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Attribution of extreme events to climate change in the Australian region – A review

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ABSTRACT

Extreme event attribution is a rapidly growing field of climate science with important implications for public and government understanding of human-induced climate change. However, there is substantial variation in how well events can be attributed to human-induced climate change, depending on the nature of the event. Focusing on Australia: at one end of the scale, large-scale heat events on both the land and in the ocean are well suited to attribution studies because climate models simulate them reasonably well, there are high-quality observations available and our understanding of the processes that lead to extreme heat events is reasonably well developed. At the other end of the scale, very important phenomenon such as changes in east coast lows, severe convective storms and long-term droughts are less well observed, are beyond our current capability to robustly simulate in climate models and the complex mechanisms that lead to intensification are not well understood. Thus, some important extreme events can be linked to human-induced climate change, with a high degree of confidence, while others cannot. We review the state of the science relevant to event attribution with a focus on Australia. We highlight where progress can be made, focusing on observations, physical understanding, and realistic climate modelling.

1. Introduction

The socio-economic and environmental costs of extreme events affecting Australia are escalating. The 2019/2020 Black Summer bushfires cost around AU$100 billion (Read and Denniss, 2020), killed 450 Australians directly or indirectly (Johnston et al., 2020) and caused significant environmental damage. In 2021 and 2022, multiple severe floods in southern and eastern Australia caused widespread infrastructure damage and multiple fatalities. Coral bleaching, drought and heatwaves have all had major impacts in the last decade. Some of these events can, at least in part, be associated with human influence on the climate, whereas others may be indistinguishable from natural climate variability. Understanding the degree to which these and similar events can be attributed to global warming is critical in determining our climate risk and where to invest to build resilience to events that might become more frequent in the future (Fiedler et al., 2021). Here, we examine the current understanding of the effects of climate change on Australian extreme weather and climate events to determine the degree to which changes can be attributed to human-induced climate change.

Extreme event attribution is the study of how some characteristics of

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observed extreme weather and climate events are likely altered by different influences on the climate, including human emissions of greenhouse gases. There have been many reviews of extreme event attribution and associated methodologies (National Academies Press, 2016; van Oldenborgh et al., 2021b; Stott et al., 2016). Each continent has a unique set of climate influences and challenges when performing event attribution, and here we focus specifically on Australia. Australia experiences high inter-annual climate variability, driven in part by large-scale modes of variability that interact on multiple timescales (Risbey et al., 2009). The prominent role played by El Niño-Southern Oscillation (ENSO), the Southern Annual Mode (SAM), the Indian Ocean Dipole (IOD), and the impact of changing ozone forcing means that assessing the role of human-induced climate change on weather and climate extremes in the Australian region, and carefully distinguishing this from natural variability, is particularly challenging.

This review documents our current understanding of the role of human-induced climate change in explaining changes in Australian weather and climate extremes, and discusses how to address key questions around the nature of the relationship between climate change and localised extreme events.

2. Background and Global Context

The field of detection and attribution has grown rapidly over the last two decades. There are two main modes of detection and attribution: trend attribution, which involves fingerprinting where the relative influences of different climate forcings are estimated (Hegerl et al., 1996; Ribes et al., 2017); and event attribution, where the influence of human-induced climate change on a specific extreme event is estimated (Allen, 2003; Stott et al., 2016). Both areas of detection and attribution rely heavily on climate models to estimate the role of human-induced climate change. This paper focuses on event attribution, and the current status of the science for its application to Australian extreme events.

Whether the frequency or intensity of a weather or climate event has been altered by human-induced climate change can be addressed using a variety of methods ranging from observations through to modelling. A common approach is the Fraction of Attributable Risk (FAR) methodology, proposed for climate applications by (Allen, 2003), which is often converted to a probability or risk ratio. From two sets of model simulations – one without human-induced climate forcings (sometimes called a “counterfactual” climate) and one that includes human-induced climate forcings (sometimes called the “factual” climate) - the change in the probability of an event can be calculated. While various other event attribution methods now exist, isolating an event in a factual and counterfactual climate simulation underpins most contemporary event attribution assessments. For all event attribution assessments, the initial framing of the question underpinning the analysis is crucial and the methods underpinning an attribution assessment need to be appropriate for the event being analysed, and for the specific question being asked (van Oldenborgh et al., 2021b).

In recent years we have seen the extension of single event attribution analyses to the use of multiple methods applied to observational data and various (typically) global model experiments. The principal tools used include multi-model ensembles of opportunity run from an initial state in around 1860 (‘free’ climate simulation mode, e.g. Coupled Model Intercomparison Projects, CMIP5 (Taylor et al., 2012) and CMIP6 (Eyring et al., 2016) and single-model initial-conditions large ensembles (SMILEs), again run in ‘free’ mode such as the Community Earth System Model large ensemble (Kay et al., 2015). Atmosphere-only single-model ensembles, such as HadGEM3-A (Christidis et al., 2013) or weather@home2 (Guillod et al., 2017) run in AMIP mode have also been used. Seasonal prediction systems, such as Predictive Ocean Atmosphere Model for Australia (Alves et al., 2003) and empirical analysis of observational data based on covariates such as atmospheric carbon dioxide concentrations or smoothed global mean surface temperature (van Oldenborgh, 2007) have also emerged as useful tools for analysing extreme events. Each of these tools result in different framing of the role of human-induced climate change on a specific event, with a key difference being whether the model is run with some initialisation and data assimilation (with some prediction of the event as it happened) or in free-running climate mode (creating an estimate of the effect of forcing on the event in a statistical sense).

Regardless of the methodologies that are used, there are a series of choices to be made in the design of an attribution study, such as how to define the event and how to evaluate the models that are used (van Oldenborgh et al., 2021b). In addition, each method involves its own choices and has its own advantages and disadvantages. For example, when employing an empirical methodology and applying a statistical fit such as the Generalised Extreme Value distribution to the data, a choice must be made as to whether to include the event in question in informing the fit. This can make a substantial difference to the return period and the FAR estimate, particularly for events that are very extreme or rare in the current climate, such as the Western North American heatwave of 2021 (Philip et al., 2020). Similar considerations would need to be addressed when attributing very extreme Australian events, with any effect on the attribution statement clearly stated. Moreover, there is greater confidence when multiple, structurally-different models agree, which is why a combination of methods and experiments is generally preferable (Otto et al., 2016) and is becoming the gold-standard for event attribution. (Lewis et al., 2019; Philip et al., 2020) provide detailed reviews of event attribution methods and their limitations.

3. Australian phenomena

Extreme weather events result from the interaction of multiple phenomenon and processes, all occurring in a system perturbed by human-induced climate change. The behaviour and dominant mechanisms of different weather events vary by region. They depend on large-scale climate variability and synoptic- and small-scale processes. Moreover, depending on the event type, there is varying scientific understanding of the influence of human-induced climate change on the event, differing quality and quantity of observational records, and differing realism of their representation in climate models. Rigorous event attribution studies require three key elements: robust observations, scientific understanding, and realistic climate modelling. Consequently, some events can be attributed to climate drivers, including anthropogenic climate change, more robustly than others.

As part of a 2019 Australian event attribution workshop (Lane et al., 2019) a qualitative assessment was conducted of the ability to observe, understand, and realistically model (using global climate models, hereafter “climate models”) the range of extreme phenomena that affect Australia. This assessment was built upon a similar assessment in the (National Academies Press, 2016) report, but with a specific focus on Australia, extended to multiple timescales, and attempting to preserve consistency between related phenomena (e.g., short-duration rainfall extremes and severe storms have the same assessment). The result of the assessment is found in Table 1 and in graphical form in Fig. 1. The terms ‘low’, ‘medium’ and ‘high’ confidence mimic the calibrated language used by other assessments (Masson-Delmotte et al., 2021). Phenomena located in the top-right of Fig. 1 should be able to be attributed to climate change with the highest confidence and those in the lower-left of Fig. 1 cannot be attributed to climate change at all (with current capabilities) or with low confidence. The assessment focused specifically on CMIP5/CMIP6 global climate models because these models are most commonly used for event attribution studies and a generalised assessment is possible. Yet, we note that some significant improvement can be gained for some phenomena using regional climate models, or very high-resolution global models. Such high-resolution modelling is rapidly progressing, but the capability of such models is very much case and phenomenon dependent; thus, it is not included as part of the model assessment here. In this section, we examine each of these phenomena, in the context of event attribution in Australia, to justify the assessment

Table 1
Qualitative assessment of: the ability of CMIP5/CMIP6 generation climate models to represent specific extremes (***model capability***), the level of understanding of the physical mechanisms that lead to changes in each extreme with human-induced climate change (***understanding***), and the quality and length of the observational record of each extreme (***observations***). Assessment categories correspond to confidence levels of high (***H**, green*), medium (***M**, yellow*), and low (***L**, red*). Grey shading represents timescales that were not considered relevant for the specific extreme in the Australian context.

Phenomenon (Section Number)	Timescale **~1 day-1 week**			Timescale **~1-3 months**			Timescale **~1-5 years**		
	Model capability	Understanding	Observations	Model capability	Understanding	Observations	Model capability	Understanding	Observations
Extreme cold events (3.1)	**M**	**M**	**H**	**H**	**H**	**H**			
Extreme heat (3.2)	**M**	**H**	**H**	**H**	**H**	**H**			
Marine heatwaves (3.3)	**M**	**M**	**M**	**H**	**H**	**H**			
Drought (3.4)				**M**	**M**	**M**	**L**	**L**	**M**
Extreme Rain (3.5, 3.6)	**L**	**M**	**M**	**M**	**M**	**H**			
Severe convective storms (3.5)	**L**	**M**	**M**						
Tropical cyclones (3.7)	**L**	**M**	**M**						
Tropical lows (3.7)	**L**	**L**	**M**						
East coast lows (3.8)	**L**	**L**	**M**						
Extra-tropical cyclones and fronts (3.9)	**M**	**M**	**M**						
Fire weather (3.10)	**L**	**M**	**M**	**L**	**M**	**M**			
Fire-relevant fuels (3.11)				**M**	**H**	**M**	**M**	**M**	**M**
Sea-level extremes/surges (excluding sea-level rise) (3.12)	**L**	**H**	**M**						

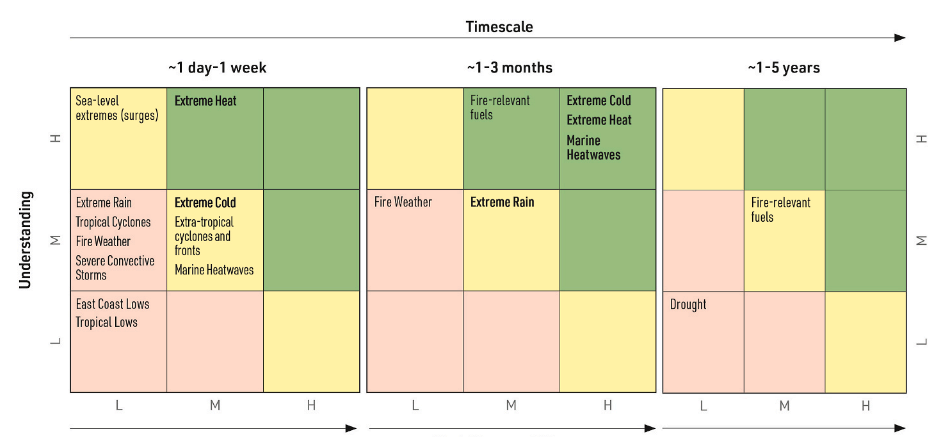

Fig. 1. Assessment of the ability to observe, understand, and model (using CMIP5/CMIP6 generation climate models) the influence of human-induced climate change on specific extreme events in the Australian region. Short-duration events (~1–7 days, left panel), long-duration events (~1–3 months, middle panel), multi-year timescales (~1–5 years, right panel). L, M, H represent Low, Medium, and High confidence levels. Bold type represents High confidence in the observational records, with all other entries having Medium confidence in the observational records.

in Table 1 and Fig. 1.

3.1. Extreme cold

Attribution studies have been successfully performed on the *reduced* likelihood of some cold extremes due to human influence, as is expected given a warming climate. Also, the impact of human influence on some *effects* of cold extremes have been found – for example, warmer temperatures led to earlier bud burst of grapevines in central Europe in March 2021, making them more vulnerable to subsequent frost damage in April (Vautard et al., 2022). No similar studies have been performed in Australia, but there is the potential for them to be conducted over the region.

In the northern hemisphere, warming and reduced sea ice cover could potentially lead to a destabilisation of the jet stream and weakening of the 'polar vortex' leading to greater cold extremes (Cohen et al., 2014; 2021; Mann et al., 2017; Zhang et al., 2016). In Australia, cold extremes result from a variety of synoptic weather setups, including positive pressure anomalies advecting air from further south, creating a cold outbreak (Ashcroft et al., 2009; Pook et al., 2012). Enhanced pressure in the mid-latitudes due to greenhouse forcing (Gillett et al., 2013) has the potential to drive more clear nights. For some regions of southern Australia, frost frequency and the length of the frost season has been increasing despite an increase in mean temperature in all seasons (Crimp et al., 2016; Dittus et al., 2014). Changes may also be driven by modifications to the strength and latitude of storm tracks or through changes to atmospheric blocking.

Attribution studies for cold extremes are very limited in Australia. An event attribution study found the exceptional MSLP anomaly south of Australia in August 2014 was more likely due to human influence, and this event was associated with a cold outbreak, frosts and snow in Tasmania (Grose et al., 2015, 2018) examined the circulation drivers of the extreme spring frosts in southwest Western Australia in September 2016 and found evidence using two attribution modelling systems for an enhancement of the MSLP anomaly and a cold outbreak in the region. Therefore, there is some evidence that broad-scale synoptic scale drivers indicated by high MSLP events show some signal of human influence, but other effects such as increasing clear night skies and meso- or micro-scale changes need further examination.

Grass frost risk can be approximated by overnight minimum temperature of <2 °C, a relatively simple metric implying a relatively long and good quality data for examining this risk in Australia. However, the proposed drivers of forced response are primarily circulation-based, and climate models perform poorly in the simulation of some important circulation features such as blocking. Climate models are also limited in their skill in simulating the smaller-scale effects related to frosts such as fine scale topography. There is therefore only medium confidence in the ability of climate models to guide attribution of these events over Australia (see Table 1). Advancements in climate model resolution should improve representations of synoptic variability and local risk factors and improve our confidence in their use for event attribution applications.

3.2. Extreme terrestrial heat

Extreme heat events in Australia are typically caused by persistent high-pressure systems, allowing for the advection of heat from hotter adjacent regions. Adiabatic heating of descending air and diabatic heating of the boundary layer influence the intensity of an extreme heat event. Modes of variability (for example, ENSO or IOD) influence soil moisture and the surface energy balance and dry conditions can enhance the development of extreme heat (Hirsch and King, 2020; Loughran et al., 2019; Parker et al., 2019; Quinting and Reeder, 2017). These processes may act in isolation or occur simultaneously affecting the intensity, duration and severity of extreme heat events, with their relative importance dependant on the region of interest (Gibson et al., 2017b; Loughran et al., 2019; Perkins et al., 2015).

Multiple attribution studies for Australian heatwaves and extreme heat have reported a clear and detectable human influence for these extremes (Angélil et al., 2017; Herring et al., 2020). Larger extreme heat events in both time and space tend to display a stronger human-induced signal, likely due to the smaller influence of internal variability (Angélil et al., 2014; Fischer et al., 2013). Significant human-induced signals have been detected for Australia's then-record temperatures of the 2012/2013 summer, and 2013 September, Spring and calendar year (Knutson et al., 2014; Lewis and Karoly, 2014). The May 2014 heatwave was found to be over 20 times more likely to occur due to human-induced climate change (Perkins and Gibson, 2015), and approximately half of the record heat in October 2015 was attributed to increasing atmospheric carbon dioxide (Hope et al., 2016), with the rest due to atmospheric variability. In contrast, the likelihood of the January 2014 heatwaves over the relatively small spatial scales of Adelaide and Melbourne had a smaller human influence, an increase of 16% in the case of Adelaide, and the sign of the influence was uncertain for Melbourne (Black et al., 2015).

Overall, there is greater confidence in attributing Australian extreme heat compared to other extreme event types. Australia has high-quality temperature datasets (Trewin, 2013; Jones et al., 2009) with a relatively dense and quality controlled observational network that can be used to identify heatwaves back to 1910 (although not over Central Australia, (Perkins and Alexander, 2013). We also have a sound understanding of the physical mechanisms that drive heatwaves, such as the prevailing synoptic systems (Gibson et al., 2017; Quinting et al., 2018), larger-scale atmospheric dynamics (Parker et al., 2014), the source and trajectories of air parcels preceding heatwaves (Loughran et al., 2017; Quinting and Reeder, 2017), links to modes of climate variability (Loughran et al., 2019; Loughran et al., 2017; Loughran et al., 2017; Parker et al., 2014; Perkins et al., 2015), links to other regional weather phenomena (Parker et al., 2013), and the importance of drought and land surface interactions and fluxes, particularly over certain regions (Gibson et al., 2017; Herold et al., 2016; Hirsch et al., 2019; Kala et al., 2015). This results in the mostly high-confidence statements presented in Table 1.

