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Abstract

High-resolution projections of climate change impacts on fire weather conditions in southeast Australia out to 2080 are presented. Fire weather is represented by the McArthur Forest Fire Danger Index (FFDI), calculated from an objectively designed regional climate model ensemble. Changes in annual cumulative FFDI vary widely, from − 337 (− 21%) to + 657 (+ 24%) in coastal areas and − 237 (− 12%) to + 1143 (+ 26%) in inland areas. A similar spread is projected in extreme FFDI values. In coastal regions, the number of prescribed burning days is projected to change from − 11 to + 10 in autumn and − 10 to + 3 in spring. Across the ensemble, the most significant increases in fire weather and decreases in prescribed burn windows are projected to take place in spring. Partial bias correction of FFDI leads to similar projections but with a greater spread, particularly in extreme values. The partially bias-corrected FFDI performs similarly to uncorrected FFDI compared to the observed annual cumulative FFDI (ensemble root mean square error spans 540 to 1583 for uncorrected output and 695 to 1398 for corrected) but is generally worse for FFDI values above 50. This emphasizes the need to consider inter-variable relationships when bias-correcting for complex phenomena such as fire weather. There is considerable uncertainty in the future trajectory of fire weather in southeast Australia, including the potential for less prescribed burning days and substantially greater fire danger in spring. Selecting climate models on the basis of multiple criteria can lead to more informative projections and allow an explicit exploration of uncertainty.

Publication Details

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Abstract

High resolution projections of climate change impacts on fire weather conditions in southeast Australia out to 2080 are presented. Fire weather is represented by the McArthur Forest Fire Danger Index (FFDI), calculated from an objectively designed regional climate model ensemble. Changes in annual cumulative FFDI vary widely, from -337 (-21%) to +657 (+24%) in coastal areas and -237 (-12%) to +1143 (+26%) in inland areas. A similar spread is projected in extreme FFDI values. In coastal regions, the number of prescribed burning days is projected to change from -11 to +10 in autumn and -10 to +3 in spring. Across the ensemble the most significant increases in fire weather and decreases in prescribed burn windows are projected to take place in spring. Partial bias correction of FFDI leads to similar projections but with a greater spread, particularly in extreme values. Partially bias corrected FFDI performs similarly to uncorrected FFDI compared to observed annual cumulative FFDI (ensemble root mean square error spans 540 to 1583 for uncorrected output and 695 to 1398 for corrected) but is generally worse for FFDI values above 50. This emphasizes the need to consider inter-variable relationships when bias-correcting for complex phenomena such as fire weather. There is considerable uncertainty in the future trajectory of fire weather in southeast Australia, including the potential for less prescribed burning days and substantially greater fire danger in spring. Selecting climate models on the basis of multiple criteria can lead to more informative projections and allow an explicit exploration of uncertainty.

1. Introduction

Fire weather conditions are a critical factor in wildfire incidence, along with fuel amount, fuel moisture and the presence of ignitions (Archibald et al. 2009; Bradstock 2010). Fire weather also drives many wildfire impacts, including fatalities (Blanchi et al. 2014), house loss (Blanchi et al. 2010) and fire severity (Bradstock et al. 2010; Storey et al. 2016). In Australia, the most widely used measure of fire weather conditions is the McArthur Forest Fire Danger Index (FFDI; Luke and McArthur 1978), which incorporates surface air temperature, relative humidity, wind speed and precipitation. There have been significant increases in FFDI over Australia in recent decades (Clarke et al. 2013a), although the impact of these changes on fire occurrence in any given region depends on the degree to which weather, rather than the other factors mentioned above, limits overall wildfire incidence (Bradstock et al. 2014).

