Sub-seasonal to seasonal climate forecasts provide the backbone of a near real-time Event Explainer service

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Capsule

The Bureau of Meteorology serves the Australian community to reduce its climate risk and is developing a suite of tools to explain the drivers of extreme events. Dynamical sub-seasonal to seasonal forecasts form the backbone of the service, potentially enabling it to be run in near real-time.

Introduction

The Australian Bureau of Meteorology (BoM) provides forecasts at daily, multi-week and seasonal timescales along with a range of other services. Customers are keen to be informed about the causes of extreme weather and climate events to help them in their planning and decision making. While attribution is often framed in terms of understanding the role of climate change, it is also useful to understand the role of climate variability and circulation changes in causing extreme events (e.g.

Mindlin et al., 2020). The focus of the Event Explainer is to reduce climate risk by informing decision makers about the causes of extreme events and, if there are *persistent* underlying drivers, the event's likelihood of recurrence over the coming season or decade.

This article describes the tools that are being developed at the BoM to explain the causes of extreme weather and climate events, and how those tools would add value to existing services. The novel aspect of the tools is that they will link with the dynamical sub-seasonal to seasonal (S2S) forecasts currently in operation. Thus, operational staff are alerted to the upcoming extreme event, and have time to diagnose and quantify the causes - facilitating earlier and more effective communication with the public and stakeholders, potentially tailoring the service to users' needs. Hence there is strong appeal in using an operational forecast system as the backbone of a real-time attribution system.

Tools being developed for the Event Explainer

We propose using a suite of applications for the Event Explainer service to enhance the benefits that can be drawn from different approaches and increase confidence in the final messages (Philip et al., 2020). Initially, regional heatwaves will be the focus of the BoM’s attribution service, but the techniques can be used to explain the causes of other extremes, including the circulation changes associated with high intensity rainfall or fire weather. The applications are still under development and the skill of the techniques will be tested for each type of event, and any relevant caveats will be considered.

To illustrate the methods described here we apply the preliminary developmental versions to the heatwave preceding the ‘Black Saturday’ fires over south-east Australia in late January and early February 2009, see Figure 1a (Bureau of Meteorology, 2009).

Modified initialization S2S Prediction Attribution (SPA) method

In the BoM's Research section, scientists developed a system to quantify the influence of increasing levels of greenhouse gases on extreme events using an initialized global dynamical coupled ocean-atmosphere S2S climate prediction system (Wang et al., 2021). In a series of case studies, the system was applied to quantify the influence of carbon dioxide increases since ~1960 on several Australian events:

- heat events on a sub-seasonal timescale (Arblaster et al., 2014; Hope et al., 2015, 2016);
- fire weather over two weeks in 2017 (combining the zero-lead forecast with observed antecedent rainfall and cooler (minus 1 ^{0}C) antecedent temperature observations to define the drought factor) (Hope et al., 2019);
- extreme monthly rainfall and associated circulation changes (Hope et al., 2018);
- frost events in south-west Australia and circulation (Grose et al., 2018); and
- extreme dry in Tasmania (Grose et al., 2019).

As this approach uses initialized forecasts, there was a potential interest in the benefit that the attribution system could be used to describe the influence from increasing greenhouse gases *prior* to the event occurring (presented at the 2018 annual meeting of International Detection and Attribution Group (IDAG) in Berkeley, USA). At the time, the approach used the BoM's low-resolution operational S2S forecast system POAMA, presenting the option of running attribution experiments alongside the operational forecast service. Since then, a major operational upgrade has provided an opportunity to use a much higher resolution coupled model with advanced physics, the Australian Community Climate and Earth-System Simulator subseasonal-to-seasonal prediction system (ACCESS-S; Hudson et al., 2017). Development is now underway to assess the skill and utility of ACCESS-S as a tool for attribution. A preliminary forecast experiment of the Black Saturday heatwave has been performed using an early version of the ACCESS-S system, ACCESS-S1. The ensemble mean ACCESS-S1 forecast reasonably captured the temperature anomaly pattern during 27 January - 8 February 2009 over south-east Australia from 17 January 2009 (i.e., 10-day lead time (Figure 1b). In comparison to the forecast with the present level of CO_2, a set of ensemble forecasts was generated for the same event but under the low CO_2 climate conditions of the early 20th Century, with CO_2 set to 297ppm (equivalent to 1905 levels) and the removal of the changed ocean-atmospheric mean state due to human influence over the last century from the initial conditions. The change state was estimated from a five-member ensemble of the HadGEM3 CMIP5 long run (2000-2020 minus 1861-1950). The resultant ensemble mean forecast difference indicates about 3 °C warming over the south-east Australia due to atmospheric CO_2 increase and the associated ocean and atmospheric mean state change for this event (Figure 1c). Further details are discussed in Abhik et al. (to be submitted). Development is still underway to apply this method in the current operational version, ACCESS-S2. A detailed analysis of the circulation changes associated with the event can be drawn from the results of the SPA technique, as shown in Grose et al. 2018.

