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The warm and extremely dry spring in 2015 in Tasmania contained the fingerprint of human influence on the climate.

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Abstract

Tasmania saw a warm and very dry spring and summer in 2015-16, including a record dry October, which had significant, wide-ranging impacts. A previous study using two probabilistic event attribution techniques found a small but statistically significant increase in the likelihood of the record dry October due to anthropogenic influence. Given the human signal is less clear amid natural variability for rainfall compared to temperature extremes, here we provide further evidence and context for this finding. An additional attribution method supports the October rainfall finding, and the median attributable risk to human influence in the three methods is about 25%, 48% and 75%.

The results suggest that human influence on rainfall was partly through increased sea level pressure in the mid-latitudes associated with fewer rain-bearing systems, a circulation driver that is consistent with recent trends that have been attributed to human influence. Dry conditions were also driven by a positive Indian Ocean Dipole and El Niño at the time, but this study can’t reliably estimate the effect of human influence on these phenomena, as each model gives a different estimate of the ocean warming pattern. Along with rainfall, attribution modelling shows a role for human influence in higher temperature and evaporation through October 2015, as well as a high drought index throughout spring. Confidence in the attribution of a human signal on this extreme dry event is increased since multiple attribution methods agree, a plausible atmospheric circulation driver is identified, and temperature and evaporation also showed an anthropogenic signal.

Keywords: event attribution; circulation; rainfall extremes; Australia
1. Introduction

Tasmania experienced very low rainfall and high temperatures in austral spring and summer 2015-16, with numerous records set. In particular, there was a record dry October 2015 (Bureau of Meteorology 2015). These warm and dry conditions had wide-ranging impacts, including on reducing hydroelectric power generation (Hydro Tasmania, pers. comm. 2016) and agricultural production. The dry and hot conditions also pre-conditioned the landscape for significant bushfires in summer that burned non-fire adapted highland vegetation. Industry sectors and the general public have a strong interest in understanding what caused the dry event, and whether human-induced climate change affected its intensity or the chances of the event occurring.

The field of probabilistic event attribution emerged in the early 2000s (e.g. Allen 2003; Stott et al. 2004), and now can give quantitative and robust information about the anthropogenic influences on both the strength and likelihood of individual extremes (Otto 2016). The Fraction of Attributable Risk (FAR) framework imported from epidemiology is a simple but powerful tool for communicating the influence of different forcing factors on the likelihood of specific climate extremes. The methods were applied to rainfall in October 2015 in Tasmania by Karoly et al. (2016), which found a role for both a contemporaneous El Niño event and human influence on the low rainfall. That study compared two attribution models and examined rainfall only. The study didn’t examine the driver of the effect of human influence in the rainfall anomaly.

It is typically straightforward to attribute human influence on the climate through thermodynamic effects from a warmer atmosphere, such as heatwaves (e.g. Stott et al. 2004) and the thermodynamic component of high-precipitation extremes (e.g. Min et al. 2011). Unambiguously detecting an anthropogenic signal on an extreme dry event is more difficult than for temperature, as the primary driver is likely to be anomalies of atmospheric circulation rather than thermodynamic drivers, and circulation changes can be much more uncertain and difficult to attribute than thermodynamic influences, as models typically have errors and forced changes to circulation can be
less clear (e.g. Risbey and O’Kane 2011). Given issues of model errors and uncertainties in circulation
change, combined with the fact that the understanding of the dynamical causes of extreme events
can be lower than thermodynamic influences, Trenberth et al. (2015) suggested that it is suitable to
only examine thermodynamic attribution at present. Otto et al. (2016) suggested that at a minimum
to understand the human influence on an event, it is essential to consider not only thermodynamics
but also explicitly examine atmospheric circulation and other local forcings, especially for events
other than heat and high-precipitation. This may allow the various influences to be illuminated and
assessed, so the overall confidence in the attribution and its drivers can be assessed. In this way, we
may be able to refine the important questions, even if we can’t give a final answer. As an example,
circulation changes were considered as an important factor driving an intense frost event in
September 2016, in opposition to the upward trends in mean temperature (Grose et al. 2018). While
this finding didn’t confidently quantify the effect of human influence in the overall probability of the
event, it at least illustrated the tension between two opposing factors behind changes to frost risk.
AS well as breaking down the causes of events into components, confidence in attribution is
enhanced where independent models lead to a similar conclusion, as long as the framing of the
specific attribution question is the same (National Academies of Sciences 2016; Otto et al. 2016; Stott
et al. 2016), but many studies to date have relied on a single model or approach. Here we further
consider the confidence in the initial finding from Karoly et al. (2016) by examining the circulation
driver for the low rainfall rather than just the rainfall itself, and present further supporting evidence
from another modelling system. We also examine the wider context of the dry conditions by looking
at temperature and evaporation.
2. Data and Methods

