on application (see section 4). However, most of the impacts of long-term changes in CO₂ will be contained in the initial ocean and land surface conditions. No aerosols and other anthropometric agents are considered in POAMA. We use the e24a version of POAMA (Cottrill et al. 2013) for the forecast experiments conducted in this study. Each reforecast of a given start date is run with 11 members. Reforecast anomalies are defined as the forecast deviation relative to the forecast climatology. No other bias correction has been used.

POAMA has significant skill in predicting austral spring season extreme heat over most of Australia at lead times of 2–3 weeks (e.g., White et al. 2013). POAMA also shows skill at predicting the drivers of heat extremes such as ENSO, the IOD, the SAM, persistent anticyclones over the Tasman Sea, and the MJO (e.g., Marshall et al. 2014). This capability would benefit extreme event attribution using POAMA as presented in this paper.

4. Estimate of the mean initial condition differences

In the POAMA model, CO₂ is prescribed with a fixed concentration. For the HighCO₂ world (factual world) prediction, CO₂ is set to the recent observed value. For the LowCO₂ world prediction, a lower value of CO₂ corresponding to the value in 1960 is used (315 ppm). The choice of 1960 to represent the counterfactual world is because it is the earliest available analyzable ocean initial condition (IC) from PEODAS. Other attribution methods (e.g., King et al. 2014) generally use greenhouse gas levels from a preindustrial period. However, the temporal progression of change in Australia’s mean temperature indicates that the warming observed over the last 105 years has predominantly occurred since 1960 (e.g., Fig. 1), so comparisons against 1960 will still be a reasonable estimate of change.

Prediction in the HighCO₂ world is initialized from realistic analysis as described in section 3. For the LowCO₂ world we adopt an assumption that the impact of greenhouse gas forcing on the initial conditions will be retained in their climatological means. That is, we can derive initial conditions for the LowCO₂ world from that of HighCO₂ world by removing the mean difference between the two worlds. As we are using a coupled model S2S system, the mean difference is approximated by the mean difference in the simulated climatologies.

The method to derive the initial conditions in the LowCO₂ world follows: Let initial conditions for variable Y for HighCO₂ and LowCO₂ worlds be expressed by Y_H and Y_L, respectively. Using our assumptions above we can express the initial state in the HighCO₂ and LowCO₂ worlds as the same anomaly added into the respective means:

\[ Y_H = \overline{Y}_H + Y', \tag{1a} \]

\[ Y_L = \overline{Y}_L + Y' = \overline{Y}_H - (\overline{Y}_H - \overline{Y}_L) + Y = Y_H - \delta_Y. \tag{1b} \]

In (1) we have expressed variable Y as the sum of its mean (bar) and anomaly (prime) for both worlds, and introduced the mean climatology difference \( \delta_Y = \overline{Y}_H - \overline{Y}_L \). From (1) we also see the anomalies in the two worlds, defined as deviations to their respective means, are identical. Thus, the task is to derive the climatological difference for a set of key variables of ocean, land, and atmosphere between HighCO₂ and LowCO₂.

These differences could be estimated from existing attribution experiments such as CMIP5. However, there are substantial differences in the results estimated with different models (e.g., Pall et al. 2011; Christidis et al. 2013). Moreover, soil moisture variables in land models are highly model dependent, making it difficult to be used in an attribution study. In addition, the inevitable interpolation of ocean variables across varying bathymetry from one ocean model to another model poses a significant challenge to maintain internal ocean dynamical balance. Clearly if we derive all the needed differences using a single model system such as the POAMA model, the above difficulties can be mostly avoided.

We derive the mean ocean state difference by running the POAMA model as a freely coupled climate mode with CO₂ concentration set at 400 ppm (equivalent to 2015, representing the present) and at 315 ppm (equivalent to 1960, representing the past) levels, respectively. No other radiative forcing agents were altered due to the limited scope for altering such factors in the POAMA. To minimize the potential impact of the decadal mode on ocean mean states, two sets of observed initial conditions were used, one decade apart, for the recent high CO₂ conditions (2000 and 2010) and the 1960s Low CO₂ conditions (1960 and 1970). That is, we initialize these free runs from the ocean initial state provided by the PEODAS reanalysis, on 1 January for 1960, 1970, 2000, and 2010. Each of the four integrations was run for 30 years. Tests show the year-to-year change in the global mean ocean subsurface heat content, defined as ocean temperatures averaged over the upper 300 m, a key indicator of ocean state, becomes small near the end of the integrations (figures not shown), suggesting that the upper ocean states have reached a quasi-equilibrium. We thus discard the first 25 years of each run and define the mean state as the last 5-yr mean of each run.

