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An investigation of future fuel load and fire weather in Australia

Hamish Clarke
University of Wollongong, hamishc@uow.edu.au

Andy Pitman
University of New South Wales

Jatin Kala
University of New South Wales

Claire C. Carouge
University of New South Wales

Vanessa E. Haverd
CSIRO Oceans and Atmosphere Flagship, vanessah@uow.edu.au

See next page for additional authors

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Authors

Hamish Clarke, Andy Pitman, Jatin Kala, Claire C. Carouge, Vanessa E. Haverd, and Jason P. Evans

An investigation of future fuel load and fire weather in Australia

Hamish Clarke[1,2], Andrew J. Pitman[1], Jatin Kala[1], Claire Carouge[1], Vanessa Haverd[3] and Jason P. Evans[1]

[1] ARC Centre of Excellence for Climate System Science and Climate Change Research Centre, University of New South Wales, Sydney, 2052, Australia

[2]Climate and Atmospheric Science Branch, NSW Office of Environment and Heritage, PO Box 3720, Parramatta, Australia

[3]CSIRO Marine and Atmospheric Research, GPO Box 664, Canberra 2601, Australia

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Address for correspondence

Hamish Clarke

Centre for Environmental Risk Management of Bushfires, University Wollongong, Northfields Avenue, Wollongong, 2522, Australia

Ph. +61 2 4221 5729, hamishc@uow.edu.au

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Abstract

We present an assessment of the impact of future climate change on two key drivers of fire risk in Australia, fire weather and fuel load. Fire weather conditions are represented by the McArthur Forest Fire Danger Index (FFDI), calculated from a 12-member regional climate model ensemble. Fuel load is predicted from net primary production, simulated using a land surface model forced by the same regional climate model ensemble. Mean annual fine litter is projected to increase across all ensemble members, by 1.2 to 1.7 t ha^{-1} in temperate areas, 0.3 to 0.5 t ha^{-1} in grassland areas and 0.7 to 1.1 t ha^{-1} in subtropical areas. Ensemble changes in annual cumulative FFDI vary widely, from 57 to 550 in temperate areas, -186 to 1372 in grassland areas and -231 to 907 in subtropical areas. These results suggest that uncertainty in FFDI projections will be underestimated if only a single driving model is used. The largest increases in fuel load and fire weather are projected to occur in spring. Deriving fuel load from a land surface model may be possible in other regions, when this information is not directly available from climate model outputs.

1 Introduction

Wildfires occur with sufficient and continuous plant biomass (fuel), fuel dry enough to burn, weather conducive to fire spread and an ignition source (Archibald et al. 2009; Bradstock 2010). Climate change effects on fire weather are frequently examined using indices that relate surface weather conditions to wildfire risk, such as the Canadian Forest Fire Weather Index system (FWI; van Wagner 1987) and the Australian McArthur Forest Fire Danger Index (FFDI; McArthur 1967; Luke and McArthur 1978). Since both are widely used in fire management agencies worldwide and can be calculated from standard climate model output, numerous studies have projected changes in FWI and FFDI (e.g. Williams et al. 2001; Bedia et al. 2013; Fox-Hughes et al. 2014; Lehtonen et al. 2014). Other fire weather elements that have been related to climate change include atmospheric stability (Luo et al. 2013), synoptic patterns (Hasson et al. 2009; Grose et al. 2014) and modes of climate variability (Cai et al. 2009). By relating observed weather patterns to fire incidence or burned area, projected changes in weather have also been used as a proxy for the presence of fire and its impacts (e.g. Mori and Johnson 2013).

In contrast to the direct use of meteorological variables for fire weather, predicting changes in biomass growth or fuel load requires a significant transformation of climate model data. The task is complicated by the need to include the potential response of vegetation to not just climate change, but also increasing carbon dioxide (CO_2; Donohue et al. 2013). Increasing CO_2 is thought to directly promote plant growth by increasing photosynthesis and decreasing stomatal conductance, although verification of these effects in large scale natural vegetation communities requires further work (Norby and Zak, 2011). There are multiple approaches to examining how climate change affects wildfire fuel loads. Statistical relationships have been developed between current vegetation patterns and meteorological variables (Matthews et al. 2012; Thomas et al. 2014; Williamson et al. 2014). These relationships allow vegetation changes to be derived from projected changes in meteorological variables, but do not account for direct CO_2 effects. Process-based approaches to fuel load and vegetation include dynamic global vegetation models (DGVMs), landscape fire succession models and biogeochemical models. These models may represent direct influences on fuel amount, such as litterfall, decomposition and fire incidence, as well as indirect causes like phenology, primary productivity, heat and moisture. Process-based models can incorporate direct effects of CO_2 on plant growth and water use efficiency (e.g. Jiang et al. 2013).