2a. Data and models

We examine October rainfall in the Australian Water Availability Project (AWAP) of Jones et al. (2009), including the mean in 1961-1990 (Figure 1a) and in 2015 (Figure 1b). The outputs from three separate attribution modelling systems are then examined: the Coupled Model Inter-comparison Project phase 5 (CMIP5) archive of Taylor et al. (2012), the Weather@Home global version 1 (W@H; Massey et al. 2014) and Weather@Home Australia and New Zealand (W@H-ANZ; Black et al. 2016) modelling system, and the seasonal forecasting model Predictive Ocean Atmosphere Model for Australia (POAMA; Hudson et al. 2013), run in attribution mode (as used in Hope et al. 2015; Hope et al. 2016).

CMIP5 comprises coupled ocean-atmosphere models, which can potentially simulate the coupled response of the climate system to forcing. However, CMIP5 models are generally coarse resolution compared to Tasmania, and feature notable biases.

W@H global uses the atmosphere-only HadAM3P model (1.875° longitude and 1.25° latitude resolution), which then drives the W@H-ANZ nested regional model (HadRM3P; 0.44 x 0.44° latitude/longitude resolution), which reproduces the difference in rainfall between west and east Tasmania despite the coarse resolution (Figure 1c). Very large ensembles were generated by running the model with perturbed initial conditions. The model was run under two climate scenarios for September 2014 to November 2015:

1) Factual (all forcings) using observed sea surface temperature (SST) and sea ice from the Operational Sea Surface Temperature and Sea Ice Analysis dataset (OSTIA; Donlon et al. 2012), as well as present-day atmospheric composition (long-lived greenhouse gases, ozone and aerosols).

2) Counterfactual (natural forcings only) realizations, driven by pre-industrial atmospheric composition and SSTs modified to remove different estimates of the warming attributable to anthropogenic forcing.
Estimates of the SST changes due to anthropogenic forcing were calculated using CMIP5 models by subtracting the ensemble-average decadal-average (1996–2005) SSTs of ‘natural’ simulations from the corresponding ‘all forcing’ simulations. An estimate was calculated for eight CMIP5 models (Table 1) and this estimated warming signal was then subtracted from the prescribed observed SSTs for 2015. Importantly, each model gives a different spatial distribution of estimated SST change since preindustrial conditions, including over the Indian and Pacific Oceans.

As an SST-forced model system, W@H has the advantage of having lower biases and reduced computational requirements than coupled models. However, SST-forced systems don’t simulate coupled responses to forcing and results are vulnerable to biases in the SST signal from other models.

The POAMA seasonal forecasting model has quite low resolution (T47, ~250 km). It does not resolve land features of Tasmania and associated rainfall pattern (Figure 1d), but does capture large-scale circulation variability (Hudson et al. 2013; Marshall et al. 2014), and the framework minimises drift (Wang et al. 2016). When used for attribution, POAMA compares a simulation with observed atmosphere, land and ocean initial conditions (‘Factual’) with simulations with CO₂ concentrations set to 1960 levels (315 ppm) and the CO₂ forced component of ocean temperature and salinity since 1960 removed from initial conditions (‘Counterfactual’), estimated from ensembles of 30-year simulations initialised from 1960 and 1970 compared to 2000 and 2010. Estimates of the CO₂ forced component of land and atmospheric (moisture and temperature) response are also removed. An ensemble of 33 simulations for Factual and 33 for Counterfactual conditions are examined. See additional material of Hope et al. (2015) and also Wang et al. (2016) for more details. An important difference between this method and the others is the ‘Counterfactual’ simulations approximate 1960 rather than pre-industrial conditions, and only the change in CO₂ forcing is considered (not ozone or aerosol).

We use W@H and POAMA for analysis of circulation anomalies, as these models have a simulation specific to the conditions of 2015 rather than the free-running CMIP5 models, and also because they
will typically have lower biases. W@H is a SST-driven, atmosphere-only model, so typically has lower
biases than in CMIP models (Massey et al. 2014; Black et al. 2016). Similarly, POAMA uses
initialisations from observations, so typically avoids large model biases (Wang et al. 2016).