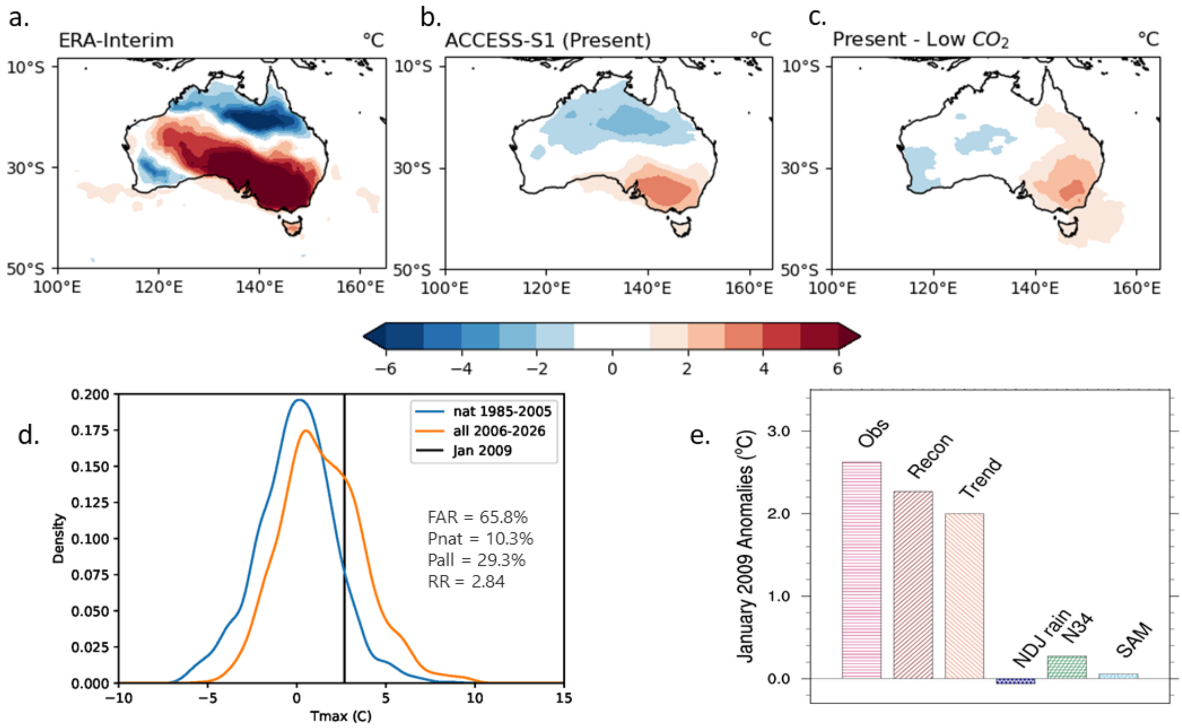

Figure 1. *Application of developmental versions of the Event Explainer methods to the heatwave period preceding Black Saturday fires in late January and early February 2009. Temperature anomalies 27 January – 8 February 2009 from a) ERA-Interim (Dee et al.,*