A wide range of studies have examined possible changes to FFDI under the influence of anthropogenic climate change in Australia (e.g. Cary 2002; Pitman et al. 2007; Bradstock et al. 2009). Without exception these studies suggest the potential for significant increases in FFDI, particularly at the upper extremes of the FFDI distribution, in southeast Australia and under high emissions scenarios. For example, Fox-Hughes et al. (2014) report increases in FFDI in Tasmania out to 2100, with the area subject to 99th percentile fire danger values in spring projected to increase from 6% to 21%. Another example is the projections by Clarke et al. (2011) of strong increases in mean and extreme FFDI and a longer overall fire season by 2100 in southeast Australia. Finally, a national report into climate change in Australia reported high confidence that future fire weather climates will be more extreme, but less confidence in the magnitude of change (CSIRO and Bureau of Meteorology 2015). Nevertheless, regions and times of year have been identified where relatively little change in

fire weather is projected, including in some cases decreases (Flannigan et al. 2009). In contrast to projections of mean and extreme fire weather, there has been very little focus to date on quantitative changes in the moderate fire weather conditions under which prescribed burning, a common risk management tool, takes place (Penman et al. 2011).

As climate models, model evaluation and computer processing power have improved, there has been a shift in the design of climate change experiments, allowing a more thorough exploration of the uncertainty described above. Major features of this shift include

- the use of regional climate models (RCMs) in preference to global climate models (GCMs), with recent examples including Parks et al. (2016) and Forzieri et al. (2016)
- the use of a subset of models that have been selected for their skill in simulating the study area e.g. Litschert et al. (2012), King et al. (2012), Lehtonen et al. (2016)
- the use of a subset of models that have been selected to span a range of plausible climate futures e.g. Bala et al. (2013), Boulanger et al. (2014), Whitman et al. (2015)

Aiding these efforts has been the creation of several major regional climate modelling ensembles, including PRUDENCE (Christensen et al. 2007), ENSEMBLES (van der Linden and Mitchell 2009), and NARCCAP (Mearns et al. 2012). Along with investigations of future fire weather conditions (Tang et al. 15; Bedia et al. 2014), these projects facilitate a wide range of climate and climate change impact research. In Australia, the NSW and ACT Regional Climate Modelling project (NARCliM; Evans et al. 2014) has delivered a set of climate projections that allows systematic exploration of the uncertainty in future fire weather and other natural hazards in Australia. NARCliM comprises a 12-member ensemble

consisting of three RCMs forced by four GCMS. The NARCliM ensemble was selected on the basis of two criteria listed above (model skill and spanning a range of future climate changes) as well as a third, model independence. Ensemble members are often regarded as equally likely independent projections of future climate, an assumption known to be incorrect (Abramowitz 2010). Using Bishop and Abramowitz's (2013) definition based on covariance in model errors, the NARCliM ensemble is selected to maximize model independence.

Clarke et al. (2016) used output from the NARCliM ensemble at 50 km horizontal resolution to analyse continental-scale trends in fire weather in the context of modelled changes in fuel load. They found that FFDI was uniformly projected to increase in temperate areas, particularly in spring, but that projections spanned decreases and increases for grassland and subtropical climate zones. The aim of this study is to extend and deepen the fire weather analysis from Clarke et al. (2016) by using higher resolution (10 km) NARCliM output and systematically exploring the future change space for fire weather in fire-prone southeast Australia. The availability of bias-corrected versions of temperature and rainfall from the NARCliM ensemble facilitates the adjunct goal of exploring the effects of partial bias-correction on fire weather projections.

2. Data and methods

2.1 Study area

RCMs were run at 50 km resolution over the CORDEX AustralAsia region (Giorgi et al. 2009) and then at 10 km resolution over the NARCliM domain, which spans NSW, Victoria, southeast Queensland and eastern South Australia. Results are presented here for NSW and are summarized by State Planning Regions (SPR; Figure 1; NSW Government 2014), which

combine human and biophysical characteristics and form the basis for government planning decisions. Dominant native vegetation in coastal SPRs is Eucalypt forest, transitioning towards Eucalypt woodlands westwards from the Great Dividing Range, followed by a mixture of chenopod, hummock grassland, mallee and Acacia woodland in the central and west of the state (Table 1). Fire occurs in all SPRs in NSW but is most frequent, severe and has had the greatest human impacts in forested areas. A further classification is made, between coastal SPRs, which share a border with the coastline and are predominantly forested, and inland SPRs.