2b. Methods

The conditions of spring and summer 2015 are examined in observations, then in attribution
modelling systems. We compare the Tasmanian October rainfall results from POAMA with the
rainfall results from W@H-ANZ and CMIP5 already presented in Karoly et al. (2016). As POAMA has
course resolution and does not resolve Tasmania, we calculate mean rainfall over a 5x5 °lat/lon box
of four cells over the region and examine the percent anomaly from the climatology as a form of bias
correction. The histograms of the 36 simulations of rainfall Tasmanian anomaly in Factual and
Counterfactual are fitted using the Generalized Extreme Value (GEV) distribution. The significance of
the differences between distributions were assessed using a Kolmogorov-Smirnoff (K-S) test at the
5% significance level, and then the FAR was calculated, where FAR = 1 – counterfactual/factual, and
FAR risk as a proportion, FAR risk = (Factual/Counterfactual)*100. As used in Karoly et al. (2016), we
define an October rainfall threshold based on the previous observed record (56 mm in 1965) rather
than the 2015 record, to reduce selection bias. The 1914 low rainfall value was not used because of
the smaller number of rainfall stations available then (the rainfall gauge network has been relatively
stable since the mid-1950s). We also examine the spatial distribution of the mean rainfall difference
between Factual and Counterfactual in POAMA and compare this to W@H.

We examine the broader context of the dry October by extending the original work looking at
precipitation alone to examine temperature, evaporation and a drought index. The increase in
temperature attributable to human influence was estimated as the mean difference in Tasmanian
temperature in Factual and Counterfactual simulations. The effect on potential evaporation is
estimated as the difference in the climatological October Penman-Monteith (Allen et al. 1998)
assuming Tasmanian climatological average wind speed, relative humidity and solar radiation remained unchanged. To examine the dryness in spring 2015, incorporating rainfall and evaporation anomalies we examine the Keetch-Byram Drought Index (KBDI) of Keetch and Byram (1968) as a measure of dryness in each month September to November and spring as a whole. The KBDI uses antecedent rainfall and evaporation estimated from temperature.

Differences in circulation between Factual and Counterfactual simulations from W@H and POAMA were examined in two ways. First, the spatial distribution of the mean differences between Factual and Counterfactual in mean sea level pressure (MSLP) and zonal wind were compared. Second, a wide-ranging set of MSLP indices were calculated and compared, including the MSLP averaged over Tasmania, MSLP in boxes adapted from Hill et al. (2009), and the subtropical ridge. Remote drivers of rainfall variability in Factual and Counterfactual simulations were explored using standard indices, namely atmospheric blocking in eastern Australia, the Southern Annular Mode (SAM), the Indian Ocean Dipole (IOD) and SST of the Indian Ocean. The differences between Factual and Counterfactual distributions of these indices were assessed using a K-S test, and FAR analysis performed. Details of the averaging boxes and indices used are listed in Table 2.

3. Observed conditions

According to Australian Bureau of Meteorology records, rainfall averaged over all of Tasmania in spring 2015 rainfall was the lowest on record at 155 mm, 42% of the 1961-1990 mean of 365 mm. Average October rainfall in Tasmania in 1961-1990 is 124 mm, with much higher rainfall on the west coast than the midlands and east coast (Figure 1a). October 2015 rainfall was also the lowest on record at 21 mm, 18% of the 1961-1990 mean of 124 mm mean (Figure 1b, 2a).

Temperature was above average in September through February, including the hottest summer on record (mean summer temperature was +1.8 °C above the 14.1 °C average). October was warmer than average (+1.3 °C), especially in daytime maximum temperature (+2.2 °C warmer than the
14.3 °C average. There was a detectable human influence on the hottest October on record for southern Australia (Black and Karoly 2016) and Australia as a whole (Hope et al. 2016), including the unusually warm conditions in Tasmania.

Turning to atmospheric circulation, variations in circulation and MSLP patterns result in a strong relationship between inter-annual variability in October MSLP in a box over Tasmania and October total rainfall with high local pressure associated with dry conditions (Table 2). In 1948-2015, MSLP from NCEP/NCAR Reanalysis 1 (Kalnay et al. 1996) has a correlation of R = -0.84 with rainfall in October (Figure 2b). October 2015 MSLP was higher than average but not an October record over Tasmania, however it was a record high north of Tasmania and record low north of the Ross Sea in NCEP/NCAR Reanalysis 1 since 1948 (Figure 2c). This spatial distribution of the MSLP anomaly with low pressure north of the Ross Sea is similar to the wave train structure of the Pacific South American (PSA) pattern and is typical of dry years in Tasmania reported in Hill et al. (2009). Wind anomalies at 850 hPa were predominantly north-easterly, promoting warm air advection from the interior of mainland Australia and preventing cold moist air advection from the southern ocean over Tasmania, consistent with warmer and drier conditions in Tasmania. The MSLP pattern also produced a high subtropical ridge index through October (+5.2 hPa, fifth highest on record since 1948).