The main concern in attributing Australian heatwaves to climate change is the capability of the models used to represent the underlying physical mechanisms. For example, physical climate models simulate land-atmosphere feedbacks on the boundary layer inconsistently (Hirsch et al., 2019; Ukkola et al., 2018) which might affect the intensity of multi-day heatwaves (Miralles et al., 2014). The simulation of synoptic systems conducive to heatwaves and associated dynamics is also questionable (Gibson et al., 2017). Heatwaves are also highly sensitive to internal climate variability (Gibson et al., 2017a; Perkins-Kirkpatrick et al., 2017; Perkins-Kirkpatrick & Lewis, 2020). It is therefore not surprising that climate models differ in their ability to simulate Australian heatwaves (Gibson et al., 2017b). These uncertainties indicate the need for some caution in interpreting attribution statements for extreme heat. Although the consistency of findings across multiple methods suggests the detection of a human-induced signal is likely robust, but the quantification of the signal is likely more uncertain than currently reported.

3.3. Marine heatwaves

A marine heatwave (MHW) is characterised at the ocean surface and/or in the subsurface by a prolonged period of warm ocean extreme temperatures relative to the time of year. In the Australian region, a MHW is typically due either to increased transport intensity of a warm ocean boundary current or net positive downward surface heat exchange from a persistent high-pressure system. Process-based analyses of MHWs usually involve local analysis of the temperature (or heat) tendency budget with a focus on changes within the upper ocean mixed layer (Holbrook et al., 2019). Remote processes can also influence the likelihood and intensity of MHWs, as well as their potential predictability (Holbrook et al., 2019; 2020).

Various studies (King et al., 2017; Oliver et al., 2017, 2018; Perkins-Kirkpatrick et al., 2018) have investigated the attribution of Australian region MHW events to human-induced climate change using the fraction of attributable risk (FAR) approach. First, based on the analysis of observations and climate models, it was found to be very likely that an event of the unprecedented 2015/16 Tasman Sea MHW duration and intensity was respectively $\geq$ 330 times and $\geq$ 6 times as likely due to human-induced climate change (Oliver et al., 2017). Second, it was found to be virtually certain that an event of the intensity and duration of the 2015/16 warming across Northern Australia was at least 8.5 and 53 times as likely, respectively, due to climate change (Oliver et al., 2018). A separate analysis attributed marine heat to the coral bleaching in the Great Barrier Reef region in 2016 (King et al., 2017) with the likelihood of marine heat expected to substantially increase as the world warms. More recently, the extensive but relatively shallow (to only ~20 m depth) 2017/18 Tasman Sea MHW event intensity was assessed to be virtually impossible without human-induced climate change (Perkins-Kirkpatrick et al., 2018). Analyses of MHWs under climate change often arrive at very strong conclusions with large increases in likelihood of extreme events due to the high signal-to-noise ratio seen in warming ocean temperatures.

Successful process-based event attribution of individual MHW events requires careful consideration of minimum expected standards for observational systems and the representation of processes in ocean and climate models. (Holbrook et al., 2020), for example, show that MHWs are influenced by preconditioning from the atmosphere (in particular, blocking) and/or the ocean (including mixed layer depth, heat content), atmosphere and ocean teleconnections (in particular Kelvin waves, Rossby waves) as well as modes of climate variability (MoVs). For global detection and attribution studies of changes in sea surface temperature (SST), ocean models at 1° resolution give broad-scale MHW changes that are closely tied to the long-term global mean warming of SST (Oliver, 2019). However, for attribution studies of individual MHW events around Australia, 1/10° resolution (Pilo et al., 2019) is required to capture the important eddy-scale processes and their changes expected under climate change, and their important role in western boundary current regions at the regional-scale (Hayashida et al., 2020; Holbrook et al., 2019; Oliver et al., 2015). Thus, the ability of climate models to replicate key MHW features, as well as the required spatiotemporal resolutions needed to appropriately simulate MHW events, results in high confidence in attribution assessments over longer timescales, but only medium confidence over shorter timescales due to the importance of eddy-scale processes (see Table 1). Ongoing improvements in the resolution of the ocean component of climate models should allow improvement in the representation of MHWs on shorter timescales.

3.4. Drought

Drought arises from climate variations associated with models of variability (MoVs) operating from seasonal to interannual and decadal time scales. While many different definitions of drought exist (Mishra and Singh, 2010), events are normally triggered by a sustained rainfall anomaly, leading to declines in streamflow, soil moisture or vegetation function. Describing how unusual multi-year droughts are in a historical context is difficult given limited instrumental data. The observational rainfall record extends to around 1900, and back to around 1860 in the southeast and east of the country (Ashcroft et al., 2014). Paleoclimate data, recorded histories of early European settlement (Fenby and Gergis, 2013; Nicholls, 1988) and potentially aboriginal oral history can extend this record for some regions. Drought reconstructions of ENSO and the IOD using proxies including corals, speleothems, tree rings and lake sediment cores, provide valuable long-term drought-like metrics (Abram et al., 2020; Gergis et al., 2012). There are inevitable challenges in all reconstructions, how to relate them to observed droughts, the lack of a strong causation between IOD or ENSO and drought, the risk that the co-variance of these might be important, and the risk that the relationship between drought and modes of variability is non-stationary (Gallant et al., 2013).

Simulating Australian droughts in climate models is particularly challenging given the MoVs cannot fully explain the persistence, over several years, reflected in observed droughts (Henley et al., 2017). For hydrological and soil moisture droughts, the additional control by the land surface on evapotranspiration and runoff adds complexity and remains difficult to evaluate in models due to a paucity of long-term observations (Ukkola et al., 2018). For ecological droughts, key processes determining how vegetation becomes stressed and succumbs to drought are not represented mechanistically in most climate models. The evaluation of climate models for drought also remains limited (Flato et al., 2013), although studies to date have highlighted systematic errors in the simulation of longer term droughts in particular. Analyses of land surface models have also revealed systematic errors in their capacity to simulate drought conditions well (Ukkola et al., 2016). However, recent analyses have highlighted improvements in the simulation of meteorological drought in CMIP6 models (Ukkola et al., 2020).

Given the relatively infrequent occurrence of severe droughts in Australia, the sparsity in the observational record, the uncertainties surrounding paleoclimate estimates of drought and the high climate variability in Australia, an observations-based attribution of a specific Australian drought to human-induced climate change is infeasible. Moreover, given the lack of persistence in climate models, particularly in the case of long (multi-year) dry periods the value of using climate models for event attribution of drought seems limited for meteorological droughts. The complexity in defining drought and the many influential processes leads to serious challenges, particularly in the consistent and robust attribution across different drought types.

Research has a long way to go before a reasonable level of confidence can be achieved in attributing drought events to human-induced climate change (Kiem et al., 2016). Table 1 shows our expert judgement assessment of the modelling capability, observational confidence and understanding of drought on three timescales: seasonal, 1–2 year and 5–10 year droughts. Three key research challenges needed to be resolved: better definitions of what is meant by drought, better documentation of historical drought and improvements in the simulation of drought on seasonal to multidecadal timescales.

3.5. Severe storms and short duration rain

Short duration (sub-daily) rainfall extremes are associated with convective processes and severe storms (Dowdy and Catto, 2017). Severe storms occur across all regions of Australia (Allen and Allen, 2016), typically associated with fronts, cyclones, the monsoon, and other synoptic-scale disturbances (Clark et al., 2018; Hitchcock et al., 2021; Pope et al., 2009; Soderholm et al., 2017; Warren et al., 2021; Zhou et al., 2021).

All else being equal, the amount of water vapour in the atmosphere increases with temperature by ~7% per ^{o}C. This Clausius-Clapeyron scaling underpins thermodynamic explanations of why precipitation extremes increase with global warming (Westra et al., 2014). At global scales, radiation plays a key role in constraining precipitation increases to 2–3% per ^{o}C (Stephens and Ellis, 2008). At smaller time and spatial scales, precipitation is more closely tied to column water vapour and rainfall extremes can increase at more than the Clausius-Clapeyron rate. For some organized precipitating systems, horizontal moisture convergence can lead to super Clausius-Clapeyron (i.e., >7% per ^{o}C) scaling (Bao et al., 2017). Changes in storm intensity can also be associated with changes in stability and moisture (Singh and O'Gorman, 2015). Dynamics also play a critical role at regional scales in explaining rainfall intensification by influencing moisture availability, stability (e.g., Convective Available Potential Energy, CAPE) and wind shear. Regional differences in circulation change can also cause trends in storm environments (Lepore et al., 2021; Singh et al., 2017; Taszarek et al., 2021).

Thus, while Clausius-Clapeyron scaling arguments help explain potential increases in sub-daily extreme rain events associated with global warming, they do not necessarily provide guidance regarding any changes to the frequency of occurrence of storms.

Hailstorm environments are expected to be affected by climate change, with Clausius-Clapeyron scaling increasing atmospheric instability and allowing for more intense storms that can grow larger hailstones, but increased melting of falling hailstones reducing surface hail occurrence (Raupach et al., 2021). While these changes lead to the broad expectation of trends toward less frequent but more severe hailstorms, offsetting effects and large geographical inhomogeneity in observed and modelled changes means there remains high uncertainty around future hailstorm evolution (Raupach et al., 2021). The few studies on hail and climate change in Australia have focussed on small areas in the south-east and are not all in agreement (Raupach et al., 2021).

Determining trends in short duration (i.e., sub-daily) rainfall extremes and severe storms is challenged by limited spatial and temporal coverage in datasets. Gauge data across Australia is concentrated in populated areas and are often limited to a few decades at sub-daily resolution (Westra et al., 2014). Short duration rainfall events and storms, tornadoes and hail are commonly localized in space and time and are poorly captured by the observational network. Radar archives (Soderholm et al., 2019) are promising for studying short duration rainfall extremes and storms although quality control and record length remain challenging (Saltikoff et al., 2019).

Despite the observational challenges, several studies have explored observed trends in short duration rainfall extremes over Australia. (Guerreiro et al., 2018) demonstrated widespread increases in recent daily and hourly rainfall extremes with trends outside the range of natural variability and exceeding the Clausius-Clapeyron scaling rate. Over Victoria, (Osburn et al., 2021) also showed increasing trends in hourly extremes, despite a background of declining annual rainfall in recent decades. Over the Sydney region, (Ayat et al., 2022) used radar data and showed a recent positive trend of over 20% per decade in subhourly extreme rainfall intensity.

Current coarse resolution climate models do not resolve storms explicitly and the relevant convective processes are parameterized. These models do not represent the dynamics of thunderstorms realistically, which causes significant errors in rainfall intensity (Stephens et al., 2010). Accordingly, over Australia climate models poorly simulate the spatial pattern of observed trends in the wettest day of the year (Rx1day) and the number of wet days (Alexander and Arblaster, 2017). CMIP5 (Alexander and Arblaster, 2017) and CMIP6 models (Grose et al., 2020) show widespread projected increases in Rx1day across Australia, with amplified trends in the tropics, broadly consistent with thermodynamic arguments (Roderick et al., 2019). However, low confidence exists for projections for Rx1day across all of Australia for the reasons given above (Alexander and Arblaster, 2017).

Examining storm environments is an alternate approach to investigate potential changes in rainfall extremes and severe storms for potential use in event attribution studies. Despite advances in development of storm-environment proxies for Australia (Allen et al., 2014; Brown and Dowdy, 2021; Raupach et al., 2022), possible climate model biases in proxy ingredients remain a confounding factor (Allen et al., 2014). In common with other parts of the world (Seeley and Romps, 2015; Brown and Dowdy, 2021) found projections of storm environments varied widely, with trends in regional severe convective wind environments ranging between −16 and +34%.

Overall, this suggests that there is medium understanding and observational capacity to explain potential changes in sub-daily rainfall and extreme storms. Inadequate climate model resolution, and large errors in the representation of storms and storm environments implies low confidence in projections of future sub-daily extremes and severe storms, particularly at regional scales. Accordingly, to date there have been no event attribution studies on this topic in Australia.

Better simulations of severe storms and short-duration rainfall extremes can be achieved using idealised modelling studies (Bao et al., 2017), combined with high-resolution modelling designed to understand the regional response to changing storm environments (Prein et al., 2017; Prein et al., 2017). Impact specific assessments, using multiple data and modelling sources (Raupach et al., 2021) may also help scientific understanding. Finally, both global and regional convection-permitting climate modelling (Kendon et al., 2021) offer promise for future event attribution studies of severe storms and short duration rainfall extremes.

3.6. Extreme rain at greater than daily timescales

Over the past century, the intensity and frequency of daily rainfall extremes in Australia have been broadly increasing (Alexander and Arblaster, 2017) with evidence of a continent-wide intensification of rainfall across the whole wet day distribution over the past 50 years (Contractor et al., 2018). There is evidence of a change toward more episodic rainfall at the expense of persistent, multi-day rainfall events (Dey et al., 2020). However, there are also marked regional and seasonal variations in changes depending on how extreme rainfall is classified (intensity, frequency, duration), what data and metrics are used (Alexander and Arblaster, 2017; King et al., 2013a,b), and what frequency (daily to multi-day) and time period (decadal to centennial) are considered (Jakob et al., 2020; Osburn et al., 2021). For example, there has been a decrease in daily-to-multi-day extreme precipitation in southwest Western Australia since the 1970s (Hope et al., 2006), southeast Australia and southeast Queensland (Dey et al., 2019b), an increase in north-west Australia (Dey et al., 2019a), with the impact of MoVs making trend estimation substantially more uncertain (King et al., 2013a; A. King et al., 2014; Sun et al., 2021) indicated that Australasia is distinct from other continents in that, amongst available stations, more stations showed negative than positive trends. However, stations with decreasing trends were mainly located in southwestern and south-eastern Australia where the strongest decreases in rainfall extremes have been observed.

Some of the causes of the observed rainfall intensity decrease in southern regions of the continent have been linked to changes in circulation, including the southward shift and intensification of the subtropical ridge due to Hadley cell expansion (Nguyen et al., 2018; Timbal and Drosdowsky, 2013; Whan et al., 2014), external forcing induced reduction in the number of synoptic systems (Dey et al., 2019; Hope et al., 2006; Raut et al., 2014) and changes in the SAM due to ozone depletion over Antarctica and increasing greenhouse gas forcing (Cai et al., 2011; Thompson et al., 2011). Increases in north-west Australia have been linked to greenhouse gas forcing (Dey et al., 2019a), aerosols associated with human activity (Dey et al., 2019; Rotstayn et al., 2007; Shi et al., 2008), changes in the Madden-Julian Oscillation (Borowiak et al., 2023) and continental warming further south enhancing the Australian monsoon (Wardle and Smith, 2004). In the context of event attribution, it is noteworthy that climate models cannot reproduce this trend.

Studies attributing long-term trends in extreme rainfall in Australia have produced mixed results mostly related to the fact that individual climate models are unable to simulate the frequency or intensity of extreme rainfall or its spatial pattern (Alexander and Arblaster, 2009). However, models do generally capture the correct sign of the observed trend in extremes based on daily data (Alexander and Arblaster, 2017).

When it comes to individual longer-term extreme rainfall events, there is limited evidence of an human influence in some studies (King et al., 2013) or a small contribution (Hendon et al., 2014; Ummenhofer et al., 2015). The fact that there are diverse conclusions among studies is not surprising given how hard it is to untangle the effects of human and natural drivers given limitations in our current observations and modelling frameworks. This underpins the mainly medium confidence reached by the authors for the attribution of rainfall extremes presented in Table 1. Improvements in confidence of attribution of longer-term rainfall extremes would require major improvements in the understanding of circulation changes and variability on Australian rainfall. In addition, major improvements in the representation of rain events of these magnitudes are required in climate models.

3.7. Tropical cyclones and tropical lows

Tropical cyclones in Australia typically occur between November to April, with 11 declared tropical cyclones occurring on average every year. Annual numbers are affected by the phase of ENSO, and intraseasonal variability is linked to the MJO. Observed Australian cyclone numbers have decreased over the last 30–40 years – consistent with international trends (Knutson et al., 2020). Modelled changes for the Australian region over past and future time-scales also suggest a reduction in numbers (Bruyère et al., 2020, 2022; Cattiaux et al., 2020; Chand et al., 2019). Conversely, there has been a clear and substantial increase in the proportion of intense cyclones (Category 4 and 5) (Bruyère et al., 2020; 2022; Knutson et al., 2020). Observations (see Holmes, 2020), theory, and modelling support an intensification of cyclones under human-induced climate change. At present our understanding of dynamical changes is poor, especially at local scales. Initial evidence suggests that rapid intensification may be increasing close to the coast around the globe (Emanuel, 2017), however this has not been confirmed by subsequent studies. The proportion of severe cyclones also appears to be increasing faster around south-east Queensland than elsewhere in Australia (Bruyère et al., 2020; 2022). Conflicting indications have been found for changed in cyclone size and translation speed (Bruyère et al., 2020) - but at low-medium confidence. While there is confidence that cyclone rainfall will increase across the globe (Knutson et al., 2020) it is less certain whether potential feedbacks between the increase in available energy from extra water vapour will increase rainfall beyond Clausius Clapeyron. Findings of reduced rainfall up to the present by (Lavender and Abbs, 2013) for Australia and globally by (Lavender and McBride, 2021) has introduced more uncertainty in how cyclones will change in the future.

Recent case studies have indicated a potential for increased longevity of cyclones over land with consequential increases in area and duration of rainfall. (Bruyère et al., 2019) found a large climate change component for the record flooding across southeast Queensland and northeastern NSW associated with Cyclone Debbie (2017) arising from increases in both rainfall intensity and area. A follow up study (Bruyère et al., 2020) indicated substantial increases in the area of rainfall >600 mm for eastern Australia from 1954 to 2030. Recently, using large ensemble simulations, Bruyère et al. (2022) found that towards the end of the century, the area of heavy rainfall over land could increase by 200%, along with an increase of over 300% in the frequency of rainfall exceeding the 99% threshold for current climate. In agreement with other assessments (Knutson et al., 2020), the large ensembles indicated an increase in the proportion of the most intense cyclones over recent decades and that this increase could continue out to the end of the century (Bruyère et al., 2022). The coastal zone impacted by tropical cyclones also may increase as a consequence of changing cyclone characteristics, e.g., Bruyère et al. (2022) found that the southern Queensland coast south of Brisbane could expect an increase in frequency of winds exceeding 70 ms^{-1} of 50% by 2070.