2.2 Regional climate model simulations

Future climate projections used the Weather Research and Forecasting (WRF) modelling system (Skamarock et al. 2008), which has demonstrated skill in simulating southeast Australian fire weather (Clarke et al. 2013b) and climate more generally (Evans and McCabe 2010, 2013). The Advanced Research WRF (ARW) version 3.3 was used. For the NARCliM ensemble four GCMs were downscaled using three configurations of WRF, giving a 12 member ensemble. GCMs were selected in three stages. First, a large set from the 3rd Coupled Model Intercomparison Project (CMIP3; Meehl et al. 2007) was evaluated and the worst performing models removed. Second, better performing models were ranked according to their independence (Bishop and Abramowitz 2013). Last, GCMs were placed within the future change space and the most independent models that span that space were chosen (Figure S1). A similar process was used to select RCMs. A large set based on different physical parameterizations was evaluated in order to remove the worst performing RCMs. A subset of the better performing models was chosen such that each selected RCM is as independent as possible from the other RCMs. GCMs are downscaled in two time slices

1990–2009 ('present') and 2060–2079 ('future'). Due to computational and resourcing constraints, a single emissions scenario, SRES A2, is used for future projections (Nakicenovic et al. 2000). A full description of the NARCliM ensemble is presented in Evans et al. (2014). Many aspects of the climate produced in the NARCliM ensemble have been tested and found to perform well in terms of general climate (Olson et al. 2016), teleconnections with large scale climate modes such as El Nino – Southern Oscillation (ENSO; Fita et al. 2017), extreme precipitation (Evans et al. 2016) and storm systems (Di Luca et al. 2016).

2.3 Fire weather estimation

Following Noble et al. (1980), FFDI is computed as

$FFDI = 2 \times \exp(0.987 \times \ln(DF) - 0.0345 \times H + 0.0338 \times T + 0.0234 \times V - 0.45)$	(1)

where DF is the drought factor, T is the daily maximum temperature (°C), V the 3pm wind speed (km h^{-1}) and H the 3pm relative humidity (%). The drought factor is an estimate of fuel dryness (Griffiths 1999) and is computed using the Keetch-Byram Drought Index (Keetch and Byram 1968) based on total daily rainfall for the previous day. Daily FFDI was calculated from the 12 member regional climate model ensemble. Observed FFDI is calculated similarly, except that the drought factor is based on daily rainfall through to 9am on the day of calculation (Lucas 2010). This is not expected to have a large impact on results.

2.4 Bias correction

Bias correction is a common tool used in interpreting and reporting results from climate change studies (Ehret et al. 2012). However, it is typically applied to individual variables for which there are high quality, long term, spatially extensive observations i.e. temperature and precipitation. The lack of appropriate data with which to bias correct relative humidity and wind speed means that any bias correction of FFDI will only be partial, with associated uncertainty in the physical consistency of this composite index. Nevertheless, partial bias correction of FFDI has been done before with reasonable results (Fox-Hughes et al. 2014). To meet stakeholder needs, the NARCliM project supplied both raw and bias corrected precipitation and temperature datasets (Evans et al. 2014). Briefly, both quantities were corrected based on the method of Piani et al. (2010), which involves adjustment of the simulated daily precipitation (temperature) cumulative probability density function (CDF) towards the observed CDF as given by fitting gamma (Gaussian) distributions. The observations used were from the Bureau of Meteorology's Australian Water Availability Project (AWAP; Jones et al. 2009), which has 5 km resolution. The availability of bias corrected data allows an analysis of both uncorrected and partially bias corrected versions of FFDI.