Looking at remote drivers of variability, there was a strong El Niño in the Pacific through spring and summer 2015/16 (October NINO3.4 index was +2.2 °C) and a strongly positive IOD event (Dipole Mode Index (DMI) index was +0.76), both of which are typically associated with dry spring conditions. There was also record temperatures for any month to date in the southern Indian Ocean (an anomaly of 0.63 °C in 30-120 °E, 0-60 °S). There was a short-lived atmospheric blocking event in the Tasman Sea early in the month, the Bureau of Meteorology blocking index (Pook and Gibson 1999) at 140 °E of the monthly mean conditions was negative. The Madden-Julian Oscillation (MJO) was active in phase 2 later in October which is associated with heat extremes in southern Australia, particularly in summer (Marshall et al. 2014; Parker et al. 2014). The Southern Annular Mode (SAM) was positive...
from around the 23rd October through to the end of the month, but the monthly mean SAM was weakly negative.

The possible effect of human influence on all of these circulation features and remote drivers of variability will be examined by comparing the Factual and Counterfactual simulations. Also, the issues regarding examining remote drivers in attribution studies are explored.

4. Results

4a. October rainfall

Results from Karoly et al. (2016) showed a small but statistically significant difference in rainfall between Factual and Counterfactual treatments in both W@H and CMIP5, and the plots are not reproduced here. Here we complement those results with analysis of rainfall in POAMA.

The distribution of the rainfall anomaly in POAMA for Tasmania has a lower median and a different shape in the Factual simulations compared to Counterfactual (Figure 3a, averaging box marked in Figure 3b). The median Tasmanian October rainfall in Factual is 8% (equivalent to -10 mm/month in observations) drier than the median in the Counterfactual simulations, which is similar to the results from W@H (7% or -8 mm/month) and CMIP5 (-6% or 7.5 mm/month) reported in Karoly et al. (2016).

The GEV distribution of the Factual not only has a lower median, but is narrower and less skewed with a thinner high tail than the Counterfactual. This change in shape suggests that human influence has driven a reduction in the likelihood of wet months given the setup in 2015.

The difference between the two POAMA distributions at the chosen threshold indicates the likelihood of low rainfall was increased (best estimate FAR risk is 48%), which is within the previous results from W@H-ANZ (at least 39%, median 75%) and CMIP5 (-12% to +82%, median of 25%) reported in Karoly et al. (2016). The 33 Counterfactual and 33 Factual samples are not significantly different (K-S test fails at 5% level). The small sample size is a contributing factor to the lack of
significance. If 100 samples are randomly drawn from the GEV distributions fitted to the Factual and Counterfactual data, this creates synthetic datasets that are consistent with those distributions and have a sample size that is commensurate with the rainfall record (and still much smaller than the W@H results). These synthetic datasets are significantly different, where a K-S test passes at the 5% level, suggesting a small but significant role for human influence in the rainfall anomaly, supporting the results from W@H and CMIP5.

Since the difference in rainfall for Tasmania is small and the coarse resolution of POAMA model doesn’t resolve the Tasmanian land mass, the results can only be considered indicative. Further insights into the rainfall signal, and the circulation drivers behind it may be derived from the spatial distribution of the rainfall differences in Counterfactual simulations compared to Factual. The spatial pattern of rainfall difference between the mean of Factual and Counterfactual in POAMA shows reduced rainfall in a band across much of 35-45 °S and in the Tasman Sea at ~25-30 °S, with enhanced rainfall south of ~45 °S (Figure 3b). This pattern in W@H is similar (Figure 3c), noting that the W@H mean is smoother and has lower values than POAMA as it is the mean of eight models, however model agreement on the sign of the difference is high (stippling). This spatial pattern is consistent with a zonally-consistent MSLP pressure anomaly around the hemisphere, similar to SAM, and is possibly also consistent with an influence from the teleconnection from the IOD that influences southern Australia.

4b. Temperature and drought index

As well as rainfall, the other components of the dry October were warm temperatures and high evaporation. The results from CMIP5, W@H and POAMA indicate that October 2015 in Tasmania was warmer than a counter-factual world without human influence (Factual compared to Counterfactual). The mean difference in October Tasmanian mean temperature between Factual and Counterfactual in the eight W@H ensembles was 0.0 to 1.2 °C (0.6 °C eight-model mean). Tasmanian
mean temperature in POAMA was 0.25 °C warmer and daily maximum temperature was 0.4 °C warmer in Factual compared to 1960 conditions. Higher temperatures are associated with higher potential evaporation: 0.6 °C warmer mean temperature suggests ~5% higher evapotranspiration (from a baseline of ~100 mm/month).

The KBDI drought index is a measure of overall dryness that integrates low rainfall as well as temperature and other variables, commonly used to gauge the contribution of dryness in the landscape to fire danger. In the W@H-ANZ simulations there is a consistent shift in the distribution to drier values in Factual compared to Counterfactual in October and in all spring months and spring as a whole (Figure 3d). This indicates a higher probability of dry conditions in spring 2015 than for a world without human influence. For example, the median spring KBDI for Tasmania is 4.6 mm in Factual and 3.2 mm in Counterfactual simulations. In October, the median KBDI is 4.2 mm in Factual simulations and 3.0 mm in Counterfactual (75th percentiles are 7.4 mm and 5.5 mm). This is a more direct measure of the climate on preconditioning the landscape for the fires late in the summer than the rainfall or temperature in isolation, and indicates that the human influence was ~30% greater in the Factual world compared to Counterfactual.