The mean difference of ocean initial conditions is obtained by subtracting the average of the two runs with low CO₂ from the average of the two runs with high CO₂ using the last 5 years of each integration. This difference can be considered as the ocean’s response to CO₂ increase since 1960. The
three-dimensional ocean temperature and salinity differences are considered. The pattern of SST difference $\delta_{\text{SST}}$ for October is shown in Fig. 2a. Although the POAMA model suffers from a substantial cold mean ocean state bias (e.g., Lim et al. 2009), this bias is similarly expressed in both the low- and high-CO$_2$ runs so that it is cancelled out when forming the High minus Low difference. Thus, the SST difference pattern that reflects the models response to the increased CO$_2$ over the period 1960s to 2010s is similar to the CMIP5 modeled trend in response to observed historical changes of greenhouse gases over the last century but with smaller magnitude because we are only considering a 50-yr difference (Bindoff et al. 2013; Pall et al. 2011). The pattern in Fig. 2a shows greatest warming near the equator across the Pacific Ocean and in the north of each ocean basin and less warming in the Southern Ocean. The pattern of subsurface change in POAMA from the top 300 m (not shown) is similar to the results of 2xCO$_2$ experiments such as DiNezio et al. (2012). We thus conclude that the pattern shown in Fig. 2a is a reasonable estimate of anthropogenically driven changes in SST over the past 50–60 years.

The above approach can also be used to derive the mean land condition differences for the high and low CO$_2$ worlds. However, this turns out to be problematic, because the SST drifts to a colder state in the long simulation and Australian rainfall tends to be unrealistically high. The high rainfall leads to high soil moisture in the LowCO$_2$ simulation. If we derive the land component difference using the long simulations, the resulting soil moisture difference is too large to be used by the POAMA model. To overcome this problem, we have developed a different method that minimizes the impact of SST drift on soil moisture in estimating the mean land condition difference.

Raupach et al. (2009) suggest that soil moisture responds to atmospheric circulation on monthly to seasonal time scales. Using two observation-based soil moisture datasets from ALI and AWAP we calculated the autocorrelation of Australian average monthly soil moisture time series. The result in Fig. 3 shows that there is little persistence beyond two months in both datasets. This confirms that soil moisture responds to atmospheric circulation changes in months, consistent with Raupach et al. (2009).

Based on these results and the mean ocean differences having been estimated, we can run an interim reforecast experiment, denoted as LowCO$_2$.Int, in which the CO$_2$ level and ocean IC are as in the LowCO$_2$ world but the land and atmosphere ICs are taken from the HighCO$_2$ (see Table 1 for details). The reforecasts in LowCO$_2$.Int were run for several months over 15 years (2000–14). An equivalent set of reforecasts were conducted for HighCO$_2$ world as well for comparison. We then make an average of the land conditions at the end of the reforecasts over 15 years to filter out influence from interannual variability.

Three different length of adjustment times (one, two, and three months) for land have been tested. For initial condition on 1 October, these reforecasts were initialized from 1 September, 1 August, and 1 July, respectively. The three estimates of land condition difference between HighCO$_2$ and LowCO$_2$.Int show soil moisture adjustment occurs mostly within the first two months, consistent with the observational
Table 1. Coupled model seasonal forecast attribution experiments described in the text and their CO$_2$ forcing and initial-conditions configuration. The attribution experiments include the current climate (HighCO$_2$), a low-CO$_2$ world (LowCO$_2$), and an ocean-only low-CO$_2$ world (LowCO$_2$ Int). The event attribution forecast experiments (HighCO$_2$ and LowCO$_2$) are initialized on 24 and 27 Sep and on 1 Oct 2015. The climatologies for these experiments are initialized on 1 Oct for 2000–14. The LowCO$_2$ Int experiments are initialized on 1 Aug for 2000–14. Each date’s forecast ensemble has 11 members.