2.5 Analysis

The analysis is focused on ensemble measures of extreme, mean and moderate FFDI and its underlying variables, both annually and seasonally, and for NSW as a whole, as well as individual SPRs. Extreme FFDI is represented by the number of days over 50. Fires that break out under these conditions are very difficult to control, with 90% of property loss from major fires in Australia occurring during times when FFDI was above 50 (Blanchi et al. 2010). Mean FFDI is represented using annual cumulative FFDI (ΣFFDI; the sum of all daily

values in a year) and seasonal mean daily FFDI. Mean changes in the variables from which FFDI is calculated are also examined. FFDI values between 3 and 12 are used as a proxy for the moderate conditions under which prescribed burning takes place, based on current guidelines for dry sclerophyll forests in NSW (NSW National Parks and Wildlife Service, pers. comm.). Operational prescriptions tend to include a range of variables and thresholds, depending on the fire agency, fuel type and local conditions. However, they all include a measure of fire weather conditions and many include both upper and lower bounds, reflecting the need to ensure a fire can start and spread but also be controlled. The prescribed burning analysis is restricted to coastal SPRs, where dry sclerophyll forests predominate and is calculated for all seasons except summer. The statistical significance of projected changes in seasonal mean FFDI, its underlying variables, and the number of prescribed burning windows is tested using a two-sided t-test ($\alpha = 0.05$) for the difference of means assuming equal variance. The test was repeated relaxing the assumption of equal variance and results were not substantially different. Very similar results were obtained using a Wilcoxon Rank Sum test, which does not assume normality of data.

2.6 Evaluation

Uncorrected and partially bias-corrected annual cumulative FFDI, seasonal mean FFDI and days with FFDI over 50 are evaluated against observations at 17 weather stations drawn from a high quality historical FFDI dataset (Figure 2; Lucas et al. 2010). The nearest grid cell to each station is used. Model error is aggregated across stations and ensemble members using mean error, error range and root mean square error (RMSE). As noted by Clarke et al. (2013b), point data is not ideal for evaluating model output, which is typically considered as

representing area-averaged rather than point processes (Osborn and Hulme 1998). However, it is the best option available in the absence of long-term grid-based FFDI observations.

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3. Results

Not all models in the 12 member ensemble agree on the direction or magnitude of change in annual cumulative FFDI under climate change (Figure 3; Table 2). Simulations forced by the CCCMA3.1 and MIROC3.2 GCM project either modest decreases or relatively little change. Simulations forced by CSIRO-MK3.0 and ECHAM5 almost uniformly project increases. Across the entire ensemble, projected increases are largest in inland SPRs. A similar pattern holds for days with FFDI above 50, although in this case only MIROC3.2-forced simulations show more decreases than increases (Figure 4). For mean and extreme FFDI, GCMs appear to exert greater influence over the magnitude of changes than RCMs.

Bar plots showing the ensemble range of projected change in mean and extreme FFDI (Figure 5) emphasize that increases are not uniformly projected in any SPR, although the ACT and Southeast and Tablelands come close. These plots also show that increases are greater inland than on the coast, and greater for extreme values than mean values. Of the four variables underlying mean FFDI, only temperature is projected by all ensemble members to increase (Figure 5). Positive and negative changes are projected for mean annual drought factor, relative humidity and wind speed, with a modest amount of spatial variation. For relative humidity and wind speed, the largest projected changes tend to favor less fire danger, whereas the largest projected changes to drought factor are increases, which favor greater fire

danger. The New England and North West SPR is the only region in which all 12 ensemble members agree on the direction of change, in this case a decrease in mean annual wind speed.