The assessment of low-medium confidence in tropical cyclone assessments over the Australian region in Table 1 was based on observational and modelling considerations including: the relatively short period of consistent and reasonably accurate observations; changes in observing practice; the non-physical boundaries of the region; and issues with the capacity of CMIP5/CMIP6 class climate models to resolve or reproduce tropical cyclone features at the regional level. Since the assessment in Table 1 was made, analysis of large model ensembles and statistical downscaling has demonstrated an improved capacity to reproduce several tropical cyclone characteristics with improved confidence for the Australian region (Bruyère et al., 2022 and references therein). Skill was found for: regional distribution of bias-corrected landfall intensities (medium); aggregate and areal rainfall (medium--high); and regional frequency distribution (medium). Modelled numbers of tropical cyclones were markedly undercounted, but the intensity and rainfall distributions within these had medium skill.

Making confident assessments of the impact of climate change on tropical cyclones is complicated, but recent research has shown promise that our ability to do this is growing. Further improvements in our ability to fully capture the processes that lead to changes in cyclone behaviour will require continuing advances in our understanding; together with improved modelling systems incorporating finer spatial resolution, large ensembles, and sophisticated statistical adjustments to isolate the changes in sub-resolution features.

3.8. East coast lows

East Coast Lows (ECL) comprise a family of low pressure systems that occur along the Australian east coast from Fraser Island (25°S) to Hobart (43°S), and into south eastern Victoria. ECLs are typically smaller than other extratropical cyclones and follow a trajectory along the coast due to the Great Dividing Range of eastern Australia and the strong gradients associated with the warm eddies of the East Australian Current (EAC). They are major contributors to damage and societal disruption, but also often provide crucial replenishments of water storages (Bruyère et al., 2020). We focus on all types of ECLs, particularly those that occur close to the coast, including warm-cored systems with surface winds close to the centre, more spread out cold-cored systems, and hybrids of the two including tropical cyclones undergoing extratropical transition. They are characterised by a belt of high winds on the poleward side and a zone of moist, tropical air wrapping around the eastern and poleward sides. Coastal ECLs occur in all seasons, but those in summer have the greatest impact from wind-driven water ingress into buildings, flash and riverine flooding, coastal erosion, and direct damage from high winds (Bruyère et al., 2020).

As indicated in Table 1, confidence in assessing the response of ECLs to climate change is reduced by the plethora of definitions that have been developed (Bruyère et al., 2020), making it difficult to cross-compare individual studies. For example, some studies include only coastal systems, while others include extratropical cyclones well out into the Tasman Sea; and some definitions produce ECL numbers that are an order of magnitude higher than others. The capacity to attribute changes in ECLs to climate change is limited by the relatively short period of observations, the large annual and decadal variability, especially for extreme ECLs, and the poor capacity of climate models to resolve ECLs (Lane et al., 2019). As such, there have been no attribution assessments of ECLs to date.

There is medium confidence from observations, damage assessments and modelling studies that the more intense, summer ECLs close to the coast have trended upwards to the present, whereas the less damaging ones have decreased (Bruyère et al., 2020). There also is low-medium confidence that the upward trend in summer systems will continue into the future as a result of climate change (Cavicchia et al., 2020) and that in winter a decreased frequency of ECLs may be expected as the planet warms (Pepler et al., 2016). Given their importance to the most populated seaboard of Australia, and the uncertainties with their response to climate change, further dedicated research in this area is strongly recommended. An agreed definition and classification of ECL is important, perhaps following (Cavicchia et al., 2020), but sustained efforts to explore the behaviour of ECLs is also required. Given climate models with spatial resolutions suitable for ECL simulation are at least a decade away, use of high resolution regional models is likely part of any program.

3.9. Extratropical cyclones and fronts

Extratropical cyclones and associated fronts deliver useful rainfall to southern Australia, but also often cause disruption due to associated winds and extreme rain. Fronts are also a critical component of fire weather, especially in southeastern Australia (Cai et al., 2022). Methods for identifying and tracking extratropical cyclones and fronts have predominantly used reanalysis products for the Australian region (Pepler et al., 2020), though some studies have supplemented these with operational weather charts (Pook et al., 2012). Therefore, detection of long-term changes is limited by the temporal quality and amount of data assimilated into the forecast system and the forecast model itself. However, studies analysing the observational and reanalysis products over the satellite era have, in general, found a reduction in the frequency of fronts and cut-off lows (Hope et al., 2006; Raut et al., 2017; Risbey et al., 2013) over southern Australia during the cool season, and a reduction in the rainfall from fronts (Pepler et al., 2021).

Projected changes in winter frontal activity (Blázquez and Solman, 2019; Catto et al., 2014) and mid-latitude winter cyclones (Grieger et al., 2014) for the southern hemisphere suggest there is generally a projected increase in storm activity over the Southern Ocean and a decrease in activity in the sub-tropics. There is structure to the sub-tropical reduction in activity, and this aligns with the changes in fronts and lows over Australia over recent decades (Pepler et al., 2020b). While projected changes are primarily associated with greenhouse gases, Antarctic stratospheric ozone recovery may offset these to some extent in the warm season (Arblaster et al., 2011).

The southern hemisphere storm tracks, which act as a waveguide for these extratropical weather features, are positioned over the Southern Ocean, where there is a lack of surface-based observations to validate both reanalysis products and models. Limited observations lead to some uncertainties in the representation of fronts and lows in reanalyses, which downscaling would not overcome. Current global coupled models can represent many features of extratropical weather systems, however, they tend to underestimate the strength of explosive extratropical cyclones and associated precipitation (Catto et al., 2015; Hawcroft et al., 2016; Seiler and Zwiers, 2016). CMIP5 models show similar performance as reanalyses in representing front activity and frequency, however, unlike reanalyses, CMIP5 models tend to overestimate precipitation amounts associated with fronts compared to observations (Blázquez and Solman, 2018). It is unclear to what extent increases in model resolution can improve the simulation of extratropical weather features (Priestley et al., 2020) and the extreme rainfall associated with them (Bador et al., 2020). Fronts and other weather features are also intricately linked with clouds (Naud et al., 2012) and biases in the representation of clouds in CMIP5-class models and associated biases in the circulation (Ceppi et al., 2012) present some challenges for their use in attribution studies.

There have been no attribution studies to date on the change in southern hemisphere extra-tropical cyclones or fronts using probabilistic methods. (Tozer et al., 2020) attempted to attribute a 2018 extreme 1-day rainfall event in Hobart, but formal attribution was not possible due to the small sample size of events of this magnitude. There have been studies that have found an human-induced signal in the structure of pressure anomalies associated with extreme frost in south-west Australia (Grose et al., 2018) and extreme dry in Tasmania (Grose et al., 2019). These have been multi-method studies with comparable findings across the methods suggesting a robust circulation response to increasing levels of greenhouse gases. Process-based attribution approaches or 'storylines' are other methods that can provide information about the expected circulation changes due to attributed factors such as the enhanced warming of the tropical upper troposphere and the strengthening of the stratospheric polar vortex (Mindlin et al., 2020). Thus, the above factors result in our medium confidence of attribution assessments of extra tropical cyclones and fronts, as indicated in Table 1.

There is some scope to extend the current studies examining observed trends and future changes in fronts and cyclones to more focused attribution studies. Aspects of the dynamics of mid-latitude synoptic-scale pressure systems should be well represented by climate models, but fronts are poorly resolved. Accordingly, the depth and intensity of the intense fronts responsible for extreme rain and fire weather are likely unrealistic or absent in climate models. A detailed evaluation of the dynamics of Australian fronts in climate models has not been completed. Given the linkages between intense cyclones and some impacts (rainfall – both heavy and low, frost), further studies on understanding the cause of model biases in intense cyclones would also be worthwhile.

Improvements in global or regional climate model resolution should improve the representation of fronts in models, but mesoscale model resolutions (i.e., horizontal grid spacing of ~10 km) may be required to obtain realistic intensities and dynamical structures. Such improvements, alongside improved understanding of the variability of fronts and cyclones linked to larger-scale climate drivers, should eventually increase the confidence in attribution assessments.

3.10. Fire weather

The likelihood and impact of wildfires relates to multiple factors including meteorological conditions, fuel loads, the state of the fuel and the probability of ignition (McArthur, 1967; Van Wagner, 1987). Efforts to understand the influence of historical global warming on wildfires have often focused on fire weather due to the existence of widely used fire danger rating systems that can readily be computed from climate model output (McArthur, 1967; Van Wagner, 1987). Nevertheless, fire weather has frequently been shown to be an important predictor of both fire incidence (Clarke et al., 2019) and subsequent impacts (Blanchi et al., 2010; 2014; Canadell et al., 2021; Collins et al., 2022). Fuel moisture has received increasing attention due to modelling and observational advances, while fuel load is arguably the most complex and poorly represented of the key biophysical drivers of wildfire risk (See Section 3.11).

The major fire danger rating systems incorporate near-surface weather variables like air temperature, humidity, rainfall and wind speed (but not generally wind direction or change). These systems exclude upper atmospheric properties relevant to wildfire risk (Sharples et al., 2016), necessitating the use of complementary (Haines, 1988; Mills and Mccaw, 2010) or new indices (Srock et al., 2018) to account for these phenomena. The multivariate nature of fire weather and the role of MoVs in influencing fire danger (Abram et al., 2021; Harris and Lucas, 2019) present major challenge for attribution assessments. Three published studies have examined recent Australian fire events within an attribution framework. (Hope et al., 2019), used a seasonal forecast attribution method to investigate the influence of historical changes in carbon dioxide on the record fire weather conditions over eastern Australia in 2017. While their model was able to resolve a clear response in both temperature and humidity to increasing atmospheric carbon dioxide, limitations in simulating wind speed and drought factor meant it was not possible to attribute overall changes in the Forest Fire Danger Index (FFDI). (Lewis et al., 2020) separately examined the influence on increasing atmospheric carbon dioxide on each of the variables contributing to the FFDI and was able to attribute the observed warmer and drier conditions to human-induced climate change. Van Oldenborgh et al. (2020) found that human-induced climate change was at least partially responsible for the record fire weather over Southeast Australia during the Black Summer, mainly driven by increases in extreme temperature. Given the complexity of the multiple drivers of fire weather in Australia, and how this will change in the future at local to regional scales, we currently have low-medium confidence in attribution assessments of Australian fire weather (see Table 1), with low confidence particularly influenced by climate model capability to appropriately simulate fire weather like intense fronts (D. Cai et al., 2022).

As for all attribution studies, the conclusions of these respective studies are conditioned on their experimental design (i.e., particular modelling setup, model resolution, ensemble size, etc.). The collective recommendations from these studies suggested that future attribution studies of fire weather over Australia would benefit from higher resolution models with larger ensemble sizes, while any bias correction should be multi-variate to preserve the relationship between interdependent variables. Combining the elements that influence fire risk (fuel, dryness, wind etc) into a risk index appropriate for both attribution assessments and future projections is also long overdue (Srock et al., 2018) although it is possible that refinements on any specific index will be event specific.

3.11. Fire relevant fuels

Fuels, and the condition of the fuels, are a fundamental pre-condition for wildfire (Archibald et al., 2009; Bradstock, 2010). The primary sources of fuel globally are woody and herbaceous plants, yielding two broad classes of fuel with distinct properties, arrangements and accumulation rates (Bradstock, 2010). In environments dominated by grassy fuels, the amount and continuity of fuel strongly constrains the occurrence of wildfire, whereas the primary constraints in litter-based fuel systems are typically fuel dryness and fire weather, rather than fuel amount (Bradstock, 2010; Clarke et al., 2020). Australia's high diversity of fuel types and climate regions results in a large number of distinct fire regimes, including infrequent but high intensity litter- and bark-driven fires in the southern and eastern extremities, and frequent low intensity grass-fuelled fires in the monsoonal north (Murphy et al., 2013). Surface fuels are critical to the spread of fire, although multiple layers (e.g. shrubs, elevated fuel) can influence fire behaviour (Gould et al., 2011; Hines et al., 2010; Zylstra et al., 2016). Although there is a good understanding of the drivers of spatiotemporal variation in fuel amount, the complexity of these drivers makes attributing episodic extreme fuel levels to climate change challenging.

Process-based models such as dynamic global vegetation models (DGVMs) incorporate direct and indirect influences on fuel amount such as litterfall, decomposition, fire incidence and primary productivity, including potential carbon dioxide fertilisation effects (Allen et al., 2020; Clarke et al., 2016; Piao et al., 2015). However, evidence from free-air carbon dioxide enrichment experiments suggests more complex effects than are currently parameterised in DGVMs (US Department of Energy, 2020; Yang et al., 2020). Further, although DGVMs and the fire modules derived from them provide an ideal framework for addressing detection and attribution, they are still limited in their ability to simulate observed fuel loads and associated fire risk (Forkel et al., 2019; Sanderson and Fisher, 2020). The processes underpinning fuel moisture are to some extent independent of the processes governing biomass accumulation. Dead fine fuel moisture is known to respond to hourly and daily variations in vapour pressure deficit (Resco de Dios et al., 2015), which climate models estimate albeit at very different spatial scales. The links between VPD and area burned are strong and consistent across a wide range of forest types (Abatzoglou and Williams, 2016; Boer et al., 2020; Clarke et al., 2022), suggesting the potential tractability of attributing extreme fuel moisture levels in individual wildfire events to climate change (Williams et al., 2019; Zhuang et al., 2021).

Statistical links between fuel properties and climate and edaphic variables have been used to spatialise fuel estimates and provide a guide to climate change effects, including a potential decline in litter fuel loads in a warmer world (McColl-Gausden et al., 2020; Thomas et al., 2014; Williamson et al., 2014). However, the distribution and abundance of woody and herbaceous plants – and the fuel they provide for wildfires – is a complex function of climate, soil, terrain, competition and disturbance, making attribution of changes in fuel load difficult, particularly at the scale of individual events. Attribution must also reconcile potentially divergent effects on fuel of changes in temperature, rainfall and atmospheric carbon dioxide concentration. However, arid regions show some promise as possible test cases for detection and attribution, given the strong links between extreme rainfall and fire in these areas (Verhoeven et al., 2020). Therefore, based on the information above, we consider attribution assessments on wildfire fuel to be of mainly medium confidence, with slightly higher confidence in assessments produced for events on monthly timescales, due to better physical understanding of these events.

3.12. Storm surges

Storm surge is a local rise in a water body arising from multiple mechanisms and, in the context of this paper, is assumed to be impacting the coast. Mechanisms include wind-driven currents, set-up from breaking waves, a barometric rise in response to low atmospheric pressures, and the angle and speed of storm approach to the coast. Local bathymetry and coastal characteristics are important factors in storm surge assessments. Concurrent riverine flooding also increases the surge height. Combinations of these mechanisms have produced Australian surges of around 12 m from tropical cyclones, and up to 1m from ECLs (citation needed).

Because of the many factors that contribute to storm surge, it is best to examine each separately in establishing confidence levels for the surge response to climate change (Bruyère et al., 2020; Lane et al., 2019). There is no doubt that sea level is rising and will continue to do so (IPCC, 2021) which increases the consequences of storm surge. There is high confidence that proportion of intense TCs has risen and will continue to rise, though decreasing total numbers and inconsistencies in observational data bases leads to uncertainty for changes in total number of intense cyclones (IPCC, 2021). There is low-medium confidence of a poleward extension of intense TCs (Bruyère et al., 2022). Intense warm-season ECLs are expected to increase in coastal regions with low-medium confidence (Pepler et al., 2016), there is low confidence for any changes to prevailing directions and speeds of TCs and ECLs at the coast (Chand et al., 2019). The amount and area of storm rainfall are both expected to increase with high confidence (Bruyère et al., 2022). The few published studies specifically on Australian TC and ECL surge changes under future climates indicate substantial increases.

(McInnes et al., 2003) projected ~25% increase in surge heights by 2050 at various return periods for the Queensland coastal areas. (Woodruff et al., 2013) also found increasing global flooding due to TCs, including Australia. The maximum storm surge associated with TC Yasi in 2011 on the Queensland coast was likely to be enhanced due to warm SST; (Lavender et al., 2018) found a substantial increase in storm surge for SST anomalies up to 2 °C but little sensitivity above this temperature. A large ensemble assessment by (Lin and Emanuel, 2016) for Cairns found that probabilities of high TC storm surges increase by more than an order of magnitude. For example, 1:100 year events increased in probability to every ~10 years).

Taken together these assessments associated with storm surge indicate high confidence that storm surge will increase with climate change. There is uncertainty on the actual amount of change, but despite the uncertainty indications are the storm surge increase is likely to be substantial. While we have high confidence on the physical understanding of storm surge, our confidence of corresponding attribution assessments is low-medium, based on current modelling capacity the relative lack of observations (see Table 1).

4. A decision tree for event attribution

Based on the knowledge outlined above, it may be difficult to discern *a priori* whether an attribution assessment on a given extreme event would be associated with reasonable confidence and is, therefore, worth undertaking. In particular, the previous sections emphasised the importance of the length and quality of the observational record, and the ability for climate models to be able to represent the observed statistics of extreme phenomena and the physical mechanisms responsible for those extremes. We, therefore, give an example of a decision-based process to assess such confidence before and during the analysis process, as well as how to synthesise the results.