<table>
<thead>
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<th>CO$_2$ level</th>
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<th>Land IC</th>
<th>Atmosphere IC</th>
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5. Application

a. Extreme heat event October 2015

According to the Bureau of Meteorology and CSIRO (2016) State of the Climate report, the observed Australian average temperatures have warmed by around 1°C since 1910, with most of that warming having occurred since 1950. In recent decades there has been an increase in maximum temperature records and a decrease in minimum temperature records (Lewis and King 2015). In recent years Australia has experienced several record-breaking October-mean maximum temperatures. Here we use October 2015 for $T_{\text{max}}$ over Australia, which remains the record for highest October $T_{\text{max}}$ since 1910, as a case for the application of the method described above (see Fig. 1) and (Hope et al. 2016).

Figure 4a shows the anomalies of October 2015 $T_{\text{max}}$ and Fig. 4b shows the September soil moisture over Australia. The maximum $T_{\text{max}}$ anomaly is in the southeast but high $T_{\text{max}}$ covers all of subtropical Australia. From Fig. 1 the Australian averaged $T_{\text{max}}$ ($T_{\text{max}}$) was at record levels in both 2014 and 2015, but the 2015 event is much stronger (3.6°C vs 2.8°C relative to 1961–90 in Fig. 1 and 2.3°C vs 1.6°C relative to 2000–14). Soil moisture in the antecedent month September (Fig. 4b) shows continental-scale dryness with a local maximum in southeast Australia.

The global climate state during October 2015 is shown in Figs. 4c and 4d for SST and MSLP. A strong El Niño was developing in October 2015 with the Niño-3.4 index being 2.4°C. Positive SST anomalies are seen from across the tropical Indian Ocean and extending southward to subtropical latitudes. The Indian Ocean DMI index was +0.62°C, indicating a positive Indian Ocean dipole event. Both El Niño and the IOD are conducive to dry and warm conditions over eastern Australia (White et al. 2013). Furthermore, warm SST anomalies were present everywhere around Australia except to the northeast.

Stationary Rossby wave trains are evident in the midlatitudes of both hemispheres, which appear to emanate from the regions of SST anomalies over the tropical Pacific and Indian Oceans. Over and to the south of Australia, high pressure anomalies dominate, as is typical during El Niño and positive IOD periods (Cai et al. 2011). The SAM was neutral (0.03).
The Madden–Julian oscillation (MJO) has the greatest impact on extreme heat over southern Australia in spring during phases 2–3 (Marshall et al. 2014). The observed MJO was active over Indian Ocean (phase 2) during later October 2015 (figure not shown).

The observed estimates of large-scale oceanic and atmospheric circulations and land conditions prior and during October 2015 share many of the characteristics of conditions that are conducive to heat waves as described by previous studies (Pezza et al. 2012; Perkins et al. 2015; Arblaster et al. 2014).

b. Development of climatologies for the HighCO2 and LowCO2 worlds

Before conducting the event attribution, we first examine the $T_{\text{max}}$ climatology for both HighCO2 and LowCO2 worlds. This step is also needed for an S2S system to define the reforecast anomaly.

HighCO2 reforecasts were initialized with observed ICs on 1 October each year from 2000 to 2014 to create a reforecast climatology. The CO2 concentration was set to the observed global mean monthly values from about 370 ppm in 2000 to 400 ppm in 2014. The observed initial conditions for atmosphere, ocean, and land states were generated from the POAMA data assimilation schemes as in the real-time operation. An ensemble of 11 members was run for a month each year from 2000 to 2014, producing a sample of 165 October monthly mean reforecasts. The $T_{\text{max}}$ from these reforecasts is used to produce a histogram as shown by solid pink bars in Fig. 5. The ensemble climatological mean October $T_{\text{max}}$ for HighCO2 is 30.5°C, very close to the observed value of 30.4°C. The correlation between observed and forecast $T_{\text{max}}$ ensemble-mean anomalies over the 15 years is 0.84 ($p < 0.01$), suggesting that POAMA provides skillful forecasts of Australian-mean October-mean $T_{\text{max}}$ at this lead. Note that the ensemble member forecasts of $T_{\text{max}}$ in Fig. 5 are not corrected in any way.

The corresponding reforecast climatology for the LowCO2 world can be obtained by running the reforecasts with initial conditions of ocean, land, and atmosphere modified as described in section 4 and a fixed value of 315 ppm for CO2 (Table 1). The $T_{\text{max}}$ histogram using 165 members from LowCO2 is shown by solid blue bars in Fig. 5. The ensemble-mean October $T_{\text{max}}$ climatology for LowCO2 is 29.5°C, 1.0°C colder than that in HighCO2 world, which is approximately the observed difference.