4c. October mean sea level pressure indices and blocking

The results in the previous section suggest that October and spring 2015 in Tasmania were more likely to be dry than in a Counterfactual world without human influence due to lower rainfall, warmer temperatures and higher evaporation. The reduced rainfall has already been shown to be partly driven by the El Niño present. The rainfall difference between Counterfactual and Factual is also consistent with a shift in MSLP and circulation similar to SAM, so next we examine a set of circulation patterns and indices.

The October MSLP anomaly from reanalysis (Figure 2c), including maxima over Australia and the southeast Pacific and minima north of the Ross Sea, was approximately replicated in the mean of
W@H (Figure 3a) and POAMA (Figure 4b). However, the difference in MSLP between Factual and Counterfactual in both W@H (Figure 4c) and POAMA (Figure 4d) shows that the forced MSLP signal was not an enhancement of the anomaly pattern but has a different spatial structure. This suggests that the specific circulation setup of the event was not enhanced due to human influence, but some elements of the background circulation state were affected by anthropogenic forcing and this explains the effect on rainfall. To determine the nature of the human forcing on this background circulation, the spatial pattern of the MSLP signal and a range of indices of various circulation features are analysed.

First, we can readily exclude the possibilities of local MSLP, STR, the PSA and blocking. MSLP over Tasmania itself is strongly correlated with rainfall (Figure 2b), however an increase in MSLP over Tasmania doesn’t appear to be a component of the human signal on rainfall in this case. There is little difference between Counterfactual and Factual for MSLP within the Tasmanian box in either modelling set up (Figure 3c and 3d), with a K-S test failing to detect significance at 5% for 6 of the 8 W@H cases and for POAMA. Similarly, the STR intensity and position is largely similar between Counterfactual and Factual (K-S test fails to detect significant differences in all cases). The forced component of the MSLP response doesn’t appear like a PSA-like pattern, and the MSLP difference between the boxes adapted from Hill et al. (2009) is not enhanced significantly between Factual and Counterfactual (K-S test fails in most cases). Blocking was present early in the month but the mean Blocking Index at 140 °E was negative in the October mean. As expected from the MSLP results, zonal wind at 500 hPa is enhanced south of Tasmania and reduced to the north in Factual compared to Counterfactual in W@H and POAMA (Figure 4e and 4f). This pattern is not consistent with an enhanced mean blocked state in the Australian sector, with October mean blocking index at 140 °E very similar in Counterfactual and Factual in all model groups.

Second, we examine the circulation feature suggested by the rainfall results: SAM. The forced mid-latitude MSLP response appears consistent with a shift in the mean state of the circulation that appears similar to SAM (Figure 4), and indeed the SAM index is significantly enhanced in Factual
compared to Counterfactual simulations in both W@H and POAMA (all K-S tests pass). The mean SAM index was higher in Factual compared to Counterfactual by 0.2 to 0.3 in W@H and 0.3 in POAMA. Therefore, direct examination of the MSLP differences between Factual and Counterfactual support the rainfall results. Namely, that human influence on the mean circulation and background state of MSLP that appears similar to SAM has changed the probability distribution rainfall in the 35-45 °S band, including a greater chance of drier conditions, including in Tasmania in October 2015, even though the specific setup during that month was not enhanced by human influence.

4d. October Indian Ocean temperature and Indian Ocean Dipole

In spring 2015 there was a strong El Niño present in the Pacific that played a role in the dry October (Karoly et al. 2016), and there was also a strong positive IOD event present and the Indian Ocean as a whole was particularly warm. Along with the influence from mean circulation described above, there may have been an effect of human influence on the El Niño and positive IOD events present that then had an influence on Tasmania’s rainfall. Mean warming of SST due to human influence is not spatially uniform. The specific SST warming pattern is an important source of uncertainty in regional rainfall projections of future climate (Watterson 2012; Grose et al. 2014), and so it fits that it is a source of uncertainty in attribution of climate change to date. Here we examine the effect of changes to the mean state on the possible influence from the Indian Ocean as another line of supporting evidence behind attributing the dry event.