Marine heatwaves in the Tasman Sea are known to be formed either due to atmospheric forcing through sustained surface heat fluxes (e.g., via a blocking high pattern) or due to enhanced East Australian Current (EAC) oceanic advection of warm water into the extension region (advective heat gain) (Holbrook et al., 2019; 2020) or a combination of both. Li et al. (2020) demonstrated that marine heatwave events in the western Tasman Sea are caused about 50% of the time by each process. These characteristics of marine heatwaves lend themselves to the below example to assess the viability and confidence of attribution studies. The proposed decision tree for this example, which is also generalised in Fig. 2, is:

Decision 1: Is the event's intensity or duration considered extreme as determined from an appropriately long observational record?

a. Yes, then go to Decision 2.
b. No, then the event is not appropriate for event attribution.

Decision 2: Does the model reproduce the observed statistics of the event in question (e.g., marine heatwaves in the Tasman Sea for the appropriate season)?

a. Yes, then go to Decision 3.
b. No, then the modelling system is not fit for purpose for the event in question. Attribution statements about the rarity of the event (based on observations) and expected changes in the event (based on physical understanding) may be appropriate with suitable caveats.

Decision 3: Does the modelling system (or systems) reproduce the statistics of the types of event under consideration in the region of interest for the right physical reasons? That is, does the modelling system capture whether the event is due to enhanced net downward surface heat flux heating and/or advective heating from intensification of the EAC extension?

a. Yes – the model(s) produce marine heatwaves in the appropriate location via a combination of atmospheric forcing and EAC extensions with the correct relative contributions of these two processes. A robust attribution statement could be made.

b.1 Maybe – the model(s) produce marine heatwaves predominantly via EAC extensions. The modelling system may still provide useful information about the trends in important processes (in this case EAC extensions), which could be an important component of the event in question. An event attribution study or statement may still be appropriate but with clear caveats around the uncertainty caused by the inability of the models to realistically represent all the physical processes.

b.2 Maybe – the model(s) produce marine heatwaves predominantly via sustained atmospheric forcing. As per outcome 3b.1 above.

c. No – the model(s) produce the phenomenon by the wrong physical processes. The model(s) are not fit-for-purpose for the event in question. Attribution statements may be made as per Outcome 2b, with the appropriate caveats.

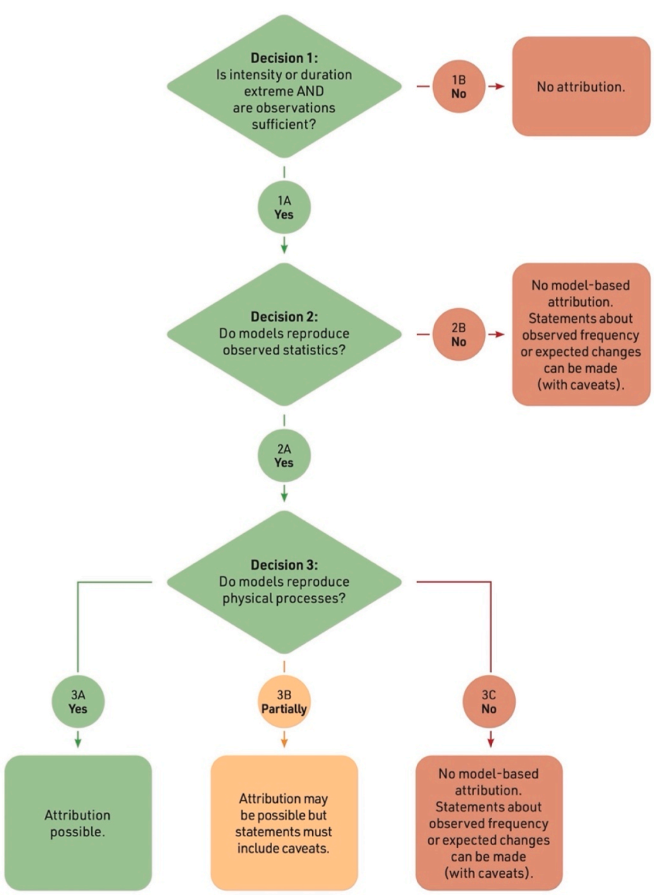

Fig. 2. Graphical depiction of the generalised decision tree for event attribution.

As per Table 1, there is high confidence in our ability to observe, simulate, and understand long duration marine heatwaves, making them a good candidate for event attribution studies. These properties suggest that for marine heatwaves represented in dynamical ocean and climate models with appropriate ocean model resolution, outcome 3a is likely. Table 1/Fig. 1 can be used as a guide for other phenomena as well. Of course, the outcomes should not necessarily be assumed, but require sufficient assessment of the appropriate observational records as well as statistical and process-based model evaluation on a case-by-case basis. Conferring with Table 1 and Fig. 1 it is apparent that for some phenomena (e.g., extreme rain, severe convective storms, east coast lows, long-duration drought, etc.) the inherent model inadequacies suggest that outcome 2b or 3c is likely. That is, the models are not fit-for-purpose so attribution statements should not be made without significant caveats.

All the required decisions outlined above require judgements about what is "good enough". These choices may be informed by statistical tests, thresholds based on previous studies in the literature, and expert judgement. The decisions ultimately introduce caveats to the event attribution statement or study, which should always be clearly articulated.

(Lewis et al., 2019) argued for the use of calibrated language for event attribution studies, including a visual dial of extreme event attribution likelihood as well as additional confidence assessments based on the methods and models used. The above decision tree and the Table 1/Fig. 1 assessment is aligned with their approach. However, our approach also suggests the importance of an additional category on the likelihood scale of "unable to make a robust event attribution statement".

5. Future opportunities

We have documented how different weather and climate extremes in Australia have changed and what can then be said about the role of human influences. After about a decade of event attribution studies on Australian extremes, it is clear that the confidence behind assessments is much greater behind some types of extremes than others. Longer duration heat events have the highest confidence, while smaller-scale events such as convective storms, tropical or east coast lows have the lowest confidence in their resulting attribution assessments (Table 1 and Fig. 1). Events associated with the land surface and vegetation (e.g., long duration drought, fire weather, and multi-year aspects of fire-relevant fuel) are also challenging to attribute. The different levels of difficulty likely explain why there are more attribution assessments on extreme heat in comparison with other events. With improving data sets, better understanding of processes and improving modelling systems there are opportunities to improve our confidence in event attribution We highlight some future opportunities for event attribution in Australia next.

5.1. Multi-method approaches to event attribution

Event attribution studies using multiple methods to assess the influence of human-linked forcings on extreme events have emerged and are becoming more widely used for Australian-based studies. The earliest event attribution analyses both in Australia (King et al., 2013; Lewis and Karoly, 2013) and elsewhere (Pall et al., 2011; Stott et al., 2004) tended to rely on a single method such as the use of coupled atmosphere-ocean general circulation models or sea surface temperature forced models with and without human influences. Recently, studies have tended to employ multiple different modelling and observational techniques more often, in an attempt to better account for uncertainties in quantifications of human-associated forcings (van Oldenborgh et al., 2021a). As different methods frame the event attribution question in different ways (see Methods and Global Context) and because Australia has very strong teleconnections to MoVs (Min et al., 2013; Nicholls et al., 1997; Perkins et al., 2015; Risbey et al., 2009), further use of methods with differing degrees of conditioning could help in understanding and quantifying the relative roles of natural variability and human-associated forcings of Australian extremes.

5.2. More dynamical and process-based analyses of extremes

Event attribution studies are driven by the occurrence of extreme weather events. As heat extremes have become more common than cold extremes (Lewis and King, 2015) we have seen far more studies on the former (Arblaster et al., 2014; Black et al., 2015; King et al., 2015; Lewis and Karoly, 2013; Perkins et al., 2013) than the latter (Grose et al., 2018). However, essentially all these studies have focused primarily on statistical analyses of a single variable (in this case temperature), which is the outcome of a sequence of processes. For example, there is growing knowledge of the dynamical mechanisms leading to heat extremes in Australia – specifically Rossby wave breaking and the links between tropical cyclones or active tropical convection to the northwest of Australia and heatwaves in southeast Australia (Parker et al., 2014; Parker et al., 2013). Unfortunately, there have been no event attribution studies focusing on the analysis of the weather systems (e.g., Rossby wave breaking) causing the heat events, and limited evaluation of these mechanisms in climate models. Extending event attribution of heat events to include the dynamical mechanisms should provide more rigor.

Process-based analysis of other (currently lower confidence) extremes may also offer some opportunities for progress. For example, despite climate models having significant difficulties representing rainfall extremes, they may provide more realistic representations of process-guided variables that are closely related to rain (such as horizontal water vapour flux – see for example (Reid et al., 2021)). Other examples include studying storm environments in the context of severe storms and studying extreme fronts in the context of fire weather events, etc. Thus, there are opportunities to extend event attribution to focus on the changing nature of the processes and weather systems responsible for the extremes, rather than the extremes of simple variables like temperature and rainfall.

5.3. Attempts at event attribution of low confidence weather and climate extremes

There have no event attribution studies examining hailstorms or fire-relevant fuels in Australia. This is due to three factors. First, we lack long-term and complete observations of most extreme events. Second, there is a relative lack of understanding of the processes behind these extremes. Finally, there is insufficient model capability in simulating these extremes. Sanderson and Fisher (2020), for example, provide a discussion of the inadequacies in the representation of Australian fires in the current set of earth system models. As understanding of these extremes and their simulation in climate models improve then we may expect more analyses of weather and climate extremes not previously studied in an event attribution framework. This may be facilitated by improvements in attribution methods or multi-method attributions, or changes in model capability facilitated by convection-permitting modelling (see below). However, some of the physical characteristics of these extremes (i.e., small-scale, short duration) are likely to be poorly represented in climate models for some time, thereby limiting our confidence in event attribution studies.

5.4. Impact-based event attribution analyses

The majority of event attribution studies have examined the human influence on weather and climate variables. More recently, however, there have been attempts to quantify the effects of human-induced climate change on specific impacts of extreme events. In particular, there has been growing focus on the effect of extreme heat events on human health with work attempting to attribute additional heat-related deaths to human-caused climate change (Mitchell et al., 2016). Attribution of structural and economic damage during extreme rainfall events to human-induced climate change has also been attempted (e.g., Frame et al., 2020; Schaller et al., 2016). However, whether trends in losses can be attributed to climate change in Australia is unclear (Gissing et al., 2021), although this is less critical than in low-income regions (King et al., 2023). The success of impact-based attribution is more complex than that of the extreme event itself, since it not only relies on the ability of climate models to simulate the event of interest, but also whether the impact can be robustly estimated from the model output. Collaboration between impacts researchers and climate scientists is essential here, so that the limitations of climate modelling and impacts estimation – as well as extreme event attribution – are properly understood and integrated into methodologies (Perkins-Kirkpatrick et al., 2022).

5.5. Prediction attribution methods

Forecast-based attribution compares the operational forecast of a specific synoptic event with an alternative forecast run with reduced atmospheric greenhouse gas concentrations and altered ocean, atmosphere and land conditions (e.g., Wang et al., 2021). Under the assumption that this synoptic state would be just as likely in a world with reduced greenhouse gas concentrations, probabilistic statements can then be made based upon the spread across the two sets of ensembles, as to how the nature (e.g., the intensity) of the event was altered by it occurring within human-influenced background conditions. Given the system provides the full state of the atmosphere and ocean, there are multiple events that can be examined.

This approach has already been demonstrated for examining Australia-wide month-long heat events (Arblaster et al., 2014; Hope et al., 2015; 2016), the heatwave preceding the Black Saturday 2009 fires (Abhik et al., 2023), extreme wet (2-weeks) over the Murray-Darling Basin (Hope et al., 2018), extreme monthly frost in south-west Australia (Grose et al., 2018) and extreme dryness over Tasmania in 2015 (Grose et al., 2019). More complex features such as fire weather indices call for a 'hybrid' approach using modified observations to represent the drought conditions in the lead up to the forecast event (Hope et al., 2019b). Seasonal prediction attribution methods could also be used to examine ocean extremes. Depending on the extreme event type, the dynamical set-up and model capability, this could be further expanded to other events. An advantage of weather/seasonal prediction-based attribution is the incorporation of the current active state of the MoVs, making attribution assessments more relevant to current conditions. Attribution information generated by this approach could (a) help emergency and infrastructure managers consider how to prepare for future events, and (b) help scientists think connect the ability of different modelling approaches to accurately model the sequence of events associated with the extreme event and their drivers (e.g., Wang et al., 2016).

5.6. Operational event attribution

The earliest event attribution studies took several years to be completed (Pall et al., 2011). More recently these analyses have become more rapid and are often completed within weeks or months after the event occurred. This raises the prospect of operational event attribution, linking human-caused climate change and extreme events in real-time. One of the earliest analyses aimed at enabling real-time event attribution statements focussed on Australian national and state-wide temperatures that exceeded existing records (Lewis et al., 2014). Using pre-existing multi-model ensembles that had been evaluated for pre-defined regions, (Lewis et al., 2014) created a set of tables that could be referred to for immediate statements in the aftermath of a new national or state-wide temperature record. Such tables are useful for large-scale climate extremes and allow for statements based on minimal conditioning (e.g., ignoring background ENSO conditions).

Since the work of (Lewis et al., 2014), there has been growing interest in providing rapid attribution statements using a range of methods. Given the potential use of sub-seasonal to seasonal prediction models for operational event attribution and the pioneering use of these models in extremes analyses in Australia (e.g., Arblaster et al., 2014; Hope et al., 2015; Hope et al., 2018; Hope and Coauthors, 2022) it is possible that operational event attribution could be undertaken in Australia in the future.

5.7. Linking event attribution with climate projections

Extreme event attribution initially focussed on comparing the frequency or intensity of weather and climate events between a world without human influences and the current or recent world. A logical extension of this was to extend the methodology to warmer climates we may experience in the future (Christidis et al., 2014) and to extend this framework to specific global warming levels such as those in the Paris Agreement (King et al., 2017; Lewis et al., 2017; Perkins-Kirkpatrick and Gibson, 2017). There are several emerging techniques in this space, including using the seasonal-forecast based attribution approach with the addition of an estimate of the change in background climate in a future world. One study used the doubled observed trend as a proxy for a warmer world (Lim et al., 2019). As a greater focus in climate science is placed on extremes generally, we would expect to see more work that employs event-attribution methodologies to make projections of extremes under further global warming.

5.8. Use of convection-permitting modelling for event attribution

The resolution of climate models is a major limitation for realistically simulating many of the extremes that affect Australia, in part due to the key role of mesoscale atmospheric processes in some extremes (e.g., severe storms, fire weather). A step-change in physical model realism occurs when models achieve kilometre scale horizontal grid spacing, allowing convective processes to be explicitly simulated (Palmer and Stevens, 2019). Such advances could allow many of those extremes that received a Low or Medium in the model capability category in Table 1/Fig. 1 to have increased modelling confidence. Expanded use of convection-permitting regional climate modelling (in the near term), and convection-permitting global climate modelling (in the longer term) holds great promise for improved understanding and projections of extremes and could be utilised for event attribution studies. However, convection-permitting modelling is not a panacea, because those models still contain many errors and biases and require extensive model development to benefit from the higher resolution. For regional convection-permitting downscaling, the quality of the global model also places limitations on the outcomes. The computational expense will also make the creation of large ensembles challenging for many years to come, which may hinder their application to event attribution.

5.9. Compound events

Compound events have recently emerged as a focus for understanding the link between changes in weather and climate and impacts on vulnerable systems (Leonard et al., 2014; Seneviratne et al., 2012; Zscheischler et al., 2020). There are multiple definitions of "compound event" but most reflect the joint occurrence of two or more hazards and/or drivers (Ridder et al., 2020; Zscheischler et al., 2018) as distinct from the occurrence of a single hazard. For example, one common compound event is the co-occurrence of strong winds and heavy precipitation associated with fronts, cyclones, and thunderstorms (Dowdy and Catto, 2017) where structural damage incurred by wind-driven rain can occur at wind speeds below meteorological maxima. Given how hard it is to simulate some single hazards (e.g. extreme rainfall) in climate models, it might be expected that these models would lack useful skill in calculating the joint probability of two rare (99th percentile) meteorological phenomena. However, (Ridder et al., 2021) have shown that some CMIP6 models display skill in capturing the statistics of two compound events (hot and dry; wet and windy). This skill, displayed by some models is surprising given the spatial resolution and challenges in capturing the drivers of many meteorological extremes. Given the importance of compound events to society (Seneviratne et al., 2012; Zscheischler et al., 2020), attribution studies are likely to increase, but remain extremely challenging given the lack of occurrences of extremes compounding in space and time.

6. Final words

Extreme event attribution is a relatively new field of climate science, which has grown rapidly in recent years. It has become prominent in public discourse on climate change, an important input for policy development, and useful for evaluating climate risk. Event attribution and attribution methods allow us to learn about the physical climate system, and how human-induced changes affect our environment. Ongoing improvement in process understanding, understanding of the impact of climate change on extreme events, and significant and ongoing improvements in climate models (especially high-resolution models) has aided the development of the field of event attribution. This paper has summarised recent work on extreme event attribution in Australia, the methods used, limitations, and opportunities for progress. It has examined the confidence and uncertainties in how human-induced climate change will affect the key phenomena that impact Australia, highlighted gaps in our knowledge, and explained challenges in the representation of some extremes in climate models.