The observed $T_{\text{max}}$ histogram using only 15 years of data (2000–14) is shown by solid gray bars in Fig. 5. We can see clearly the distribution of the observed $T_{\text{max}}$ is closer to that
that in the low CO2 world. The shift in the mean is very likely due to CO2 increase is significant (p < 0.01 for both tests) but the variance change is not (p > 0.7). This suggests the distribution of Australia average October maximum temperature during 2000–14 has shifted toward warmer temperatures by 1.0°C with little change in distribution shape compared with that in the low CO2 world. The shift in the mean is very likely (>90%) caused by the CO2 increase since 1960. We use the “very likely” statement as in IPCC assessment reports (Mastrandrea et al. 2011). The conclusions are the same either using members or ensemble means as samples in the tests.

Note here we have attributed the anthropogenic warming in Australian max to CO2 changes alone. This is a limitation as other radiative forcing agents were not altered due to the limited scope for altering such factors in the POAMA. However, CO2 is the most important of long-lived greenhouse gases. Since around 1950 it became the dominant source of anthropogenic emissions to the atmosphere (Friedlingstein et al. 2019) and is largely responsible for increasing global temperature (IPCC 2013). Thus, it is reasonable to expect much of the observed mean surface temperature increase can be attributed to the CO2 increase in the atmosphere.

c. Attribution of an event

We now conduct event attribution for the extreme heat event in October 2015. The event reforecasts were initialized from three start dates, 24 and 27 September and 1 October 2015, producing 33 members. Using three starts for the events done to increase the ensemble size.

The October 2015 reforecast ensemble-mean $T_{\text{max}}$ is a record (compared to other reforecast ensemble means for Octobers of 2000–14) at 31.4°C and the anomaly is +0.9°C relative to HighCO2 reforecast climatology. The observed $T_{\text{max}}$ of 32.7°C was also a record, and the anomaly was 2.3°C relative to 2000–14. The $T_{\text{max}}$ histogram using the 33 member reforecasts is shown by bars outlined in red in Fig. 6. The magnitudes of the ensemble-mean forecast for 2015 $T_{\text{max}}$ and its anomaly are both smaller than their observed counterparts. This is partly because we have used an ensemble mean whereas there is only one member in observations. If we look at reforecast members, we do find there is one member whose $T_{\text{max}}$ is larger than the observed and two members reach the record (Table 2 and Fig. 6). Alternatively, the ensemble-mean $T_{\text{max}}$ reforecast reaches the 90th percentile in the HighCO2 climatology estimated using all 165 members (the solid pink bars in Fig. 5). The $T_{\text{max}}$ reforecast at the 90th percentile can be considered as an extreme as the variability of ensemble mean is inherently smaller than that of members (see above). Thus, the POAMA October 2015 forecast adequately represents the extreme nature observed in 2015.

We now conduct attribution reforecast of the same event using the LowCO2 configurations (see Table 1). The October 2015 LowCO2 ensemble-mean $T_{\text{max}}$ is a record at 30.6°C compared to the other years’ October ensemble-mean forecasts from the LowCO2 2000–14 climatology and the anomaly is 1.1°C relative to the LowCO2 climatology. The histogram of all the ensemble members of the LowCO2 event reforecasts is shown by the blue line bars in Fig. 6. Similar to HighCO2, there

![Figure 5](image52x564tos76x693)

**Fig. 5.** October $T_{\text{max}}$ climatology distribution during 2000–14 from observations (gray bars), and the climatology estimated using 11 member October forecasts for the current climate (pink solid bars) and the low CO2 climate of 1960 (light blue solid bars). The climatology means are shown in dashed vertical lines: black for observations, red for high CO2, and blue for low CO2. The x-axis tick indicates bin center temperature with a bin width of 0.5°C. Note that no bias correction is applied. Figure is taken from Hope et al. (2016, their Fig. 24.2) with modification.

![Figure 6](image291x565tos516x693)

**Fig. 6.** The distribution of $T_{\text{max}}$ forecast for October 2015 estimated with 33 members for HighCO2 (red open bars) and LowCO2 (blue open bars). The observed $T_{\text{max}}$ is shown by the black dot, and the event ensemble-mean $T_{\text{max}}$ for HighCO2 in red and LowCO2 in blue along the top edge of the panel. Figure is taken from Hope et al. (2016, their Fig. 24.2) with modification.
are two LowCO2 members whose \( T_{\text{max}} \) forecasts are a record and the ensemble-mean \( T_{\text{max}} \) forecast is above the 90th percentile of the climatology ensemble members (Table 2, Figs. 5 and 6). Hence, it is true to say that October 2015 would qualify as an extreme heat event over Australia with or without human influence.