In the Indian Ocean, a different warming in the eastern Indian Ocean compared to the west would affect the mean state of the DMI, and change the probabilities of IOD positive and negative events. Any persistent shift in the IOD is expected to have flow-on effects to atmospheric circulation and rainfall. The W@H modelling takes the SST signal from eight CMIP5 models, and the mean of these models shows a fairly uniform warming on the Indian Ocean and an enhanced warming of the equatorial Pacific (Figure 5a). This mean SST warming suggests no strong change in the IOD, but a
change to a more El Niño-like mean state in the Pacific. Each CMIP5 model gives a different estimate
of the mean warming in the Indian Ocean and Pacific to date (Appendix 1), and this gives each set of
W@H simulations a different estimate of the mean shift in the DMI, including some with a more
positive and some more negative DMI (Figure 5c).

POAMA generates its own SST difference between 1961 and the present, and the October difference
shows a north-south gradient in Indian Ocean warming and a slight enhancement of warming in the
equatorial Pacific (Figure 5b). The POAMA Factual simulations have a slightly higher DMI than the
Counterfactual simulations (mean difference 0.03, Figure 5d).

Without a reliable estimate of the forced warming signal in the Indian and Pacific Oceans, it is not
possible to determine the true effect of human influence on the ENSO and IOD to date and examine
the effect on individual extremes of circulation and rainfall. The results are more consistent regarding
the mean temperature of the Indian Ocean, which is notably higher in the Factual simulations than in
Counterfactual for both W@H and POAMA (Figure 5e, 4f).

5. Discussion and conclusions

The aim of this paper is to supplement the initial probabilistic event attribution results on Tasmanian
rainfall in October 2015 from Karoly et al. (2016) with further supporting evidence and a wider
context. Three lines of new evidence were presented: rainfall results from another modelling system;
an examination of temperature, evaporation and drought index; and analysis of the circulation
drivers behind the rainfall anomaly.

The outputs of three modelling systems were used, and they differ in how they simulate the current
climate and how they condition the counterfactual climate. POAMA uses a coupled seasonal forecast
model to simulate the Factual climate from a given initialisation and generate a Counterfactual
climate by removing the ocean warming and atmospheric CO₂ concentration changes from that initial

state. W@H uses an atmosphere-only model using the observed ocean state to generate many
simulations of the atmosphere given the observed ocean conditions, then generates a Counterfactual
climate by removing an estimated ocean warming pattern as well as atmospheric conditions from
CMIP5 climate models. CMIP5 models were also used directly, which are free-running simulations of
the global climate system not initialised to the observed conditions, run with either observed forcings
or natural forcings only. Any agreement between all three modelling systems indicates a consistent
simulation of a human signal in the underlying climate and is less likely to be affected by the model
bias of any one system.

The three systems do broadly agree on a statistically significant difference between Factual and
Counterfactual simulations of Tasmanian rainfall in October 2015, but with a fairly small mean
difference, as would be expected due to the lower signal to noise ratio of rainfall compared to
variables such as temperature. Rainfall was on average 8% lower in POAMA Factual simulations
compared to Counterfactual, similar to 7% in W@H and 6% in CMIP5. Considering that POAMA is an
 initialised forecast model, W@H is an atmospheric model using the ocean state of 2015 and CMIP5
are free-running climate models, this similarity of results suggests a fairly consistent human signal in
reduced rainfall, and is reflected in a mean-state difference (CMIP5) as well as in the ocean
conditions specifically of that year (POAMA, W@H). These results also suggest there was a greater
chance of record-breaking dry conditions due to human influence on the climate, since a drier mean
climate for the given ocean and atmospheric state. Specifically on the rainfall record in Tasmania in
October, the results suggests the probability was increased due to human influence, with a median
estimate of the increase in attributable risk for the previous record threshold (56 mm, experienced in
1965) of about 48% in POAMA, which is of similar order as W@H (75%) and CMIP5 (25%). Detecting
and attributing a human signal in rainfall is less clear than for variables such as temperature, and
consistent results from three model systems that are relatively independent and quite distinct in
their overall approach provides stronger evidence than the results from one model alone.
Another contributor to the extreme dry conditions in spring 2015 in Tasmania was high temperature and evaporation. The combination of rainfall and evaporation is summarised by the KBDI drought index. The results suggest that human influence contributed to both the warmer temperature (by \(~0.4\) to \(0.6\) °C), and higher evaporation rate (\(~10\) mm/month or \(10\%\)) in October. Results from one modelling method indicate that dryness measured using KBDI was enhanced in each month of spring by values of \(~30\%\). Despite the simple methods used here, the effect of human influence on temperature is well established so there is high confidence in this attribution finding than in rainfall. The drought index is perhaps the most relevant metric to the drying of the landscape that preceded the fires, so this result is particularly relevant there.