Among other things, this review has highlighted the importance of three key elements that underpin rigorous event attribution studies in Australia (and elsewhere). These are observations, understanding, and realistic climate modelling. Thus, if we are to improve our ability to predict changes to extremes and attribute extreme events to human-induced climate change, we need to continue to collect and curate high-quality observational datasets, support fundamental research into weather and climate processes, and invest in the continued development and improvement of climate models.

Declaration of competing interest

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Data availability

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References

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proc. Natl. Acad. Sci. U.S.A. 113 (42), 11770–11775. https://doi.org/10.1073/pnas.1607171113.

Abram, N.J., Wright, N.M., Ellis, B., Dixon, B.C., Wurtzel, J.B., England, M.H., et al., 2020. Coupling of Indo-Pacific climate variability over the last millennium. Nature 579 (7799), 385–392. https://doi.org/10.1038/s41586-020-2084-4.

Abram, N.J., Henley, B.J., Sen Gupta, A., Lippmann, T.J.R., Clarke, H., Dowdy, A.J., et al., 2021. Connections of climate change and variability to large and extreme forest fires in southeast Australia. Commun. Earth Environ. 2 (1), 1–17. https://doi.org/10.1038/s43247-020-00065-8, 2021 2:1.

Alexander, L.V., Arblaster, J.M., 2009. Assessing trends in observed and modelled climate extremes over Australia in relation to future projections. Int. J. Climatol. 29 (3), 417–435. https://doi.org/10.1002/joc.1730.

Alexander, L.V., Arblaster, J.M., 2017. Historical and projected trends in temperature and precipitation extremes in Australia in observations and CMIP5. Weather Clim. Extrem. 15, 34–56. https://doi.org/10.1016/J.WACE.2017.02.001.

Allen, J., Allen, E., 2016. A review of severe thunderstorms in Australia. Atmos. Res. 178–179, 347–366. https://doi.org/10.1016/j.atmosres.2016.03.011.

Allen, J.R.M., Forrest, M., Hickler, T., Singarayer, J.S., Valdes, P.J., Huntley, B., 2020. Global vegetation patterns of the past 140,000 years. J. Biogeogr. 47 (10), 2073–2090. https://doi.org/10.1111/jbi.13930.

Allen, J.T., Karoly, D.J., Walsh, K.J., 2014. Future australian severe thunderstorm environments. Part I: a novel evaluation and climatology of convective parameters from two climate models for the late twentieth century. J. Clim. 27 (10), 3827–3847. https://doi.org/10.1175/JCLI-D-13-00425.1.

Allen, M.R., 2003. Liability for climate change. Nature 421 (6926), 891–892. https://doi.org/10.1038/421891a.

Alves, O., Wang, G., Zhong, A., Smith, N., Tseitkin, F., Warren, G., et al., 2003. POAMA: bureau of Meteorology operational coupled model seasonal forecast system. In: National Drought Forum, pp. 49–56 (Brisbane).

Angélil, O., Stone, D.A., Tadross, M., Tummon, F., Wehner, M., Knutti, R., 2014. Attribution of extreme weather to anthropogenic greenhouse gas emissions: sensitivity to spatial and temporal scales. Geophys. Res. Lett. 41 (6), 2150–2155. https://doi.org/10.1002/2014GL059234.

Angélil, O., Stone, D.A., Wehner, M., Paciorek, C.J., Krishnan, H., Collins, W., 2017. An independent assessment of anthropogenic attribution statements for recent extreme temperature and rainfall events. J. Clim. 30 (1), 5–16. https://doi.org/10.1175/JCLI-D-16-0077.1.

Arblaster, J.M., Meehl, G.A., Karoly, D.J., 2011. Future climate change in the Southern Hemisphere: competing effects of ozone and greenhouse gases. Geophys. Res. Lett. 38 (2), 2701. https://doi.org/10.1029/2010GL045384.

Arblaster, J.M., Lim, E.-P., Hendon, H.H., Trewin, B.C., Wheeler, M.C., Liu, G., Braganza, K., 2014. Understanding Australia's hottest September on record. Bull. Am. Meteorol. Soc. 95 (9), S37–S41. https://doi.org/10.1175/1520-0477-95.9.S1.1.

Archibald, S., Roy, D.P., van Wilgen, B.W., Scholes, R.J., 2009. What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Biol. 15 (3), 613–630. https://doi.org/10.1111/j.1365-2486.2008.01754.x.

Ashcroft, L., Pezza, A.B., Simmonds, I., 2009. Cold events over southern Australia: synoptic climatology and hemispheric structure. J. Clim. 22 (24), 6679–6698. https://doi.org/10.1175/2009JCLI2997.1.

Ashcroft, L., Karoly, D.J., Gergis, J., 2014. Southeastern Australian climate variability 1860-2009: a multivariate analysis. Int. J. Climatol. 34 (6), 1928–1944. https://doi.org/10.1002/joc.3812.

Ayat, H., Evans, J.P., Sherwood, S.C., Soderholm, J., 2022. Intensification of subhourly heavy rainfall. Science 378 (6620), 655–659. https://doi.org/10.1126/SCIENCE.ABN8657/SUPPL_FILE/SCIENCE.ABN8657_SM.PDF.

Bador, M., Boé, J., Terray, L., Alexander, L.V., Baker, A., Bellucci, A., et al., 2020. Impact of higher spatial atmospheric resolution on precipitation extremes over land in global climate models. J. Geophys. Res. Atmos. 125 (13), e2019JD032184 https://doi.org/10.1029/2019JD032184.

Bao, J., Sherwood, S.C., Alexander, L.V., Evans, J.P., 2017. Future increases in extreme precipitation exceed observed scaling rates. Nat. Clim. Change 7 (2), 128–132. https://doi.org/10.1038/nclimate3201.

Black, M.T., Karoly, D.J., King, A., 2015. The contribution of anthropogenic forcing to the Adelaide and Melbourne heatwaves of January 2014. Bull. Am. Meteorol. Soc. 96 (12), S145–S148. https://doi.org/10.1175/BAMS-D-15-00097.1.

Blanchi, R., Lucas, C., Leonard, J., Finkele, K., Blanchi, R., Lucas, C., et al., 2010. Meteorological conditions and wildfire-related houseloss in Australia. Int. J. Wildland Fire 19 (7), 914–926. https://doi.org/10.1071/WF08175.

Blanchi, R., Leonard, J., Haynes, K., Opie, K., James, M., Oliveira, F. D. de, 2014. Environmental circumstances surrounding bushfire fatalities in Australia 1901–2011. Environ. Sci. Pol. 37, 192–203. https://doi.org/10.1016/J.ENVSCI.2013.09.013.

Blázquez, J., Solman, S.A., 2018. Fronts and precipitation in CMIP5 models for the austral winter of the Southern Hemisphere. Clim. Dynam. 50 (7–8), 2705–2717. https://doi.org/10.1007/s00382-017-3765-z.

Blázquez, J., Solman, S.A., 2019. Relationship between projected changes in precipitation and fronts in the austral winter of the Southern Hemisphere from a suite of CMIP5 models. Clim. Dynam. 52 (9–10), 5849–5860. https://doi.org/10.1007/s00382-018-4482-y.

Boer, M., Resco de Dios, V., Bradstock, R.A., 2020. Unprecedented burn area of Australian mega forest fires. *Nature Climate Change*. Nature Res. https://doi.org/10.1038/s41558-020-0716-1.

Borowiak, A., King, A., Lane, T., 2023. The link between the Madden-Julian Oscillation and rainfall trends in northwest Australia. Geophysical Research Letters 50. https://doi.org/10.1029/2022GL101799 e2022GL101799.

Bradstock, R.A., 2010. A biogeographic model of fire regimes in Australia: current and future implications. In: Global Ecology and Biogeography. John Wiley & Sons, Ltd. https://doi.org/10.1111/j.1466-8238.2009.00512.x.

Brown, A., Dowdy, A., 2021. Severe convective wind environments and future projected changes in Australia. J. Geophys. Res. Atmos. 126 (16), e2021JD034633 https://doi.org/10.1029/2021JD034633.

Bruyère, C.L., Done, J.M., Jaye, A.B., Holland, G.J., Buckley, B., Henderson, D.J., et al., 2019. Physically-based landfalling tropical cyclone scenarios in support of risk assessment. Weather Clim. Extrem. 26, 100229 https://doi.org/10.1016/j.wace.2019.100229.

Bruyère, C.L., Buckley, B., Prein, A., Holland, G., Leplastrier, M., Henderson, D., et al., 2020. Severe Weather in a Changing Climate, second ed. https://doi.org/10.5065/b64x-e729

Bruyère, C.L., Buckley, B., Jaye, A.B., Done, J.M., Leplastrier, M., Aldridge, J., Chan, P., Towler, E., Ge, M., 2022. Using large climate model ensembles to assess historical and future tropical cyclone activity along the Australian east coast. Weather Clim. Extrem. 38, 100507 https://doi.org/10.1016/j.wace.2022.100507.

Cai, D., Abram, N.J., Sharples, J.J., Perkins-Kirkpatrick, S.E., 2022. Environ. Res. Lett. 17, 094044. https://doi.org/10.1088/1748-9326/ac8e88.

Cai, W., Van Rensch, P., Borlace, S., Cowan, T., 2011. Does the Southern Annular Mode contribute to the persistence of the multidecade-long drought over southwest Western Australia? Geophys. Res. Lett. 38 (14) https://doi.org/10.1029/2011GL047943.

Canadell, J.G., Meyer, C.P., Cook, G.D., et al., 2021. Multi-decadal increase of forest burned area in Australia is linked to climate change. Nat Commun 12, 6921. https://doi.org/10.1038/s41467-021-27225-4.

Cattiaux, J., Chauvin, F., Bousquet, O., Malardel, S., Tsai, C.L., 2020. Projected changes in the southern indian ocean cyclone activity assessed from high-resolution experiments and CMIP5 models. J. Clim. 33 (12), 4975–4991. https://doi.org/10.1175/JCLI-D-19-0591.1.

Catto, J.L., Nicholls, N., Jakob, C., Shelton, K.L., 2014. Atmospheric fronts in current and future climates. Geophys. Res. Lett. https://doi.org/10.1002/2014gl061943, 2014GL061943.

Catto, J.L., Jakob, C., Nicholls, N., 2015. Can the CMIP5 models represent winter frontal precipitation? Geophys. Res. Lett. 42 (20), 8596–8604. https://doi.org/10.1002/2015GL066015.

Cavicchia, L., Pepler, A.S., Dowdy, A., Evans, J.P., Di Luca, A., Walsh, K., 2020. Future changes in the occurrence of hybrid cyclones: the added value of cyclone classification for the East Australian low-pressure systems. Geophys. Res. Lett. 47 (6), e2019GL085751 https://doi.org/10.1029/2019GL085751.

Ceppi, P., Hwang, Y.T., Frierson, D.M.W., Hartmann, D.L., 2012. Southern Hemisphere jet latitude biases in CMIP5 models linked to shortwave cloud forcing. Geophys. Res. Lett. 39 (19), 19708 https://doi.org/10.1029/2012GL053115.

Chand, S.S., Dowdy, A.J., Ramsay, H.A., Walsh, K.J.E., Tory, K.J., Power, S.B., et al., 2019. Review of tropical cyclones in the Australian region: climatology, variability, predictability, and trends. Wiley Interdiscipl. Rev.: Clim. Change 10 (5), e602. https://doi.org/10.1002/WCC.602.

Christidis, N., Stott, P.A., Scaife, A.A., Arribas, A., Jones, G.S., Copsey, D., et al., 2013. A new HadGEM3-A-based system for attribution of weather- and climate-related extreme events. J. Clim. 26 (9), 2756–2783. https://doi.org/10.1175/JCLI-D-12-00169.1.

Christidis, N., Jones, G.S., Stott, P.A., 2014. Dramatically increasing chance of extremely hot summers since the 2003 European heatwave. Nat. Clim. Change 5 (1), 46–50. https://doi.org/10.1038/nclimate2468.

Clark, S., Reeder, M.J., Jakob, C., 2018. Rainfall regimes over northwestern Australia. Q. J. R. Meteorol. Soc. 144 (711), 458–467. https://doi.org/10.1002/QJ.3217.

Clarke, H., Pitman, A.J., Kala, J., Carouge, C., Haverd, V., Evans, J.P., 2016. An investigation of future fuel load and fire weather in Australia. Climatic Change 139 (3–4), 591–605. https://doi.org/10.1007/s10584-016-1808-9.

Clarke, H., Gibson, R., Cirulis, B., Bradstock, R.A., Penman, T.D., 2019. Developing and testing models of the drivers of anthropogenic and lightning-caused wildfire ignitions in south-eastern Australia. J. Environ. Manag. 235, 34–41. https://doi.org/10.1016/J.JENVMAN.2019.01.055.

Clarke, H., Penman, T., Boer, M., Cary, G.J., Fontaine, J.B., Price, O., Bradstock, R., 2020. The proximal drivers of large fires: a pyrogeographic study. Front. Earth Sci. 8, 90. https://doi.org/10.3389/feart.2020.00090.

Clarke, H., Nolan, R.H., Resco De Dios, V., Bradstock, R., Griebel, A., Khanal, S., Boer, M. M., 2022. Forest fire threatens global carbon sinks and population centres under rising atmospheric water demand. Nat. Commun. 13, 7161. https://doi.org/10.1038/s41467-022-34966-3.

Cohen, J., Screen, J.A., Furtado, J.C., Barlow, M., Whittleston, D., Coumou, D., et al., 2014. Recent Arctic amplification and extreme mid-latitude weather. In: Nature Geoscience. Nature Publishing Group. https://doi.org/10.1038/ngeo2234. August 17.

Cohen, J., Agel, L., Barlow, M., Garfinkel, C.I., White, I., 2021. Linking Arctic variability and change with extreme winter weather in the United States. Science 373 (6559), 1116–1121. https://doi.org/10.1126/SCIENCE.ABI9167.

Collins, L., Clarke, H., Clarke, M.F., McColl Gausden, S.C., Nolan, R.H., Penman, T., Bradstock, R., 2022. Warmer and drier conditions have increased the potential for large and severe fire seasons across south-eastern Australia. Global Ecol. Biogeogr. 31 (10), 1933–1948. https://doi.org/10.1111/GEB.13514.

Contractor, S., Donat, M.G., Alexander, L.V., 2018. Intensification of the daily wet day rainfall distribution across Australia. Geophys. Res. Lett. 45 (16), 8568–8576. https://doi.org/10.1029/2018GL078875.

Crimp, S.J., Gobbett, D., Kokic, P., Nidumolu, U., Howden, M., Nicholls, N., 2016. Recent seasonal and long-term changes in southern Australian frost occurrence. Climatic Change 139 (1), 115–128. https://doi.org/10.1007/s10584-016-1763-5.

Dey, R., Lewis, S.C., Abram, N.J., 2019a. Investigating observed northwest Australian rainfall trends in Coupled Model Intercomparison Project phase 5 detection and attribution experiments. Int. J. Climatol. 39 (1), 112–127. https://doi.org/10.1002/joc.5788.

Dey, R., Lewis, S.C., Arblaster, J.M., Abram, N.J., 2019b. A review of past and projected changes in Australia's rainfall. In: Wiley Interdisciplinary Reviews: Climate Change. Wiley-Blackwell. https://doi.org/10.1002/wcc.577. May 1.

Dey, R., Gallant, A.J.E., Lewis, S.C., 2020. Evidence of a continent-wide shift of episodic rainfall in Australia. Weather Clim. Extrem. 29, 100274 https://doi.org/10.1016/j.wace.2020.100274.

Dittus, A.J., Karoly, D.J., Lewis, S.C., Alexander, L.V., 2013. An investigation of some unexpected frost day increases in southern Australia. Austr. Meteorol. Oceanograp.J. 64, 261–271. https://doi.org/10.1071/ES14023.

Dowdy, A.J., Catto, J.L., 2017. Extreme weather caused by concurrent cyclone, front and thunderstorm occurrences. Sci. Rep. 7 (1), 1–8. https://doi.org/10.1038/srep40359, 2017 7:1.

Emanuel, K., 2017. Will global warming make hurricane forecasting more difficult? Bull. Am. Meteorol. Soc. 98 (3), 495–501. https://doi.org/10.1175/BAMS-D-16-0134.1.

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. Overview of the coupled model Intercomparison project phase 6 (CMIP6) experimental design and organization. Geosci. Model Dev. (GMD) 9 (5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016.

Fenby, C., Gergis, J., 2013. Rainfall variations in south-eastern Australia part 1: consolidating evidence from pre-instrumental documentary sources, 1788-1860. Int. J. Climatol. 33 (14), 2956–2972. https://doi.org/10.1002/joc.3640.

Fiedler, T., Pitman, A.J., Mackenzie, K., Wood, N., Jakob, C., Perkins-Kirkpatrick, S.E., 2021. Business risk and the emergence of climate analytics. Nat. Clim. Change 11 (2), 87–94. https://doi.org/10.1038/s41558-020-00984-6, 2021 11:2.

Fischer, E.M., Beyerle, U., Knutti, R., 2013. Robust spatially aggregated projections of climate extremes. Nat. Clim. Change 3 (12), 1033–1038. https://doi.org/10.1038/nclimate2051.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., Collins, W., et al., 2013. Evaluation of Climate Models. In: Climate change 2013: the physical science basis. contribution of working group I to the fifth assess- ment report of the intergovernmental panel on climate change.

Forkel, M., Andela, N., P Harrison, S., Lasslop, G., Van Marle, M., Chuvieco, E., et al., 2019. Emergent relationships with respect to burned area in global satellite observations and fire-enabled vegetation models. Biogeosciences 16 (1), 57–76. https://doi.org/10.5194/bg-16-57-2019.