Quantitative, integrated assessments of the impact of climate change on multiple fire drivers are relatively rare (Pechony and Shindell 2010; Kloster et al. 2012; Loepfe et al. 2012; Eliseev et al. 2014). In Australia, Bradstock (2010) provides a qualitative assessment based on case studies of five fire regimes drawing on quantitative and qualitative data. Bradstock concludes that increasing temperatures and dryness may lead to divergent impacts on fire activity across Australia, with potential increases in temperate forests, but decreases in areas where fires are currently limited by fuel amount rather than fire weather conditions. The impact of climate change on multiple wildfire drivers in forested and grassland regions of southeast Australia was estimated by King et al. (2011, 2012). Both studies examined potential changes in fire weather and fuel load, but only the grassland study included fuel moisture (curing) as well as direct CO_2 effects, via a process-based grassland and water-balance model. Each study projected increases in fire weather conditions and overall decreases in fuel load, which translated to increases in fire incidence and area burned in forests, but minimal changes in fire risk in grasslands.

Our study aims to provide the first quantitative, regional assessment of the impact of projected changes in climate and CO_2 on fuel load and fire weather in Australia. Fire weather projections are derived from a regional climate model, which is then used to force a land surface model from which fuel load is estimated (Section 2.4), incorporating both direct and indirect effects of elevated atmospheric CO_2. Variation in Regional Climate Models (RCMs) and their forcing Global Climate Models (GCMs) is a major source of uncertainty in climate impact projections (Lung et al. 2013). We aim to explore the uncertainty of these projections by using a 12-member ensemble, selected for its skill in representing the regional climate and the independence of individual ensemble members (Evans et al. 2014). By accounting for uncertainty in climate models and including direct CO_2 effects on fuel load, we provide a more complete estimate of future changes in key aspects of wildfire risk.

2 Materials and Methods

Our study combines new and pre-existing regional climate and land surface model simulations (Figure 1).

2.1 Regional climate model simulations

We used the Weather Research and Forecasting (WRF) modelling system (Skamarock et al. 2008), which has been extensively evaluated and performs well in terms of regional Australian climate (Evans and McCabe 2010) and fire weather (Clarke et al. 2013). The simulations used in this study are drawn from the NSW and ACT Regional Climate Modelling (NARCliM) project (Evans et al. 2014).

NARCliM uses the Advanced Research WRF version 3.3. Four GCMs are downscaled using three configurations of WRF resulting in a 12 member ensemble (Figure 1). A three step GCM selection process was used. First, a large set drawn from the 3rd Coupled Model Intercomparison Project (CMIP3; Meehl et al. 2007) was evaluated in order to remove the worst performing models. Second, better performing models were ranked according to their independence (Bishop and Abramowitz 2013). Last, GCMs were placed within the future change space for temperature and precipitation and the most independent models spanning that space were chosen (Online Resource 1). RCMs were selected similarly. A large set consisting of different physical parameterisations was evaluated in order to remove the worst performing RCMs (Evans et al. 2012). From the better performing models, a subset was chosen such that each chosen RCM is as independent as possible from the other RCMs. Although partial bias correction of FFDI is possible (Fox-Hughes et al. 2014), we opted to maintain physical consistency in model dynamics by using direct model output. We address model bias via ensemble design and reporting of change values, rather than only absolute values.

GCMs were downscaled at hourly resolution in two time slices, 1990–2008 (‘present’) and 2060–2078 (‘future’). For future projections the SRES A2 emissions scenario is used (IPCC 2000), a reasonable choice given emissions continue to track the high end of emissions scenarios (Friedlingstein et al. 2014). RCMs were run at 50 km grid resolution.

2.2 Land surface model simulations

Fuel load projections are developed from the Community Atmosphere-Biosphere Land Exchange (CABLE, version 2.0) land surface model, which is designed to simulate fluxes of energy, water, and carbon at the land surface (Wang et al. 2011). CABLE has been extensively tested against observational data (Abramowitz et al. 2008; Wang et al. 2011). CABLE can be run with prescribed meteorology (e.g. Kala et al. 2014), or coupled in a global or regional climate model. CABLE is a key part of the Australian Community Climate Earth System Simulator (ACCESS), a fully coupled earth system science model and contributor to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). CABLE uses a small set of fixed plant functional types to represent vegetation, such as evergreen needleleaf, deciduous broadleaf, savanna and grassland.