The POAMA and W@H models both suggested that human influence did not drive an enhancement of the particular atmospheric setup of the dry month, as expressed in MSLP over Tasmania, STR, PSA or blocking. The results do suggest that human influence led to enhanced MSLP around the southern hemisphere in October 2015 in a pattern reminiscent of the Southern Annular Mode (SAM), and this contributes to a shift in probabilities of rainfall, including the rainfall linked to the particular monthly setup in October 2015. Human signals on circulation changes are not always clear or detectable (Vallis et al. 2015), but these results are suggestive and consistent with a previously identified forced response, namely that MSLP has been increasing in this latitude band in recent decades and this is partly attributable to human influence (e.g. Gillett et al. 2013). While a higher SAM index is associated with lower rainfall across Tasmania in spring (Risbey et al. 2009), the SAM index was not particularly high in October 2015, so the difference between Factual and Counterfactual is a relative enhancement of the SAM-like state of the atmosphere, not an extreme SAM event. An increased likelihood of a SAM-like MSLP anomaly driving lower rainfall for a particular month is a logical extension of this known change in the mean state. Also, the result is consistent with the evidence that high MSLP south of Australia in August 2014 was more likely due to human influence (Grose et al. 2015). MSLP and SAM changes have been found to be driven by changes to not only greenhouse gases but also stratospheric ozone changes. POAMA doesn’t include the forcing from ozone
depletion, and its interaction with greenhouse gas forcing in summer (Morgenstern et al. 2014), and this may affect the results from this model.

The results don’t suggest that anthropogenic forcings notably affected mean monthly MSLP over Tasmania itself, mean monthly atmospheric blocking at 140 °E, the STR, or the PSA-like MSLP pattern. There has not been a published attribution of a change to these drivers due to human influence previously, so these new results support previous work.

Along with SAM, the results suggest that human influence drove a warmer Indian Ocean, and this may have affected rainfall over southern Australia, and may have also influenced the IOD. However, the analysis has revealed a particular concern with the framework for examining this question. Gauging the role of the IOD and other SST-based indices relies entirely on the estimate of mean SST warming, and so varies between models and methods. The W@H framework uses SST signals generated by GCMs, and these vary widely, while the POAMA framework generates its own distinct SST change signal. The range of these estimates and their possible effects suggests that we need a reliable estimate of mean SST warming to date to properly account for the human influence on phenomena such as IOD, and also the El Niño Southern Oscillation in the Pacific.

Attribution of rainfall change or extreme rainfall events remains difficult and less clear than for temperature for several reasons. Rainfall events have a low signal-to-noise ratio, meaning any potential signal can be harder to distinguish. Models contain errors and biases in the simulation of the relevant processes, where both dynamic and thermodynamic processes are involved and it is essential to consider both (e.g. Otto et al. 2016). Tasmanian rainfall is strongly determined by the interaction of weather systems with topography, and models typically don’t finely resolve the topography of Tasmania.

Given these uncertainties, one useful line of evidence for attributing a rainfall event is the reliable attribution of a large-scale circulation driver that partly or largely influenced the rainfall anomaly, to establish a physical basis or narrative behind the attribution. Here, the results suggest that a SAM-
like pressure pattern was enhanced due to human influence, and a change in the mean state of this
SAM-like pattern has previously been attributed to human influence. This adds some confidence that
at least the circulation component of the rainfall event has some physical basis. But the analysis of
circulation and drivers presented here is not comprehensive, and in fact the results illustrate some
barriers to fully quantifying the effect of climate change to date on regional rainfall extremes.
Thermodynamic drivers, including the direct effects of warmer temperatures, is likely to be more
reliably accounted for in the models than circulation.

Overall, three lines of additional evidence presented here strengthen the attribution statement for
the record low rainfall conditions in Tasmania in spring 2015 of a small but significant contribution
from human influence, but confidence in this attribution is still weaker than for events such as
heatwaves or other heat extremes.

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provided by the NOAA/CIRES Climate Diagnostics Center in Boulder (USA).

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Black, M.T. and Karoly, D.J. (2016). Southern Australia’s warmest October on record: The role of


Table 1: CMIP5 models used for estimating patterns of SST warming due to anthropogenic forcing.

<table>
<thead>
<tr>
<th>Model</th>
<th>Ensemble members</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCSM4</td>
<td>r1i1p1, r2i1p1, r4i1p1, r6i1p1</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r8i1p1</td>
</tr>
<tr>
<td>CanESM2</td>
<td>r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1</td>
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<tr>
<td>GFDL-CM3</td>
<td>r1i1p1, r3i1p1, r5i1p1</td>
</tr>
<tr>
<td>GISS-E2-H</td>
<td>r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>r1i1p1, r2i1p1, r3i1p1, r4i1p1</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>r1i1p1, r2i1p1, r3i1p1</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>r1i1p1, r2i1p1, r3i1p1</td>
</tr>
</tbody>
</table>