Frame, D.J., Wehner, M.F., Noy, I., et al., 2020. The economic costs of Hurricane Harvey attributable to climate change. Climatic Change 160, 271–281. https://doi.org/10.1007/s10584-020-02692-8.

Gallant, A.J.E., Phipps, S.J., Karoly, D.J., Mullan, A.B., Lorrey, A.M., 2013. Nonstationary Australasian teleconnections and implications for paleoclimate reconstructions. J. Clim. 26 (22), 8827–8849. https://doi.org/10.1175/JCLI-D-12-00338.1.

Gergis, J., Gallant, A.J.E., Braganza, K., Karoly, D.J., Allen, K., Cullen, L., et al., 2012. On the long-term context of the 1997-2009 "Big Dry" in South-Eastern Australia: insights from a 206-year multi-proxy rainfall reconstruction. Climatic Change 111 (3), 923–944. https://doi.org/10.1007/s10584-011-0263-x.

Gibson, P.B., Perkins-Kirkpatrick, S.E., Alexander, L.V., Fischer, E.M., 2017a. Comparing Australian heat waves in the CMIP5 models through cluster analysis. J. Geophys. Res. 122 (6), 3266–3281. https://doi.org/10.1002/2016JD025878.

Gibson, P.B., Pitman, A.J., Lorenz, R., Perkins-Kirkpatrick, S.E., 2017b. The role of circulation and land surface conditions in current and future Australian heat waves. J. Clim. 30 (24), 9933–9948. https://doi.org/10.1175/JCLI-D-17-0265.1.

Gillett, N.P., Fyfe, J.C., Parker, D.E., 2013. Attribution of observed sea level pressure trends to greenhouse gas, aerosol, and ozone changes. Geophys. Res. Lett. 40 (10), 2302–2306. https://doi.org/10.1002/grl.50500.

Gissing, A., Timms, M., Browning, S., Crompton, R., McAneney, J., 2021. Compound natural disasters in Australia: a historical analysis. Https://Doi.Org/10.1080/17477891.2021.1932405. https://doi.org/10.1080/17477891.2021.1932405, 21(2), 159–173.

Gould, J.S., Lachlan McCaw, W., Phillip Cheney, N., 2011. Quantifying fine fuel dynamics and structure in dry eucalypt forest (Eucalyptus marginata) in Western Australia for fire management. For. Ecol. Manag. 262 (3), 531–546. https://doi.org/10.1016/j.foreco.2011.04.022.

Grieger, J., Leckebusch, G.C., Donat, M.G., Schuster, M., Ulbrich, U., 2014. Southern Hemisphere winter cyclone activity under recent and future climate conditions in multi-model AOGCM simulations. Int. J. Climatol. 34 (12), 3400–3416. https://doi.org/10.1002/joc.3917.

Grose, M.R., Black, M.T., Risbey, J.S., Karoly, D.J., 2015. Attribution of exceptional mean sea level pressure anomalies south of Australia in August 2014. Bull. Am. Meteorol. Soc. 96 (12), S158–S162. Retrieved from. https://www.jstor.org/stable/26233161.

Grose, M.R., Black, M.T., Risbey, J.S., Uhe, P., Hope, P.K., Haustein, K., Mitchell, D., 2018. Severe frosts in western Australia in september 2016. Bull. Am. Meteorol. Soc. 99 (1), S150–S154. https://doi.org/10.1175/BAMS-D-17-0088.1.

Grose, M.R., Narsey, S., Delage, F.P., Dowdy, A.J., Bador, M., Boschat, G., et al., 2020. Insights from CMIP6 for Australia's future climate. Earth's Future 8 (5). https://doi.org/10.1029/2019EF001469.

Grose, M.R., Black, Mitchell T., Wang, G., King, A., Hope, P.K., Karoly, D.J., 2020. The warm and extremely dry spring in 2015 in Tasmania contained the fingerprint of human influence on the climate. J. Southern Hemisphere Earth Syst. Sci. (in press).

Guerreiro, S.B., Fowler, H.J., Barbero, R., Westra, S., Lenderink, G., Blenkinsop, S., et al., 2018. Detection of continental-scale intensification of hourly rainfall extremes. Nat. Clim. Change 8 (9), 803–807. https://doi.org/10.1038/s41558-018-0245-3, 2018 8: 9.

Guillod, B.P., Jones, R.G., Bowery, A., Haustein, K., Massey, N.R., Mitchell, D.M., et al., 2017. weather@home 2: validation of an improved global–regional climate modelling system. Geosci. Model Dev. (GMD) 10 (5), 1849–1872. https://doi.org/10.5194/gmd-10-1849-2017.

Haines, D.A., 1988. A lower atmospheric severity index for wildland fires. Natl. Weather Digest 13 (3), 23–27. Retrieved from. https://www.frames.gov/catalog/11664.

Harris, S., Lucas, C., 2019. Understanding the variability of Australian fire weather between 1973 and 2017. In: PLoS ONE. Public Library of Science. https://doi.org/10.1371/journal.pone.0222328.

Hawcroft, M.K., Shaffrey, L.C., Hodges, K.I., Dacre, H.F., 2016. Can climate models represent the precipitation associated with extratropical cyclones? Clim. Dynam. 47 (3–4), 679–695. https://doi.org/10.1007/s00382-015-2863-z.

Hayashida, H., Matear, R.J., Strutton, P.G., Zhang, X., 2020. Insights into projected changes in marine heatwaves from a high-resolution ocean circulation model. Nat. Commun. 11 (1), 1–9. https://doi.org/10.1038/s41467-020-18241-x.

Hegerl, G.C., Storch, H. von, Hasselmann, K., Santer, B.D., Cubasch, U., Jones, P.D., et al., 1996. Detecting Greenhouse-Gas-Induced Climate Change with an Optimal Fingerprint Method. https://doi.org/10.1175/1520-0442(1996)009<2281:DGGICC>2.0.CO;2, 10.1175/1520-0442(1996)009<2281:DGGICC>2.0.CO;2.

Hendon, H.H., Lim, E.P., Arblaster, J.M., Anderson, D.L.T., 2014. Causes and predictability of the record wet east Australian spring 2010. Clim. Dynam. 42 (5–6), 1155–1174. https://doi.org/10.1007/s00382-013-1700-5.

Henley, B.J., Meehl, G., Power, S., Folland, C.K., King, A., Brown, J.N., et al., 2017. Spatial and temporal agreement in climate model simulations of the Interdecadal Pacific Oscillation. Environ. Res. Lett. 12 (4) https://doi.org/10.1088/1748-9326/aa5cc8.

Herold, N., Kala, J., Alexander, L.V., 2016. The influence of soil moisture deficits on Australian heatwaves. Environ. Res. Lett. 11 (6), 064003 https://doi.org/10.1088/1748-9326/11/6/064003.

Herring, S.C., Christidis, N., Hoell, A., Hoerling, M.P., Stott, P.A., 2020. Explaining extreme events of 2018 from a climate perspective. Bull. Am. Meteorol. Soc. 101 (1), S1–S140. https://doi.org/10.1175/bams-explainingextremeevents2018.1.

Hines, F., Tolhurst, K.G., Wilson, A.A., Mccarthy, G.J., 2010. Overall Fuel Hazard Assessment Guide Fire and Adaptive Management. Retrieved from. www.dse.vic.gov.au.

Hirsch, A.L., King, M.J., 2020. Atmospheric and land surface contributions to heatwaves: an Australian perspective. J. Geophys. Res. Atmos. 125 (17) https://doi.org/10.1029/2020JD033223.

Hirsch, A.L., Evans, J.P., Di Virgilio, G., Perkins-Kirkpatrick, S.E., Argüeso, D., Pitman, A. J., et al., 2019. Amplification of Australian heatwaves via local land-atmosphere coupling. J. Geophys. Res. Atmos. 124 (24), 13625–13647. https://doi.org/10.1029/2019JD030665.

Hitchcock, S.M., Lane, T.P., Warren, R.A., Soderholm, J., 2021. Linear rainfall features and their association with rainfall extremes near Melbourne, Australia. Mon. Weather Rev. 149 (10), 3401–3417. https://doi.org/10.1175/MWR-D-21-0007.1.

Holbrook, N.J., Scannell, H.A., Sen Gupta, A., Benthuysen, J.A., Feng, M., Oliver, E.C.J., et al., 2019. A global assessment of marine heatwaves and their drivers. Nat. Commun. 10 (1), 1–13. https://doi.org/10.1038/s41467-019-10206-z.

Holbrook, N.J., Sen Gupta, A., Oliver, E.C.J., Hobday, A.J., Benthuysen, J.A., Scannell, H. A., et al., 2020. Keeping pace with marine heatwaves. Nat. Rev. Earth Environ. 1 (9), 482–493. https://doi.org/10.1038/s43017-020-0068-4.

Holmes, J.D., 2020. Land-falling tropical cyclones on the queensland coast -and implications of climate change for wind loads. Aust. J. Struct. Eng. 21 (2), 135–142. https://doi.org/10.1080/13287982.2020.1717842.

Hope, P.K., Drosdowsky, W., Nicholls, N., 2006. Shifts in the synoptic systems influencing southwest Western Australia. Clim. Dynam. 26 (7–8), 751–764. https://doi.org/10.1007/s00382-006-0115-y.

Hope, P.K., Lim, E.-P., Wang, G., Hendon, H.H., Arblaster, J.M., 2015. Contributors to the record high temperatures across Australia in late spring 2014. Bull. Am. Meteorol. Soc. 96 (12), S149–S153. https://doi.org/10.1175/BAMS-D-15-00096.1.

Hope, P.K., Wang, G., Lim, E.-P., Hendon, H.H., Arblaster, J.M., 2016. What caused the record-breaking heat across Australia in October 2015? Bull. Am. Meteorol. Soc. 97 (12), S122–S126. https://doi.org/10.1175/BAMS-D-16-0142.1.

Hope, P.K., Lim, E.-P., Hendon, H.H., Wang, G., 2018. The effect of increasing CO2 on the extreme september 2016 rainfall across southeastern Australia. Bullet. Am.Meteorol. Soc. Bulletin of the Am. Meteorol.Soc. Bull. Amer. Meteor. Soc 99 (991), S133–S138. https://doi.org/10.1175/BAMS-D-17-0094.1.

Hope, P.K., Black, M.T., Lim, E.-P., Dowdy, A., Wang, G., Fawcett, R.J.B., Pepler, A.S., 2019. On determining the impact of increasing atmospheric CO_2 on the record fire weather in eastern Australia in february 2017. Bull. Am. Meteorol. Soc. 100 (1), S111–S117. https://doi.org/10.1175/BAMS-D-18-0135.1.

Hope, P., Coauthors, 2022. Subseasonal to seasonal climate forecasts provide the backbone of a near-real-time event explainer service. Bull. Am. Meteorol. Soc. 103 https://doi.org/10.1175/BAMS-D-21-0253.1. S7–S13.

IPCC, 2021. Summary for policymakers. In: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S., Péan, C., Berger, S., et al. (Eds.), Climate Change 2021: the Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, USA, pp. 3–32. https://doi.org/10.1017/9781009157896.001.

Jakob, D., Osburn, L., Hope, P., Smith, L., 2020. Short-duration, heavy rainfall is intensifying, but not everywhere, and not all the time – a literature review. Retrieved from http://www.bom.gov.au/research/publications/researchreports/BRR-049.pdf.
.

Johnston, F.H., Borchers-Arriagada, N., Morgan, G.G., Jalaludin, B., Palmer, A.J., Williamson, G.J., Bowman, D.M.J.S., 2020. Unprecedented health costs of smoke-related PM2.5 from the 2019–20 Australian megafires. Nat. Sustain. 4 (1), 42–47. https://doi.org/10.1038/s41893-020-00610-5.

Jones, D.A., Wang, W., Fawcett, R., 2009. High-quality spatial climate data-sets for Australia. Austr. Meteorol. Oceanograp.J. 58, 233–248. Retrieved from. http://www.bom.gov.au/jshess/docs/2009/jones_hres.pdf.

Kala, J., Evans, J.P., Pitman, A.J., 2015. Influence of antecedent soil moisture conditions on the synoptic meteorology of the Black Saturday bushfire event in southeast Australia. Q. J. R. Meteorol. Soc. 141 (693), 3118–3129. https://doi.org/10.1002/qj.2596.

Kay, J.E., Deser, C., Phillips, A., Mai, A., Hannay, C., Strand, G., et al., 2015. The community earth system model (cesm) large ensemble project: a community resource for studying climate change in the presence of internal climate variability. Bull. Am. Meteorol. Soc. 96 (8), 1333–1349. https://doi.org/10.1175/BAMS-D-13-00255.1.

Kendon, E.J., Prein, A.F., Senior, C.A., Stirling, A., 2021. Challenges and outlook for convection-permitting climate modelling. Philosop.Trans. Royal Soc.A 379. https://doi.org/10.1098/RSTA.2019.0547, 2195.

Kiem, A.S., Johnson, F., Westra, S., van Dijk, A., Evans, J.P., O'Donnell, A., et al., 2016. Natural hazards in Australia: droughts. Climatic Change 139 (1), 37–54. https://doi.org/10.1007/s10584-016-1798-7.

King, A., Alexander, L.V., Donat, M.G., 2013a. Asymmetry in the response of eastern Australia extreme rainfall to low-frequency Pacific variability. Geophys. Res. Lett. 40 (10) https://doi.org/10.1002/grl.50427.

King, A., Lewis, S.C., Perkins, S.E., Alexander, L.V., Donat, M.G., Karoly, D.J., Black, M. T., 2013b. Limited evidence of anthropogenic influence on the 2011-12 extreme rainfall over Southeast Australia. Bull. Am. Meteorol. Soc. 94 (9).

King, A., Alexander, L.V., Donat, M.G., 2013c. The efficacy of using gridded data to examine extreme rainfall characteristics: a case study for Australia. Int. J. Climatol. 33 (10), 2376–2387. https://doi.org/10.1002/joc.3588.

King, A., Klingaman, N.P., Alexander, L.V., Donat, M.G., Jourdain, N.C., Maher, P., 2014. Extreme rainfall variability in Australia: patterns, drivers, and predictability. J. Clim. 27 (15) https://doi.org/10.1175/JCLI-D-13-00715.1.

King, A., Black, M.T., Karoly, D.J., Donat, M.G., 2015. Increased likelihood of Brisbane, Australia, G20 heat event due to anthropogenic climate change. Bull. Am. Meteorol. Soc. 96 (12) https://doi.org/10.1175/BAMS-D-15-00098.1.

King, A.D., Grose, M.R., Kimutai, J., et al., 2023. Event attribution is not ready for a major role in loss and damage. Nat. Clim. Chang. 13, 415–417. https://doi.org/10.1038/s41558-023-01651-2.

King, A., Karoly, D.J., Henley, B.J., 2017. Australian climate extremes at 1.5 °C and 2 °C of global warming. Nat. Clim. Change 7 (6), 412–416. https://doi.org/10.1038/nclimate3296.

Knutson, T.R., Zeng, F., Wittenberg, A.T., 2014. MULTIMODEL ASSESSMENT OF EXTREME ANNUAL-MEAN WARM ANOMALIES DURING 2013 OVER REGIONS OF AUSTRALIA AND THE WESTERN TROPICAL PACIFIC, vol. 8.

Knutson, T.R., Camargo, S.J., Chan, J.C.L., Emanuel, K., Ho, C.H., Kossin, J., et al., 2020. Tropical cyclones and climate change assessment part II: projected response to anthropogenic warming. Bull. Am. Meteorol. Soc. 101 (3), E303–E322. https://doi.org/10.1175/BAMS-D-18-0194.1.

Lane, T.P., Hope, P.K., King, A., Perkins-Kirkpatrick, S.E., Alexander, L.V., Arblaster, J. M., et al., 2019. Workshop report extreme event attribution in Australia. Bullet. Austr.Meteorol.Oceanograp. Soc. 18–19. https://doi.org/10.1038/421891a (Herring).

Lavender, S.L., Abbs, D.J., 2013. Trends in Australian rainfall: contribution of tropical cyclones and closed lows. Clim. Dynam. 40 (1–2), 317–326. https://doi.org/10.1007/s00382-012-1566-y.

Lavender, S.L., McBride, J.L., 2021. Global climatology of rainfall rates and lifetime accumulated rainfall in tropical cyclones: influence of cyclone basin, cyclone intensity and cyclone size. Int. J. Climatol. 41 (S1), E1217–E1235. https://doi.org/10.1002/joc.6763.

Lavender, S.L., Hoeke, R.K., Abbs, D.J., 2018. The influence of sea surface temperature on the intensity and associated storm surge of tropical cyclone Yasi: a sensitivity study. Nat. Hazards Earth Syst. Sci. 18 (3), 795–805. https://doi.org/10.5194/nhess-18-795-2018.

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., McInnes, K., et al., 2014. A compound event framework for understanding extreme impacts. Wiley Interdiscipl. Rev.: Clim. Change 5 (1), 113–128. https://doi.org/10.1002/WCC.252.

Lepore, C., Abernathey, R., Henderson, N., Allen, J.T., Tippett, M.K., 2021. Future global convective environments in CMIP6 models. Earth's Future 9 (12), e2021EF002277. https://doi.org/10.1029/2021EF002277.

Lewis, S.C., Karoly, D.J., 2013. Anthropogenic contributions to Australia's record summer temperatures of 2013. Geophys. Res. Lett. 40 (14), 3705–3709. https://doi.org/10.1002/grl.50673.