There are strong seasonal patterns to the projected changes in FFDI (Figure 6; Table S1). Although positive and negative changes are projected in all seasons, the greatest increases in both mean and extreme FFDI are in spring and summer. The greatest decreases in mean FFDI occur in autumn, whereas the autumn and winter baseline levels of days with FFDI above 50 are too low to allow any substantial decrease under climate change. The clearest climate change signal appears to be in spring. Multiple ensemble members project significant changes in FFDI, maximum temperature, drought factor and wind speed in every SPR and for NSW as a whole (Table S2). Further, all models projecting such changes agree on the direction of change; positive for FFDI, temperature and drought factor and negative for wind speed. Temperature is projected to increase significantly in all SPRs and in all seasons. Results are mixed for relative humidity in spring, with significant decreases generally limited to central and southern coastal areas and some significant increases in the coastal north. Many significant changes are projected in winter, but there is almost no model agreement on the direction of change, except for increasing relative humidity in the North Coast SPR and decreasing wind speed in several regions. In most regions only one or two models project a significant change in autumn FFDI, usually negative. In contrast, while no more than five ensemble members project a significant change in summer FFDI, the North Coast is the only region where this change is not uniformly positive. Interestingly, these summer changes appear to be driven largely by temperature; in only one region (Central West and Orana) is there agreement between multiple models in projecting a significant change (in relative humidity) that would lead to a greater FFDI.

A seasonal analysis also reveals potential changes in the distribution of prescribed burning days in coastal SPRs (Fig 7; Table S2). As with mean FFDI and its drivers, the clearest climate change signal is in spring, with projected changes ranging from -10 to +3. Out of 24 significant spring changes across all simulations in coastal SPRs, only one is positive (in the Hunter, where 5 ensemble members project significant declines). No spring increases are projected in the Central Coast and South East and Tablelands SPRs. In autumn projections span -11 to +10 burning days, but only 5 significant changes in total are projected across all coastal SPRs, with just one increase in Illawarra. Also similar to mean daily FFDI and its drivers, there are many significant changes in winter but little model agreement, with 38 significant changes overall comprised of 20 increases and 18 decreases and a model range of -16 to +22.

The full ensemble tends to underestimate both mean and extreme FFDI on average, with the exception of simulations forced by ECHAM5 (Table 3; Figures 8 and 9). The absolute error tends to be largest and negative in inland areas, where baseline values of mean and extreme FFDI are high. For annual cumulative FFDI the model error range narrows and tends towards overestimates moving from inland to coastal locations and from north to south. Two exceptions are Broken Hill and Hay, which are known to have significant data inhomogeneity issues (Lucas 2010). Overall the ensemble range spans the actual observation in most cases. Grouping evaluation results by GCM and RCM, the ECHAM5-R3 combination stands out as having the smallest error on average. Nevertheless, the diversity in performance is such that the worst performing ensembles are not worst at all stations, and can actually be the best at a

given station e.g. MIROC3.2-R1 has the highest mean error in simulating annual cumulative FFDI but the lowest error for the Richmond station. Partial bias correction does not systematically improve model performance (Table 3). Rather, it tends to lead to an increase in mean and extreme FFDI values. In some cases this improves performance but in other cases it is degraded. It also leads to a much greater spread of values in extreme FFDI (Figure 9). Model error bounds for corrected and uncorrected annual cumulative FFDI and days with FFDI over 50 are in Table S3.

4. Discussion and conclusions

These findings reinforce previous studies showing the potential for major increases in fire danger in southeast Australia under climate change, particularly in spring (Fox-Hughes et al. 2014; CSIRO and Bureau of Meteorology 2015). The uppermost ensemble values represent major increases in fire weather - a doubling or worse in days over 50 each year and strong increases in mean conditions out to 2070. Across all ensemble members and all regions analysed here, the most significant changes and the biggest increases in fire weather conditions are projected for spring, suggesting an intensification and/or lengthening of the fire season, depending on when the current peak fire season is. However, the lowermost ensemble values represent little change overall in fire danger, including some significant decreases outside the peak fire season in autumn and winter. Based on the NARCliM ensemble there is considerable uncertainty over projected fire weather, in terms of both magnitude and direction of change. Clarke et al. (2011) also found regions of little change or decrease in fire weather in eastern Australia. However, these were limited to northeastern Australia, including the north of the present study area in NSW, and to the middle rather than

later part of the 21st century. In contrast, the uncertainty in future fire weather reported here extends to western NSW and the far southeast of continental Australia.