Table 2: Atmospheric circulation indices and analyses examined in this paper

<table>
<thead>
<tr>
<th>Driver</th>
<th>Index</th>
<th>Details</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean sea level pressure (MSLP) over Tasmania</td>
<td>MSLP in box</td>
<td>144-149 °E, 39-45 °S</td>
<td></td>
</tr>
<tr>
<td>MSLP over Tasmania and north of Ross Sea</td>
<td>Adapted from Hill et al. (2009) Pacific-South America (PSA) like pattern</td>
<td>Boxes: 140-160 °E, 40-50 °S minus 170-210 °E, 55-65 °S</td>
<td>Adapted from Hill et al. (2009)</td>
</tr>
<tr>
<td>Subtropical Ridge (STR)</td>
<td>Revised L-index</td>
<td>Peak MSLP in section 140-150 °E, 10-45 °S</td>
<td>Drosdowsky (2005)</td>
</tr>
<tr>
<td>Atmospheric blocking</td>
<td>Bureau of Meteorology blocking index at 140 °E</td>
<td>Zonal wind at 500 hPa for various latitudes</td>
<td>Pook and Gibson (1999)</td>
</tr>
<tr>
<td>Indian Ocean Dipole</td>
<td>Dipole Mode Index (DMI)</td>
<td>Difference between normalised anomaly in Southeast box (SEIO)</td>
<td>Saji et al. (1999)</td>
</tr>
</tbody>
</table>

22
<table>
<thead>
<tr>
<th>Indian Ocean temperature</th>
<th>SST in box</th>
</tr>
</thead>
<tbody>
<tr>
<td>90-110 °E, 0-10 °S</td>
<td>30-120 °E, 0-60 °S</td>
</tr>
</tbody>
</table>

550
Figure 1 Mean October rainfall in Tasmania: a) mean in 1961-1990 in the AWAP dataset; b) October 2015 in AWAP, c) mean in climatology simulations of W@H; d) mean in POAMA climatology simulations.
Figure 2 Rainfall and MSLP; (a) Observed spring and October Tasmanian rainfall, circles highlight the records in 2015; (b) October Tasmanian MSLP in NCEP/NCAR Reanalysis 1 and observed Tasmanian rainfall in 1948-2015, 2015 shown in red (R = -0.84); (c) MSLP anomaly during Oct 2015 from NCEP/NCAR Reanalysis 1 from 1948-2015 (highest/lowest on record outlined in grey)
Figure 3 Spring and October rainfall and dryness index: (a) histograms of Tasmanian rainfall anomaly (%) in 33 POAMA Factual and Counterfactual simulations, with GEV fits and rainfall threshold for FAR shown as dashed line; (b) difference in October rainfall in the mean of POAMA Factual compared to Counterfactual; (c) October rainfall difference in the mean of W@H Factual - Counterfactual simulations (mean of 8 model ensemble, stippling indicates where seven or more out of eight models agree on the sign of difference); (d) distribution plots of the Keetch-Byram Drought Index for spring and each spring month 2015 for Tasmania from Factual and Counterfactual W@H-ANZ simulations (based on the number of simulations, dashed lines represent the inter-quartile range, a higher value represents a more severe drought than a lower number).
Figure 4 Simulated MSLP and zonal wind for October 2015; (a) mean simulated MSLP anomaly for October 2015 in W@H (mean of eight models); (b) MSLP anomaly in POAMA; (C) mean Factual-Counterfactual difference in MSLP in W@H; (d) Factual - Counterfactual MSLP in POAMA; (e) mean Factual - Counterfactual difference in zonal wind at 500 hPa in W@H; (f) Factual - Counterfactual zonal wind at 500 hPa in POAMA. In MSLP plots, dotted lines show latitude bands for calculating the SAM index; black lines show boxes for dry year pattern adapted from Hill et al. (2009); green box shows band for calculating STR index. In zonal wind plots, lines show the latitudes for calculating the Bureau blocking index.
Figure 5 Sea surface temperature, Dipole Mode Index (DMI) and Indian Ocean surface temperature; (a) mean Factual - Counterfactual difference in surface temperature in October 2015 in W@H (mean of 8 models), black boxes are areas used for DMI, green box is area used for Indian Ocean temperature; (b) Factual - Counterfactual SST in POAMA; (c) October DMI histogram and Generalised Extreme Value (GEV) distributions in W@H, histogram and GEV distribution of Factual ensemble in red, GEV distributions of eight Counterfactual ensembles in blue; (d) DMI histograms in POAMA; (e) histograms of Indian Ocean temperature in W@H (details as for DMI); (f) histograms of Indian Ocean temperature in POAMA.
Appendix 1 Mean Factual-Counterfactual surface temperature difference in each of the W@H model ensembles (directly inherited from GCM, names indicated in title), showing different estimates of mean warming and also spatial distribution of warming from each model.