If the atmospheric CO2 concentration had not increased since 1960, the forecast climatological mean at present should be the same as the LowCO2 climatological mean. If we express the 2015 event forecast as an anomaly relative to the LowCO2 climatological mean, then the LowCO2 2015 \( T_{\text{max}} \) forecast was +1.1°C, and the HighCO2 2015 forecast was +2.0°C (from Table 2).

This means that +0.9°C of the +2.0°C anomaly can be explained by the warming and circulation changes that resulted from the net CO2 added to the atmosphere since 1960. We thus conclude that anthropogenic global warming since 1960 is a major factor in causing the extreme heat across Australia in October 2015 (about half of the October 2015 Australia-wide temperature anomaly).

Attributing extreme event to an external factor can also be quantified using the fraction of attributable risk (FAR), given by \( \text{FAR} = 1 - \frac{P_0}{P_1} \) (Stott et al. 2004), where \( P_0 \) is the probability of exceeding the previous threshold in the “natural” world, and \( P_1 \) is the probability of exceeding the same threshold in the current world. To estimate the FAR for the October 2015 heat event, we use the warmest \( T_{\text{max}} \) reforecast ensemble mean in the HighCO2 climatology, with a value of 31.4°C, as the threshold. Here we estimate \( P_0 \) and \( P_1 \) by taking the proportion of the event reforecast ensemble members whose \( T_{\text{max}} \) exceeded the threshold (the “frequentist interpretation”; Weigel 2012). Among the 33 members of the 2015 event, five exceeded this threshold in the LowCO2, while 17 exceeded it in the HighCO2, leading to a FAR value of 0.71. To account for uncertainty in FAR, we use a bootstrap approach generating 10,000 values of FAR estimates by randomly taking 17 out of 33 members (approximately 50% of the original samples), following Lewis and Karoly (2014). The median of the FAR values is 0.75, which can be considered as a “best estimate” (Lewis et al. 2019). This represents a fourfold increase in the risk of October 2015 \( T_{\text{max}} \) exceeding the threshold in the HighCO2 experiment compared to that in the LowCO2.

The above event attribution reforecasts provide additional information about how the mean warming due to CO2, combined with a particular configuration of ocean, atmosphere, and land initial states, giving rise to an extreme heat event. While the mean change is about 1°C, the actual \( T_{\text{max}} \) forecast difference between HighCO2 and LowCO2 can vary from year to year because of the nonlinear interaction between the mean state and the perturbation (i.e., internal variability). From (1) we see the anomalies at the initial time in the HighCO2 and LowCO2 worlds, defined as deviations to their respective means, are identical. This means our event attribution conclusions for October 2015 \( T_{\text{max}} \) are conditional on the specific circulation setup contained in the initial conditions.

The results from the reforecasts can also be used to examine the large-scale drivers that might be associated with the production of the heat, and they can be assessed to determine if the heat develops in the same way as observed. As described above, and detailed in Wang et al. (2016), the model faithfully forecasts a combination of Tasman Sea blocking, a high positioned over the southeast of the country, a strong El Niño, and a positive IOD. Thus, our method can be considered as fitting the description of the storyline approach of Shepherd (2016).

6. Summary, discussion, and future plans

In this study a new method for attribution of extreme climate events has been presented. This method uses an initialized S2S prediction system to define initial conditions of the ocean, atmosphere, and land for a “low-CO2 world” that assumes no CO2 increase since 1960.

Compared with other methods, this method has the advantages of 1) demonstrated predictive skill of the event of interest (actual skill has been obtained), 2) reduced impact from climate model biases (only the first month reforecasts were used), and 3) absence of interference arising from decadal variability on attribution (same reference years 2000–14 were used for both the current climate and the low-CO2 world), and 4) being based on observed synoptics that ultimately cause the extreme event (better depiction of dynamical situation leading to the event).

This method was demonstrated by application to the record Australian heat event that occurred in October 2015. The results show that the last 55 years of CO2 warming contributed
The FAR estimate confirms there is about a fourfold increase in the Tasman Sea were well forecast and contributed to approximately an additional 1.1°C for October 2015 event relative to LowCO2 climatology.