2011) and b) ACCESS-S1 forecasts initialized on 17 January 2009 and c) the present-day forecast minus the same forecast on a low CO_2 background mean state. CMIP5-based (Taylor et al., 2012) *distributions (d) of average January daily maximum temperature for Victoria from the present climate (orange: 2006-2026, RCP8.5) and natural-forcing only simulations (blue: 1985-2005), based on the method of Lewis et al. (2014). The observed 2009 January anomaly (Jones et al., 2009) is shown as a vertical black line). Finally, January 2009 loading values from a multiple linear regression (MLR; 1979-2019) of known drivers of Victorian climate in January (e). Drivers include (from the right) detrended indices of Southern Annular Mode (SAM)[1], Niño3.4 (Reynolds et al., 2002), antecedent seasonal rainfall (Jones et al., 2009) and the trend (years). The reconstructed anomaly in January 2009 is primarily driven by the trend, with some contribution from the moderate La Niña.*

Fraction of Attributable Risk (FAR) Method

A second, established approach that can be applied to understand the likelihood of surpassing certain thresholds for a particular variable (e.g., Victoria state-averaged month-long temperature) is to define the probabilities of exceedance in large ensembles of climate model simulations with full historical (or near future) forcing versus those with natural forcing (e.g., Lewis et al., 2014). The PDFs are being re-created so that we have scope to update the thresholds used and move to include new CMIP simulations as they become available. Preliminary results suggest that the average January 2009 daily maximum temperature in Victoria, Australia, was 2.8 times more likely in the modelled present climate compared to a world with only natural forcing. The FAR technique could be applied to extremes forecast in the S2S outlook period using appropriate bias correction to instantly provide an estimate of the contribution from anthropogenic climate change to the likelihood of that event under different climate conditions. An evaluation of the forecast skill would precede efforts using

[1] http://www.nerc-bas.ac.uk/icd/gjma/sam.html

this approach, and discussion has begun with BoM Research to Operations staff working on verification and bias correction.

Statistical multivariate analysis of drivers

While climate change is one factor influencing extreme events over Australia, large-scale drivers such as El Niño-Southern Oscillation (ENSO) (e.g., Black and Karoly, 2016; Karoly et al., 2016) and the Indian Ocean Dipole (IOD) (e.g., Abram et al., 2021) lead to large climate anomalies in Australia. Thus, both scientists and Australian climate information stakeholders are keen to understand the interplay of these factors. For instance, the extreme rainfall across eastern Australia in September 2016 was linked to the negative phase of the IOD (King, 2018), and if this information were provided in real-time, decision-makers could anticipate a continuation of wet conditions through spring. If we have more accurate quantification of the impacts from influential large-scale climate drivers on the intensity or likelihood of regional climate extreme events and the influence of climate change on the drivers, then for future extreme events communities will be able to take appropriate adaptation measures, such as flood defences.

To quantify the contribution from the large-scale drivers, we follow the approach of Wang et al. (2016), who describes a multiple linear regression (MLR) approach, with predictors chosen to represent the variability from ENSO, IOD, the Southern Annular Mode (SAM), gridded antecedent soil moisture over Australia and the mean global temperature, as used by Arblaster et al. (2014) and Hope et al. (2016). A deep understanding of the features that influence the climate of a region and season, and their interactions, is needed prior to setting up the system (e.g. Min et al., 2013), and further development of the statistical approach might be considered to help provide causal reasoning based on the statistical relationships (e.g. Kretschmer et al., 2021). Once that understanding is established, the evaluation of the seasons and regions where large-scale modes of variability have high forecast skill for the event in question will guide the development of the MLR system to be applied to *forecast* extremes (e.g. Marshall et al., 2013, 2021; White et al., 2014).

The average January 2009 Victorian daily maximum temperature is reconstructed in Figure 1e using the MLR approach. In this case, the majority of the anomalous heat can be explained by the linear trend, with small positive contributions from tropical and extratropical drivers. Slightly wet conditions in the months preceding January 2009 added a weak cooling effect to the reconstructed maximum temperature. Note that the current MLR holds little skill for January, explaining only ~25% of the average monthly daily maximum temperature.