Given that maximum temperature is uniformly projected to increase across the entire study area, it alone cannot explain the variation in FFDI projections. The NARCliM ensemble intentionally includes GCMs projecting overall declines and increases in rainfall over the study area, in order to span the range of plausible climate futures. Drought factor is derived largely from antecedent rainfall and is projected to decrease significantly in the few instances where FFDI is projected to decrease significantly. Likewise changes in relative humidity tend to correlate with the direction of change in FFDI. Wind speed, in contrast, is frequently projected to decline, often significantly. The strong increases in FFDI in spring appear to occur in spite of these decreases in wind speed. Future research should explore patterns in FFDI drivers coincident with the most extreme values of FFDI, which will not necessarily align with those at the centre of the distribution (Harris et al. 2017).

The uncertainty in the future trajectory of mean and extreme FFDI also applies to moderate values, used here as a proxy for windows of opportunity for conducting prescribed burning. These are currently conducted largely in autumn and spring in NSW (NSW National Parks and Wildlife Service 2012). Although there is wide uncertainty over changes in the total days available each year for such burning, there are seasonal patterns. The clearest of these is in spring, with significant declines in the number of suitable burning days projected in every region in NSW. Only in two regions – New England and North West and Hunter – are significant increases in spring burning days projected, and even here there are many more

models projecting decreases than increases. There is far less certainty in autumn, with very few significant changes in suitable burning days projected. In some scenarios spring declines are accompanied by a compensating increase in prescribed burning conditions in winter. Any significant changes in the amount or timing of these windows could have important implications for fire management and resource sharing across jurisdictions, particularly if they coincide with more severe weather conditions during the peak fire season. More work is required to understand climate change impacts on the precise meteorological conditions underpinning prescribed burning.

Evaluation of the NARCliM ensemble with respect to observed fire weather shows a tendency to underestimate mean and extreme values, particularly in the inland of the state. This is consistent with previous evaluations of the WRF modelling system over NSW, which found that errors in humidity and wind speed were particularly influential in mean and extreme FFDI values respectively (Clarke et al. 2013b). The ensemble as a whole captures the overall magnitude and spatial gradient in mean and extreme FFDI, with the ECHAM5 GCM in combination with the R2 RCM having the lowest errors on average. However, model performance varies strongly by region and measure, meaning the selection of a 'best' model will depend on user priorities. In contrast to a previous Tasmanian study (Fox-Hughes et al. 2014), our findings suggest that partial bias-correction of FFDI does not consistently improve model performance and can lead to a much greater spread in model projections, particularly for extreme values. Until and unless suitable observational datasets are available with which to bias correct relative humidity and wind speed, and include inter-variable relationships, bias correction of FFDI should proceed with caution. Given that the bias correction was done independent of and prior to this study, a rigorous evaluation of this and other bias correction

techniques with respect to FFDI is a topic that merits further research. Interestingly, recent efforts to undertake systematic bias correction of WRF fire weather simulations in Victoria show promise and may be applicable to future climate projection studies (Brown et al. 2016).

Overall, model selection on the basis of multiple criteria leads to more informative projections with greater utility to end users. Such ensembles allow an explicit exploration of uncertainty in projections, highlighting regions and times of agreement and suggesting targets for future research to narrow uncertainty bounds. For example, uncertainty is greatest in winter, where despite a majority of models projecting significant changes in FFDI there is no agreement on the direction of change. This is reversed in spring, with around half of the models projecting significant increases in FFDI in all regions and none projecting significant declines. In spring there is also model agreement where projected changes are significant for drought factor (increase), prescribed burning days (decline) and, in the other direction, wind speed (decline). Although the number of models projecting significant changes in autumn is small, there is agreement amongst these for drought factor (decrease), relative humidity (increase), wind speed (decrease) and prescribed burning days (decline). Again, temperature increases occur in all models and all seasons and are all statistically significant. While NARCliM represented best practice at the time of its design, ensemble design and interpretation remains an active area of study, with recent developments including Bayesian model averaging (Olson et al. 2016), 'representative democracies' (Sanderson et al. 2015) and other weighting schemes (Haughton et al. 2015).