Lewis, S.C., Karoly, D.J., 2014. 9. The role of anthropogenic forcing in the record 2013 Australia-wide annual and spring temperatures. Retrieved from. http://www.ncdc.noaa.gov.

Lewis, S.C., King, A., 2015. Dramatically increased rate of observed hot record breaking in recent Australian temperatures. Geophys. Res. Lett. 42 (18), 7776–7784. https://doi.org/10.1002/2015GL065793.

Lewis, S.C., Karoly, D.J., Yu, M., 2014. Quantitative estimates of anthropogenic contributions to extreme national and State monthly, seasonal and annual average temperatures for Australia. Austr. Meteorol. Oceanograp.J. 64, 215–230. Retrieved from. https://pdfs.semanticscholar.org/c7ca/60fcc552aa9c471029c3d8b0a6f9895d0694.pdf.

Lewis, S.C., King, A., Mitchell, D.M., 2017. Australia's unprecedented future temperature extremes under Paris limits to warming. Geophys. Res. Lett. 44 (19) https://doi.org/10.1002/2017GL074612.

Lewis, S.C., Perkins-Kirkpatrick, S.E., King, A., 2019a. Approaches to attribution of extreme temperature and precipitation events using multi-model and single-member ensembles of general circulation models. Adv. Statist.Climatol., Meteorol. Oceanograp. 5 (2), 133–146. https://doi.org/10.5194/ASCMO-5-133-2019.

Lewis, S.C., King, A., Perkins-Kirkpatrick, S.E., Wehner, M.F., 2019b. Toward calibrated language for effectively communicating the results of extreme event attribution studies. Earth's Future 7 (9), 1020–1026. https://doi.org/10.1029/2019EF001273.

Lewis, S.C., Blake, S.A.P., Trewin, B.C., Black, M.T., Dowdy, A.J., Perkins-Kirkpatrick, S. E., et al., 2020. Deconstructing factors contributing to the 2018 fire weather in Queensland, Australia. Bull. Am. Meteorol. Soc. 101 (1), S115–S121. https://doi.org/10.1175/BAMS-ExplainingExtremeEvents2018.1.

Li, Z., Holbrook, N.J., Zhang, X., Oliver, E.C.J., Cougnon, E.A., 2020. Remote Forcing of Tasman Sea Marine Heatwaves. J. Climate 33, 5337–5354. https://doi.org/10.1175/JCLI-D-19-0641.1.

Lim, E.-P., Hendon, H.H., Hope, P.K., Chung, C., Delage, F., McPhaden, M.J., 2019. Continuation of tropical pacific ocean temperature trend may weaken extreme El Niño and its linkage to the southern annular mode. Sci. Rep. 9 (1), 1–15. https://doi.org/10.1038/s41598-019-53371-3.

Lin, N., Emanuel, K., 2016. Grey swan tropical cyclones. Nat. Clim. Change 6 (1), 106–111. https://doi.org/10.1038/nclimate2777.

Loughran, T.F., Perkins-Kirkpatrick, S.E., Alexander, L.V., Pitman, A.J., 2017a. No significant difference between Australian heat wave impacts of Modoki and eastern Pacific El Niño. Geophys. Res. Lett. 44 (10), 5150–5157. https://doi.org/10.1002/2017GL073231.

Loughran, T.F., Perkins-Kirkpatrick, S.E., Alexander, L.V., 2017b. Understanding the spatio-temporal influence of climate variability on Australian heatwaves. Int. J. Climatol. 37 (10), 3963–3975. https://doi.org/10.1002/joc.4971.

Loughran, T.F., Pitman, A.J., Perkins-Kirkpatrick, S.E., 2019. The El Niño–Southern Oscillation's effect on summer heatwave development mechanisms in Australia. Clim. Dynam. 52 (9–10), 6279–6300. https://doi.org/10.1007/s00382-018-4511-x.

Mann, M.E., Rahmstorf, S., Kornhuber, K., Steinman, B.A., Miller, S.K., Coumou, D., 2017. Influence of anthropogenic climate change on planetary wave resonance and extreme weather events. Sci. Rep. 7 (1), 1–12. https://doi.org/10.1038/srep45242.

Masson-Delmotte, Valérie, Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., et al., 2021. Climate Change 2021 Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

McArthur, A.G., 1967. *Fire Behaviour in Eucalypt Forests*. Forestry and Timber Bureau. Retrieved from. https://books.google.com.au/books/about/Fire_Behaviour_in_Eucalypt_Forests.html?id=YO32GwAACAAJ&redir_esc=y.

McColl-Gausden, S.C., Bennett, L.T., Duff, T.J., Cawson, J.G., Penman, T.D., 2020. Climatic and edaphic gradients predict variation in wildland fuel hazard in south-eastern Australia. Ecography 43 (3), 443–455. https://doi.org/10.1111/ecog.04714.

McInnes, K.L., Walsh, K.J.E., Hubbert, G.D., Beer, T., 2003. Impact of sea-level rise and storm surges in a coastal community. Nat. Hazards 30 (2), 187–207. https://doi.org/10.1023/A:1026118417752.

Mills, G.A., Mccaw, L., 2010. Atmospheric Stability Environments and Fire Weather in Australia-extending the Haines Index. Bureau of Meteorology. CAWCR Technical Report number 4.

Min, S.-K., Cai, W., Whetton, P., 2013. Influence of climate variability on seasonal extremes over Australia. J. Geophys. Res. Atmos. 118 (2), 643–654. https://doi.org/10.1002/jgrd.50164.
Mindlin, J., Shepherd, T.G., Vera, C.S., Osman, M., Zappa, G., Lee, R.W., Hodges, K.I., 2020. Storyline description of Southern Hemisphere midlatitude circulation and precipitation response to greenhouse gas forcing. Clim. Dynam. 54, 4399–4421. https://doi.org/10.1007/s00382-020-05234-1.
Miralles, D.G., Teuling, A.J., van Heerwaarden, C.C., Vilà-Guerau de Arellano, J., 2014. Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation. Nat. Geosci. 7 (5), 345–349. https://doi.org/10.1038/ngeo2141.
Mishra, A.K., Singh, V.P., 2010. A review of drought concepts. J.Hydrology. Elsevier. https://doi.org/10.1016/j.jhydrol.2010.07.012.
Mitchell, D., Heaviside, C., Vardoulakis, S., Huntingford, C., Masato, G., P Guillod, B., et al., 2016. Attributing human mortality during extreme heat waves to anthropogenic climate change. Environ. Res. Lett. 11 (7), 074006 https://doi.org/10.1088/1748-9326/11/7/074006.
Murphy, B.P., Bradstock, R.A., Boer, M.M., Carter, J., Cary, G.J., Cochrane, M.A., et al., 2013. Fire regimes of Australia: a pyrogeographic model system. J. Biogeogr. 40 (6), 1048–1058. https://doi.org/10.1111/JBI.12065.
National Academies Press, 2016. Attribution of extreme weather events in the context of climate change. In: Attribution of Extreme Weather Events in the Context of Climate Change. https://doi.org/10.17226/21852.
Naud, C.M., Posselt, D.J., Van Den Heever, S.C., 2012. Observational analysis of cloud and precipitation in midlatitude cyclones: northern versus Southern hemisphere warm fronts. J. Clim. 25 (14), 5135–5151. https://doi.org/10.1175/JCLI-D-11-00569.1.
Nguyen, H., Hendon, H.H., Lim, E.P., Boschat, G., Maloney, E., Timbal, B., 2018. Variability of the extent of the Hadley circulation in the southern hemisphere: a regional perspective. Clim. Dynam. 50 (1–2), 129–142. https://doi.org/10.1007/s00382-017-3592-2.
Nicholls, N., 1988. More on early ENSOs: evidence from Australian documentary sources in: bulletin of the American meteorological society. Bullet. Am. Meteorol.Soc.4–6 69 (1), 1988. https://journals.ametsoc.org/view/journals/bams/69/1/1520-0477_1988_069_0004_moeeef_2_0_co_2.xml.
Nicholls, N., Drosdowsky, W., Lavery, B., 1997. Australian rainfall variability and change. Weather 52 (3), 66–72. https://doi.org/10.1002/j.1477-8696.1997.tb06274.x.
van Oldenborgh, G.J., 2007. How unusual was autumn 2006 in Europe? Clim. Past 3 (4), 659–668. https://doi.org/10.5194/cp-3-659-2007.
van Oldenborgh, G.J., Krikken, F., Lewis, S.C., Leach, N.J., Lehner, F., Saunders, R., et al., 2021a. Attribution of the Australian bushfire risk to anthropogenic climate change. Nat. Hazards Earth Syst. Sci. 21, 941–960. https://doi.org/10.5194/nhess-21-941-2021.
van Oldenborgh, G.J., van der Wiel, K., Kew, S., Philip, S., Otto, F., Vautard, R., et al., 2021b. Pathways and pitfalls in extreme event attribution. Climatic Change 166 (1–2), 13. https://doi.org/10.1007/s10584-021-03071-7.
Oliver, E.C.J., 2019. Mean warming not variability drives marine heatwave trends. Clim. Dynam. 53 (3–4), 1653–1659. https://doi.org/10.1007/s00382-019-04707-2.
Oliver, E.C.J., O'Kane, T.J., Holbrook, N.J., 2015. Projected changes to Tasman Sea eddies in a future climate. J. Geophys. Res.: Oceans 120 (11), 7150–7165. https://doi.org/10.1002/2015JC010993.
Oliver, E.C.J., Benthuysen, J.A., Bindoff, N.L., Hobday, A.J., Holbrook, N.J., Mundy, C. N., Perkins-Kirkpatrick, S.E., 2017. The unprecedented 2015/16 Tasman Sea marine heatwave. Nat. Commun. 8, 16101 https://doi.org/10.1038/ncomms16101.
Oliver, E.C.J., Perkins-Kirkpatrick, S.E., Holbrook, N.J., Bindoff, N.L., 2018. Anthropogenic and Natural Influences on Record 2016 Marine Heat Waves. Bulletin of the American Meteorological Society. S44–S48. Retrieved from. http://www.ametsoc.net/eee/2016/ch9.pdf.
Osburn, L., Hope, P., Dowdy, A., 2021. Changes in hourly extreme precipitation in victoria, Australia, from the observational record. Weather Clim. Extrem. 31, 100294 https://doi.org/10.1016/j.wace.2020.100294.
Otto, F.E.L., van Oldenborgh, G.J., Eden, J., Stott, P.A., Karoly, D.J., Allen, M.R., 2016. The attribution question. Nat. Clim. Change 6 (9), 813–816. https://doi.org/10.1038/nclimate3089.
Pall, P., Aina, T., Stone, D.A., Stott, P.A., Nozawa, T., Hilberts, A.G.J., et al., 2011. Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature 470 (7334), 382–385. https://doi.org/10.1038/nature09762.
Palmer, T., Stevens, B., 2019. The scientific challenge of understanding and estimating climate change. Proc. Natl. Acad. Sci. U.S.A. 116 (49), 34390–34395. https://doi.org/10.1073/pnas.1906691116.
Parker, T., Berry, G.J., Reeder, M.J., 2013. The influence of tropical cyclones on heat waves in Southeastern Australia. Geophys. Res. Lett. 40 (23), 6264–6270. https://doi.org/10.1002/2013GL058257.
Parker, T., Berry, G.J., Reeder, M.J., Nicholls, N., 2014a. Modes of climate variability and heat waves in Victoria, southeastern Australia. Geophys. Res. Lett. 41 (19), 6926–6934. https://doi.org/10.1002/2014GL061736.
Parker, T., Berry, G.J., Reeder, M.J., 2014b. The structure and evolution of heat waves in Southeastern Australia. J. Clim. 27 (15), 5768–5785. https://doi.org/10.1175/JCLI-D-13-00740.1.
Parker, T., Quinting, J., Reeder, M., 2019. The synoptic-dynamics of summertime heatwaves in the Sydney area (Australia). J.Southern Hemisp. Earth Syst. Sci. 69, 116–130. https://doi.org/10.1071/ES19004.
Pepler, A.S., Di Luca, A., Ji, F., Alexander, L.V., Evans, J.P., Sherwood, S.C., 2016. Projected changes in east Australian midlatitude cyclones during the 21st century. Geophys. Res. Lett. 43 (1), 334–340. https://doi.org/10.1002/2015GL067267.
Pepler, A.S., Dowdy, A.J., van Rensch, et al., 2020. The contributions of fronts, lows and thunderstorms to southern Australian rainfall. Clim. Dynam. 55, 1489–1505. https://doi.org/10.1007/s00382-020-05338-8.
Pepler, A.S., Dowdy, A.J., Hope, P., 2021. The differing role of weather systems in southern Australian rainfall between 1979–1996 and 1997–2015. Clim. Dynam. 56, 2289–2302. https://doi.org/10.1007/s00382-020-05588-6.
Perkins-Kirkpatrick, S.E., Stone, D.A., Mitchell, D.M., Rosier, S., King, A., Lo, Y.T.E., et al., 2022. On the attribution of the impacts of extreme weather events to anthropogenic climate change. Environ. Res. Lett. 17 (2), 024009 https://doi.org/10.1088/1748-9326/AC44C8.
Perkins-Kirkpatrick, S.E., Gibson, P.B., 2017. Changes in regional heatwave characteristics as a function of increasing global temperature. Sci. Rep. 7 (1), 12256 https://doi.org/10.1038/s41598-017-12520-2.
Perkins-Kirkpatrick, S.E., Fischer, E.M., Angélil, O., Gibson, P.B., 2017. The influence of internal climate variability on heatwave frequency trends. Environ. Res. Lett. 12 (4), 044005 https://doi.org/10.1088/1748-9326/aa63fe.
Perkins-Kirkpatrick, S.E., King, A., Cougnon, E.A., Grose, M.R., Oliver, E.C.J., Holbrook, N.J., et al., 2018. THE ROLE OF NATURAL VARIABILITY AND ANTHROPOGENIC CLIMATE CHANGE IN THE 2017/18 TASMAN SEA MARINE HEATWAVE. https://doi.org/10.1175/BAMS-D-18-0116.1.
Perkins, S.E., Alexander, L.V., 2013. On the measurement of heat waves. J. Clim. 26 (13), 4500–4517. https://doi.org/10.1175/JCLI-D-12-00383.1.
Perkins, S.E., Gibson, P.B., 2015. Increased risk of the 2014 Australian May heatwave due to anthropogenic activity. Bull. Am. Meteorol. Soc. 96 (12), S154–S157.
Perkins, S.E., Lewis, S.C., King, A., Alexander, L.V., 2013. Increased simulated risk of the hot Australian summer of 2012/13 due to anthropogenic activity as measured by heat wave frequency and intensity. Bull. Am. Meteorol. Soc. 95 (9), S34–S37. Retrieved from. https://journals.ametsoc.org/doi/pdf/10.1175/1520-0477-95.9.S1.1.
Perkins, S.E., Argüeso, D., White, C.J., 2015. Relationships between climate variability, soil moisture, and Australian heatwaves. J. Geophys. Res. Atmos. 120 (16), 8144–8164. https://doi.org/10.1002/2015JD023592.
Philip, S., Kew, S., van Oldenborgh, G.J., Otto, F., Vautard, R., van der Wiel, K., et al., 2020. A protocol for probabilistic extreme event attribution analyses. Adv. Statist. Climatol., Meteorol. Oceanograp. 6 (2), 177–203. https://doi.org/10.5194/ASCMO-6-177-2020.
Piao, S., Yin, G., Tan, J., Cheng, L., Huang, M., Li, Y., et al., 2015. Detection and attribution of vegetation greening trend in China over the last 30 years. Global Change Biol. 21 (4), 1601–1609. https://doi.org/10.1111/gcb.12795.
Pilo, G.S., Holbrook, N.J., Kiss, A.E., Hogg, A.M.C., 2019. Sensitivity of marine heatwave metrics to ocean model resolution. Geophys. Res. Lett. 46 (24), 14604–14612. https://doi.org/10.1029/2019GL084928.
Pook, M.J., Risbey, J.S., Mcintosh, P.C., 2012. The synoptic climatology of cool-season rainfall in the Central Wheatbelt of Western Australia. Mon. Weather Rev. 140 (1), 28–43. https://doi.org/10.1175/MWR-D-11-00048.1.
Pope, M., Jakob, C., Reeder, M.J., 2009. Regimes of the north Australian wet season. J. Clim. 22 (24), 6699–6715. https://doi.org/10.1175/2009JCLI3057.1.
Prein, A.F., Liu, C., Ikeda, K., Trier, S.B., Rasmussen, R.M., Holland, G.J., Clark, M.P., 2017a. Increased rainfall volume from future convective storms in the US. Nat. Clim. Change 7 (12), 880–884. https://doi.org/10.1038/s41558-017-0007-7, 2017 7:12.
Prein, A.F., Liu, C., Ikeda, K., Bullock, R., Rasmussen, R.M., Holland, G.J., Clark, M., 2017b. Simulating North American mesoscale convective systems with a convection-permitting climate model. Clim. Dynam. 55 (1), 95–110. https://doi.org/10.1007/S00382-017-3993-2, 2017 55:1.
Priestley, M.D.K., Ackerley, D., Catto, J.L., Hodges, K.I., McDonald, R.E., Lee, R.W., 2020. An overview of the extratropical storm tracks in CMIP6 historical simulations. J. Clim. 33 (15), 6315–6343. https://doi.org/10.1175/JCLI-D-19-0928.1.
Quinting, J.F., Reeder, M.J., 2017. Southeastern Australian heat waves from a trajectory viewpoint. Mon. Weather Rev. 145 (10), 4109–4125. https://doi.org/10.1175/MWR-D-17-0165.1.
Quinting, J.F., Parker, T., Reeder, M.J., 2018. Two synoptic routes to subtropical heat waves as illustrated in the Brisbane region of Australia. Geophys. Res. Lett. 45 (19) https://doi.org/10.1029/2018GL079261, 10,700-10,708.
Raupach, T.H., Martius, O., Allen, J.T., Kunz, M., Lasher-Trapp, S., Mohr, S., et al., 2021. The effects of climate change on hailstorms. Nat. Rev. Earth Environ. 2 (3), 213–226. https://doi.org/10.1038/s43017-020-00133-9, 2021 2:3.
Raupach, T.H., Soderholm, J., Protat, A., Sherwood, S.C., 2022. An improved instability–shear hail proxy for Australia. Mon. Weather Rev. 1 (aop) https://doi.org/10.1175/MWR-D-22-0127.1.
Raut, B.A., Jakob, C., Reeder, M.J., 2014. Rainfall changes over Southwestern Australia and their relationship to the southern annular mode and ENSO. J. Clim. 27 (15), 5801–5814. https://doi.org/10.1175/JCLI-D-13-00773.1.
Raut, B.A., Reeder, M.J., Jakob, C., 2017. Trends in CMIP5 rainfall patterns over southwestern Australia. J. Clim. 30 (5), 1779–1788. https://doi.org/10.1175/JCLI-D-16-0584.1.
Read, P., Denniss, R., 2020. With Costs Approaching $100 Billion, the Fires Are Australia's Costliest Natural Disaster. Retrieved June 11, 2021, from. https://theconversation.com/with-costs-approaching-100-billion-the-fires-are-australias-costliest-natural-disaster-129433.
Reid, K.J., O'Brien, T.A., King, A., Lane, T.P., 2021. Extreme water vapor transport during the March 2021 Sydney floods in the context of climate projections. Geophys. Res. Lett. 48 (22), e2021GL095335 https://doi.org/10.1029/2021GL095335.
Resco de Dios, V., Fellows, A.W., Nolan, R.H., Boer, M., Bradstock, R.A., Domingo, F., Goulden, M.L., 2015. A semi-mechanistic model for predicting the moisture content of fine litter. Agric. For. Meteorol. 203, 64–73. https://doi.org/10.1016/j.agrformet.2015.01.002.