Summary of attribution message using three methods, and next steps

For the 2009 heatwave event, preliminary results using three attribution methods indicate that the heatwave was made almost three times more likely and around 3 ^{o}C hotter in the present climate than in a world without human influence on the climate. The usual drivers of heat in south-east Australia (ENSO, SAM) contributed only a small amount to the January temperature anomaly.

The SPA approach can capture the magnitude of the anomaly due to the background human influence on climate, while the MLR approach uses only a linear trend, which may be appropriate for heat extremes, but may not work as well for rainfall. Likewise the circulation changes shown in the SPA experiments will capture the nuance of the forecast drivers of the event, which may differ from what might be captured with indices alone.

Improvements and developments might include moving the MLR or FAR approaches to sub-monthly values to better encompass the heatwave dates, or including further predictors such as the Madden Julian Oscillation in the MLR analysis e.g. (Marshall et al., 2021). More details about the drivers and circulation changes due to human influence could be gained from further examination of the S2S attribution experiment. Testing of the MLR and FAR for forecast events will also form part of the next steps.

Note that in all of these approaches, there is a reliance on the veracity of the forecasts, and the service will describe the *forecast* event, rather than an actual event. In the development of the system the hindcast skill will inform how much confidence can be given to the attribution assessments. For events with known low forecast skill, guidance would be given that more certain results will be provided shortly following the event using the two statistics-based methods (MLR and FAR) based upon observations.

Other methods

Another approach to determining the influence from large-scale drivers and their interplay with long-term trends on an event again uses the BoM's S2S prediction attribution system with modified initial conditions, such as the addition of the observed long-term trends on the canonical state of the ocean during El Niño (Lim et al., 2019) or La Niña (Lim et al., 2016). In each of those studies, the interactions with the underlying observed ocean trend were accounted for in the experimental design. These sorts of experiments could be pre-defined and triggered with the forecast of an extreme event; however, they are computationally expensive and thus are likely to form part of a post-event review rather than an integral part of the real-time service.

Another source of information could be drawn from methods being developed for other real-time attribution services in Europe[2] and New Zealand[3].

The potential of the Extreme Event Explainer Service to boost existing services within the Bureau of Meteorology

Decision support: Staff in this area of the BoM work to support the weather and climate information needs of users, such as fire agencies. As we described our plans for the real-time Event Explainer systems to these staff, they were quick to see the value for the post-event reviews that they produce following major fires. These reviews help highlight what worked well and what could be improved across the actions taken towards preparedness and response to the event. A part of this is an

[2] European Climate and weather events: interpretation and attribution | Copernicus
[3] Extreme weather event real-time attribution machine - Bodeker Scientific

understanding of the drivers of the event – including the meteorological set-up and the larger-scale modes of variability such as ENSO, IOD and the SAM and their interactions. The contribution of climate change is also important because it will add to the information around the conditions forecast for any upcoming fire season, allowing for informed risk assessments and longer-term planning that incorporates the changing likelihood and nature of extremes.

Seasonal prediction: The development of the Event Explainer service is closely linked to the operational seasonal forecast service. Understanding and quantifying the various causes of events in the outlook helps provide clarity and confidence in the messages provided. The tools used can also inform the model forecast skill verification and understanding – for example, the reasons that a seasonal forecast verifies poorly may be untangled if one looks to the relative contributions *post priori* (Lim et al., 2021).

Climate services for emergency management, hydrology, agriculture: The BoM provides targeted services for key sectors across the community. For instance, forecasts are used to provide a heatwave service following learnings from the 2009 heatwave (Bettio et al., 2018). The service for hydrology presents historical risk, real-time forecasts and projections information all in one place: http://awo.bom.gov.au/. An additional statement around the drivers of extremes as they are forecast would complement those services and provide the link between what we are currently seeing and the projected changes in those same variables. Extending the Event Explainer service to include hydrological variables could form an important next step.

Weather forecasters: the real-time aspect of the system will help forecasters articulate informed answers to questions such as 'how much did climate change influence this particular weather event?', often asked during media interviews about recent extremes. Furthermore, climate change can influence extreme weather events, pushing them outside the range of past experience. This information is thus important in communicating the current forecast risk, so actions are equal to the actual risk and not dependent on past behaviour.

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