This means around half of the record anomaly during October 2015 can be attributed to the CO2 increase since 1960. The FAR estimate confirms there is about a fourfold increase in risk of October 2015 \( T_{\text{max}} \) exceeding the threshold in the HighCO2 compared to that in the LowCO2 world. We, therefore, conclude that the human induced global warming is the single major contributor to the Australian heat extreme of October 2015. These conclusions, together with Figs. 5 and 6, can serve as a very effective communication tool when attributing extreme climate events to both climate change and natural variability.

Wang et al. (2016) also assessed the influences of climatic and synoptic initial conditions for simulating the same extreme event. By scrambling atmospheric and ocean initial conditions, they showed that the atmospheric circulation anomalies played a more important role than the direct impact from the ocean in promoting extreme heat in Australia. This conclusion is valid in the context of reforecasts at a monthly time scale.

The ocean’s role will inevitably become more important for lower-frequency events influenced by extreme El Niño and the IOD, and the reforecasts for those events can be still skillful at longer lead times. This implies that the prediction of climate extremes at subseasonal scales can be enhanced through improving the initialization procedure for the atmosphere and the atmospheric general circulation model, whereas the improvements in the ocean initial conditions and the ocean model may be important for the prediction of climate extremes at seasonal scales.

The anthropogenic-driven change in ocean temperature and salinity derived in this paper with POAMA is likely model dependent, though it generally agrees with the mean change depicted in CMIP5 models (Bindoff et al. 2013). Other caveats include that aerosol and other warming agents are not considered directly in POAMA, although they are evident in the observation-based aspects of this method. These issues could be addressed by using more advanced climate models and/or a multimodel approach.

Two studies have compared results from this method with those using an AGCM-based approach, and the methods agree in their conclusions (Grose et al. 2018, 2020). The studies were particularly focused on the circulation changes that have been driven by climate change in the southern Australian region, and there is evidence of consistent circulation changes using these two methods.

Early steps have been taken to apply this same method in the U.K. Met Office seasonal forecast model used at the Bureau of Meteorology in Australia (termed ACCESS-S; e.g., Hudson et al. 2017). The approach differs because there is a long CMIP5 simulation with comparable ocean fields from which to derive ocean changes since earlier periods.

Applying the attribution method described in this paper in an operational setting presents the opportunity to provide attribution statements and understanding of extreme events as they are forecast. This approach is being considered for real-time attribution by some operational weather and climate centers around the world. To this end we need to assess the accuracy and reliability of the attribution statement. This is a challenging task as there is no verification data available (Lott and Stott 2016). Another issue is the resource needed that mainly involves running reforecasts for the real world and the counterfactual world over an extended reference period. Assuming an operational system consists of reforecasts with 11 members and lead time of two months initialized once a month over a reference period of 15 years. This is equivalent to a simulation of 660 model years, representing a substantial demand on computation and storage.

A further step in the journey to illustrating our changing climate with examples from observed extreme events, and the influence that climate change has on their occurrence, intensity, or duration is to simulate observed events under near-future conditions (Hazeleger et al. 2015). Using a similar method to that outlined above and the POAMA model, Lim et al. (2019) have simulated seasonal forecasts of each of the three recent big El Niño events with the addition (rather than the subtraction) of the observed oceanic trend since 1960. This is certainly an area that can provide policy makers, industry leaders and the public with the illustrative information and guidance needed to inform decisions.

A weakness of this approach is that we cannot untangle whether climate change directly impacted the synoptic evolution that causes extreme event. Our approach is to ask what would happen if those exact same synoptics occurred in a cooler climate. This approach circumvents the problem of a model not being able to simulate the precise synoptic setup that causes the extreme event. However, while the removal of the pattern of the background mean states provides some indication of shifts in the synoptic systems, any nonlinear interactions between the mean state and resultant synoptic setup will not be adequately present in the initial conditions.

Acknowledgments. This research was supported by partial funding from the Australian government’s National Environmental Science Program, Earth Systems, and Climate Change hub. JMA acknowledges support from the Australian Research Council Centre of Excellence for Climate Extremes (Grant CE170100023) and the Regional and Global Model Analysis component of the Earth and Environmental System Modeling Program of the U.S. Department of Energy’s Office of Biological & Environmental Research via the National Science Foundation (IA 1947282). The authors thank Drs. Michael Grose, Andrew Marshall, and Andrew Watkins for reviewing an early version of the paper and thank the three anonymous reviewers for their constructive comments on the manuscript.

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