Our results suggest that changes in fire weather in NSW by the latter part of the 21st century are uncertain and location and model-dependent. The high end of ensemble projections represents substantial increases in severe fire weather conditions combined with decreases in available prescribed burning windows, particularly in spring. The lower end represents little change or even modest decreases in severe fire weather conditions and a potential increase in the amount of suitable days for conducting prescribed burning. It may be prudent for fire managers to understand their sensitivity to both of these possibilities, which will be based in part on how seasonal fire weather conditions currently influence fire risk (Williamson et al. 2016). The impacts of projected changes in fire weather conditions will depend on the relative importance of weather as a limiting switch on overall fire incidence (Bradstock 2010; Bedia et al. 2015). Broadly speaking, coastal forested areas are more likely to respond to greater fire weather conditions with more fire than inland areas, where overall fire incidence is limited more by fuel amount than weather. More comprehensive analyses therefore will need to draw in climate change impacts on fuel load, over which there remains much uncertainty (e.g. Clarke et al. 2016; Collins et al. 2017), and other drivers of fire incidence. Impacts of these projected fire weather changes will also be contingent on the wide range of fire management activities available to mitigate fire risk, such as prescribed burning and suppression (e.g. Plucinski 2012; Price et al. 2015).

Supporting information

Figure S1 Change from 1990-2009 to 2060-2079 for the GCMs considered, numbered by independence rank (from Evans et al. 2014). Models selected are MIROC3.2-medres (1), ECHAM5 (5), CCCM3.1 (9) and CSIRO-Mk3.0 (12).

Table S1 Projected change (upper and lower ensemble bounds) in FFDI and related variables by state planning region – seasonal

Table S2 Significance and model agreement of projected changes by state planning region

Table S3 Model error (lower and upper ensemble bounds) in annual cumulative FFDI and days with FFDI over 50 by station, for uncorrected and partially bias corrected model output

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Fig 1 Study area and state planning regions

Fig 2 Weather stations used to evaluate simulations

Fig 3 Projected change in annual cumulative FFDI. The 12 member ensemble is derived from four global climate models (rows) and three regional climate models (columns). Stipling indicates a significant change.

Fig 4 Projected change in days with FFDI over 50. The 12 member ensemble is derived from four global climate models (rows) and three regional climate models (columns). Stipling indicates a significant change.

Fig 5 Projected change in annual cumulative FFDI, days with FFDI over 50 and drivers of FFDI by state planning region. Lines represent individual models. Regions are NSW, Far West (FW), New England and North West (NE&NW), Central West and Orana (CW&O), Murray Murrumbidgee (MM), ACT, North Coast (NC), Hunter (H), Central Coast (CC), Metropolitan Sydney (MS), Illawarra (I) and South East and Tablelands (SE&T).

Fig 6 Projected change in annual cumulative FFDI, days with FFDI over 50 and drivers of FFDI by season in NSW. Lines represent individual models.

Fig 7 Projected change in prescribed burning days (3<FFDI<12) in autumn, winter and spring for coastal state planning regions. Lines represent individual models. Regions are North Coast (NC), Hunter (H), Central Coast (CC), Metropolitan Sydney (MS), Illawarra (I) and South East and Tablelands (SE&T).

Fig 8 Model error in annual cumulative FFDI and days with FFDI over 50 by station. Lines represent individual models.

Fig 9 Mean error in annual cumulative FFDI and days with FFDI over 50 across all stations by ensemble member, for uncorrected and partially bias corrected model output