Ribes, A., Zwiers, F.W., Azaïs, J.M., Naveau, P., 2017. A new statistical approach to climate change detection and attribution. Clim. Dynam. 48 (1–2), 367–386. https://doi.org/10.1007/s00382-016-3079-6.
Ridder, N.N., Pitman, A.J., Westra, S., Ukkola, A.M., Do, H.X., Bador, M., et al., 2020. Global hotspots for the occurrence of compound events. Nat. Commun. 11 (1), 1–10. https://doi.org/10.1038/s41467-020-19639-3, 2020 11:1.
Ridder, N.N., Pitman, A.J., Ukkola, A.M., 2021. Do CMIP6 climate models simulate global or regional compound events skillfully? Geophys. Res. Lett. 48 (2), e2020GL091152 https://doi.org/10.1029/2020GL091152.
Risbey, J.S., Pook, M.J., McIntosh, P.C., Wheeler, M.C., Hendon, H.H., 2009. On the remote drivers of rainfall variability in Australia. Mon. Weather Rev. 137 (10), 3233–3253. https://doi.org/10.1175/2009MWR2861.1.
Risbey, J.S., Pook, M.J., McIntosh, P.C., 2013. Spatial trends in synoptic rainfall in southern Australia. Geophys. Res. Lett. 40 (14), 3781–3785. https://doi.org/10.1002/grl.50739.
Roderick, T.P., Wasko, C., Sharma, A., 2019. Atmospheric moisture measurements explain increases in tropical rainfall extremes. Geophys. Res. Lett. 46 (3), 1375–1382. https://doi.org/10.1029/2018GL080833.
Rotstayn, L.D., Cai, W., Dix, M.R., Farquhar, G.D., Feng, Y., Ginoux, P., et al., 2007. Have Australian rainfall and cloudiness increased due to the remote effects of Asian anthropogenic aerosols? J. Geophys. Res. Atmos. 112 (9), 9202. https://doi.org/10.1029/2006JD007712.
Saltikoff, E., Friedrich, K., Soderholm, J., Lengfeld, K., Nelson, B., Becker, A., et al., 2019. An overview of using weather radar for climatological studies: successes, challenges, and potential. Bull. Am. Meteorol. Soc. 100 (9), 1739–1752. https://doi.org/10.1175/BAMS-D-18-0166.1.
Sanderson, B.M., Fisher, R.A., 2020. A fiery wake-up call for climate science. In: Nature Climate Change. Nature Research. https://doi.org/10.1038/s41558-020-0707-2.
Schaller, N., Kay, A.L., Lamb, R., Massey, N.R., van Oldenborgh, G.J., Otto, F.E.L., et al., 2016. Human influence on climate in the 2014 southern England winter floods and their impacts. Nat. Clim. Change 6 (6), 627–634. https://doi.org/10.1038/nclimate2927.
Seeley, J.T., Romps, D.M., 2015. The effect of global warming on severe thunderstorms in the United States. J. Clim. 28 (6), 2443–2458. https://doi.org/10.1175/JCLI-D-14-00382.1.
Seiler, C., Zwiers, F.W., 2016. How well do CMIP5 climate models reproduce explosive cyclones in the extratropics of the Northern Hemisphere? Clim. Dynam. 46 (3–4), 1241–1256. https://doi.org/10.1007/s00382-015-2642-x.
Seneviratne, S., Nicholls, N., Easterling, D., Rusticucci, M., Semenov, V., Alexander, L.V., et al., 2012. Changes in Climate Extremes and Their Impacts on the Natural Physical Environment. Cambridge University Press, Cambridge UK and New York USA.
Sharples, J.J., Cary, G.J., Fox-Hughes, P., Mooney, S., Evans, J.P., Fletcher, M.S., et al., 2016. Natural hazards in Australia: extreme bushfire. Climatic Change 139 (1), 85–99. https://doi.org/10.1007/S10584-016-1811-1/FIGURES/3.
Shi, G., Cai, W., Cowan, T., Ribbe, J., Rotstayn, L., Dix, M., 2008. Variability and trend of North West Australia rainfall: observations and coupled climate modeling. J. Clim. 21 (12), 2938–2959. https://doi.org/10.1175/2007JCLI1908.1.
Singh, M.S., O'Gorman, P.A., 2015. Increases in moist-convective updraught velocities with warming in radiative-convective equilibrium. Q. J. R. Meteorol. Soc. 141 (692), 2828–2838. https://doi.org/10.1002/QJ.2567.
Singh, M.S., Kuang, Z., Maloney, E.D., Hannah, W.M., Wolding, B.O., 2017. Increasing potential for intense tropical and subtropical thunderstorms under global warming. Proc. Natl. Acad. Sci. USA 114 (44), 11657–11662. https://doi.org/10.1073/PNAS.1707603114.
Soderholm, J., McGowan, H., Richter, H., Walsh, K., Weckwerth, T.M., Coleman, M., 2017. An 18-year climatology of hailstorm trends and related drivers across southeast Queensland, Australia. Q. J. R. Meteorol. Soc. 143 (703), 1123–1135. https://doi.org/10.1002/QJ.2995.
Soderholm, J., Protat, A., Jakob, C., 2019. Australian Operational Weather Radar Dataset. *National Computing Infrastructure*. Retrieved from. https://www.openradar.io/operational-network.
Srock, A.F., Charney, J.J., Potter, B.E., Goodrick, S.L., 2018. The hot-dry-windy index: a new fire weather index. Atmosphere 2018 9 (7), 279. https://doi.org/10.3390/ATMOS9070279. *Page 279, 9*.
Stephens, G.L., Ellis, T.D., 2008. Controls of global-mean precipitation increases in global warming GCM experiments. J. Clim. 21 (23), 6141–6155. https://doi.org/10.1175/2008JCLI2144.1.
Stephens, G.L., L'Ecuyer, T., Forbes, R., Gettelmen, A., Golaz, J.-C., Bodas-Salcedo, A., et al., 2010. Dreary state of precipitation in global models. J. Geophys. Res. Atmos. 115 (D24) https://doi.org/10.1029/2010JD014532.
Stott, P.A., Stone, D.A., Allen, M.R., 2004. Human contribution to the European heatwave of 2003. Nature 432 (7017), 610–614. https://doi.org/10.1038/nature03089.
Stott, P.A., Christidis, N., Otto, F.E.L., Sun, Y., Vanderlinden, J.-P., van Oldenborgh, G.J., et al., 2016. Attribution of extreme weather and climate-related events. Wiley Interdiscipl. Rev.: Clim. Change 7 (1), 23–41. https://doi.org/10.1002/wcc.380.
Sun, Q., Zhang, X., Zwiers, F.W., Westra, S., Alexander, L.V., 2021. A global, continental, and regional analysis of changes in extreme precipitation. J. Clim. 34 (1), 243–258. https://doi.org/10.1175/JCLI-D-19-0892.1.
Taszarek, M., Allen, J.T., Brooks, H.E., Pilguj, N., Czernecki, B., 2021. Differing trends in United States and European severe thunderstorm environments in a warming climate. Bull. Am. Meteorol. Soc. 102 (2), E296–E322. https://doi.org/10.1175/BAMS-D-20-0004.1.
Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93 (4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1.
Thomas, P.B., Watson, P.J., Bradstock, R.A., Penman, T.D., Price, O.F., 2014. Modelling surface fine fuel dynamics across climate gradients in eucalypt forests of South-Eastern Australia. Ecography 37 (9), 827–837. https://doi.org/10.1111/ecog.00445.
Thompson, D.W.J., Solomon, S., Kushner, P.J., England, M.H., Grise, K.M., Karoly, D.J., 2011. Signatures of the Antarctic ozone hole in Southern Hemisphere surface climate change. In: Nature Geoscience. Nature Publishing Group. https://doi.org/10.1038/ngeo1296.
Timbal, B., Drosdowsky, W., 2013. The relationship between the decline of Southeastern Australian rainfall and the strengthening of the subtropical ridge. Int. J. Climatol. 33 (4), 1021–1034. https://doi.org/10.1002/joc.3492.
Tozer, C.R., Risbey, J.S., Grose, M.R., Monselesan, D.P., Squire, D.T., Black, A.S., et al., 2020. A 1-Day Extreme Rainfall Event in Tasmania: Process Evaluation and Long Tail Attribution. Bulletin of the American Meteorological Society. S123–S128. Retrieved from. https://journals.ametsoc.org/view/journals/bams/101/1/bams-d-19-0219.1.xml.
Trewin, B., 2013. A daily homogenized temperature data set for Australia. Int. J. Climatol. 33 (6), 1510–1529. https://doi.org/10.1002/joc.3530.
Ukkola, A.M., De Kauwe, M.G., Pitman, A.J., Best, M.J., Abramowitz, G., Haverd, V., et al., 2016. Land surface models systematically overestimate the intensity, duration and magnitude of seasonal-scale evaporative droughts. Environ. Res. Lett. 11 (10), 104012 https://doi.org/10.1088/1748-9326/11/10/104012.
Ukkola, A.M., Pitman, A.J., De Kauwe, M.G., Abramowitz, G., Herger, N., Evans, J.P., Decker, M., 2018. Evaluating CMIP5 model agreement for multiple drought metrics. J. Hydrometeorol. 19 (6), 969–988. https://doi.org/10.1175/JHM-D-17-0099.1.
Ukkola, A.M., De Kauwe, M.G., Roderick, M.L., Abramowitz, G., Pitman, A.J., 2020. Robust future changes in meteorological drought in CMIP6 projections despite uncertainty in precipitation. Geophys. Res. Lett. 47 (11) https://doi.org/10.1029/2020GL087820 e2020GL087820.
Ummenhofer, C.C., Sen Gupta, A., England, M.H., Taschetto, A.S., Briggs, P.R., Raupach, M.R., 2015. How did ocean warming affect Australian rainfall extremes during the 2010/2011 La Niña event? Geophys. Res. Lett. 42 (22), 9942–9951. https://doi.org/10.1002/2015GL065948.
US Department of Energy, 2020. U.S. Department of Energy Free-Air CO2 Enrichment Experiments: FACE Results, Lessons, and Legacy. https://doi.org/10.2172/1615612.
Vautard, R., Jan van Oldenborgh, G., Bonnet, R., Li, S., Robin, Y., Kew, S., et al., 2022. Human Influence on Growing-Period Frosts like the Early April 2021 in Central France. *Natural Hazards and Earth System Sciences Discussion*. https://doi.org/10.5194/nhess-2022-41.
Verhoeven, E.M., Murray, B.R., Dickman, C.R., Wardle, G.M., Greenville, A.C., 2020. Fire and rain are one: extreme rainfall events predict wildfire extent in an arid grassland. Int. J. Wildland Fire 29 (8), 702–711. https://doi.org/10.1071/WF19087.
Van Wagner, C.E., 1987. Development and Structure of the Canadian Forest Fire Weather Index System, vol. 35.
Wang, G., Hope, P.K., Lim, E.-P., Hendon, H.H., Arblaster, J.M., 2016. Three Methods for the Attribution of Extreme Weather and Climate Events. Bureau of Meteorology Research Report 018. Bureau of Meteorology Research Report 018.
Wang, G., Hope, P., Lim, E.P., Hendon, H.H., Arblaster, J.M., 2021. An initialized attribution method for extreme events on subseasonal to seasonal time scales. J. Clim. 34, 1453–1465. https://doi.org/10.1175/JCLI-D-19-1021.1.
Wardle, R., Smith, I., 2004. Modeled response of the Australian monsoon to changes in land surface temperatures. Geophys. Res. Lett. 31 (16) https://doi.org/10.1029/2004GL020157.
Warren, R.A., Jakob, C., Hitchcock, S.M., White, B.A., 2021. Heavy versus extreme rainfall events in southeast Australia. Q. J. R. Meteorol. Soc. 147 (739), 3201–3226. https://doi.org/10.1002/QJ.4124.
Westra, S., Fowler, H.J., Evans, J.P., Alexander, L.V., Berg, P., Johnson, F., et al., 2014. Future changes to the intensity and frequency of short-duration extreme rainfall. Rev. Geophys. 52 (3), 522–555. https://doi.org/10.1002/2014RG000464.
Whan, K., Timbal, B., Lindesay, J., 2014. Linear and nonlinear statistical analysis of the impact of sub-tropical ridge intensity and position on south-east Australian rainfall. Int. J. Climatol. 34 (2), 326–342. https://doi.org/10.1002/joc.3689.
Williams, A.P., Abatzoglou, J.T., Gershunov, A., Guzman-Morales, J., Bishop, D.A., Balch, J.K., Lettenmaier, D.P., 2019. Observed impacts of anthropogenic climate change on wildfire in California. Earth's Future 7 (8), 892–910. https://doi.org/10.1029/2019EF001210.
Williamson, G.J., Prior, L.D., Grose, M.R., Harris, R.M.B., Bowman, D.M.J.S., 2014. Projecting canopy cover change in Tasmanian eucalypt forests using dynamically downscaled regional climate models. Reg. Environ. Change 14 (4), 1373–1386. https://doi.org/10.1007/s10113-013-0577-5.
Woodruff, J.D., Irish, J.L., Camargo, S.J., 2013. Coastal flooding by tropical cyclones and sea-level rise. Nature. Nature Publishing Group. https://doi.org/10.1038/nature12855.
Yang, J., Medlyn, B.E., De Kauwe, M.G., Duursma, R.A., Jiang, M., Kumarathunge, D., et al., 2020. Low sensitivity of gross primary production to elevated CO2 in a mature eucalypt woodland. Biogeosciences 17 (2), 265–279. https://doi.org/10.5194/bg-17-265-2020.
Zhang, J., Tian, W., Chipperfield, M.P., Xie, F., Huang, J., 2016. Persistent shift of the Arctic polar vortex towards the Eurasian continent in recent decades. Nat. Clim. Change 6 (12), 1094–1099. https://doi.org/10.1038/nclimate3136.
Zhou, Z., Zhang, Q., Allen, J.T., Ni, X., Ng, C.P., 2021. How many types of severe hailstorm environments are there globally? Geophys. Res. Lett. 48 (23), e2021GL095485 https://doi.org/10.1029/2021GL095485.
Zhuang, Y., Fu, R., Santer, B.D., Dickinson, R.E., Hall, A., 2021. Quantifying contributions of natural variability and anthropogenic forcings on increased fire weather risk over the western United States. Proc. Natl. Acad. Sci. U.S.A. 118 (45),

e2111875118 https://doi.org/10.1073/PNAS.2111875118/SUPPL_FILE/PNAS.2111875118.SAPP.PDF.
Zscheischler, J., Westra, S., Van Den Hurk, B.J.J.M., Seneviratne, S.I., Ward, P.J., Pitman, A., et al., 2018. Future climate risk from compound events. In: Nature Climate Change. Nature Publishing Group. https://doi.org/10.1038/s41558-018-0156-3.
Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R.M., et al., 2020. A typology of compound weather and climate events. Nat. Rev. Earth Environ. 1 (7), 333–347. https://doi.org/10.1038/s43017-020-0060-z, 2020 1:7.
Zylstra, P., Bradstock, R.A., Bedward, M., Penman, T.D., Doherty, M.D., Weber, R.O., et al., 2016. Biophysical mechanistic modelling quantifies the effects of plant traits on fire severity: species, not surface fuel loads, determine flame dimensions in eucalypt forests. PLoS One 11 (8), e0160715. https://doi.org/10.1371/journal.pone.0160715.