CABLE was used within the NASA Land Information System version 6.1 (LIS-6.1; Kumar et al. 2008) at 25 km grid resolution. 12 offline simulations were run at half hourly time resolution, each forced with meteorological data from one of the 12 regional climate model ensemble members described above (Figure 1). The emissions scenarios used in WRF were also used with CABLE. Within CABLE Leaf Area Index (LAI) is prescribed from the mean of a monthly LAI ensemble based on the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product and weather observations (Kala et al. 2014).

2.3 Fire weather estimation

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

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

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. Daily FFDI was calculated from the 12 member regional climate model ensemble. We lack the curing data needed to calculate the related Grassland Fire Danger Index (Noble et al. 1980). Although the Forest and Grassland indices behave similarly, results in Australia's extensive grasslands therefore remain more uncertain.

2.4 Fuel load estimation

Fuel load is calculated from net primary productivity (NPP), since NPP represents the rate of production of vegetation. NPP has been equated to litter production (Matthews 1997) and is strongly correlated with aboveground biomass (Kindermann et al. 2008).

The relationship between fuel load and NPP is derived from the BIOS2 modelling environment, which simulates both quantities (Figure 1; Haverd et al. 2013). BIOS2 simulates the energy, water and carbon balances of the Australian continent at fine spatial (0.05°, ~5 km) and temporal (hourly) resolution. Central to BIOS2 is the CABLE model, resulting in a similar representation of NPP by BIOS2 and CABLE v2.0. However, in BIOS2 the soil and carbon modules are replaced by the SLI soil model (Haverd and Cuntz 2010) and the CASA-CNP biogeochemical model (Wang et al. 2010). Further, BIOS2 simulations are constrained by observations of streamflow, evapotranspiration, net ecosystem production and litterfall. BIOS2 was run from 1990 to 2011 using meteorological forcing from the Bureau of Meteorology's Australian Water Availability Project data set (AWAP) (Jones et al. 2009). The use of observational constraints along with the best available gridded weather observations for Australia means the simulations BIOS2 are likely the best available continental estimates of fuel load in the absence of high quality, long term, landscape-scale observations.

The Pearson product-moment correlation coefficient was used to calculate the relationship between annual NPP and annual fuel load in BIOS2 for the period 1990 to 2011. CASA-CNP divides carbon into plant, litter and soil pools, and litter into metabolic, structural and coarse woody debris pools (Wang et al. 2010). Taken together, the metabolic and structural litter pools are referred to as fine litter, which we use to represent fuel load. Where the correlation between NPP and fine litter was significant ($p < 0.05$), fine litter was related to NPP using ordinary least squares linear regression. Although there is no physical reason why this relationship should be strictly linear, the correlation was generally high with no clear evidence for a non-linear relationship. Since the link between fine litter and NPP is statistical, this model cannot account for mechanistic changes in litterfall and litter decomposition (e.g. carbon:nitrogen ratio), which mediate the translation of primary productivity into fuel load. However, the model of NPP in CABLE is mechanistic and is sensitive to changes in climate forcing and CO_2 concentration (Wang et al. 2011). Our model does not include fire so fuel load values should be considered steady state (equilibrium), albeit an equilibrium that fluctuates in response to NPP.

To understand regional variations, the same methods were applied to model grid cells averaged over a modified Köppen classification, which separates Australia into 6 mostly contiguous and climatically similar regions (Figure 2; Stern et al. 1999). The major Köppen zones are: equatorial, tropical, subtropical, desert, temperate and grassland. They capture general trends in vegetation across Australia, but necessarily omit important vegetation differences between fire regimes within each region. The lag-1 correlations between NPP and fine litter were significant ($p < 0.05$) for all 6 climate zones with the highest correlations in the subtropical ($r^2 = 0.86$), temperate ($r^2 = 0.80$) and grassland ($r^2 = 0.78$) climate zones (Online Resource 2).

The linear models for each climate zone and model grid cell were then applied to the present study, allowing fuel load (g C m^{-2}) to be calculated from NPP simulated by the 12 member land surface model ensemble (Figure 1). Load (t ha^{-1}) is obtained by assuming a carbon fraction of 47% (Roberts et al. 2008). We focus on the temperate, grassland and subtropical zones because of the high correlation between NPP and load in these regions. Model grid cells without a significant lag-1 correlation between NPP and fine litter are not shown (6% of all cells; 23% of equatorial and tropical climate zone cells).

2.5 Fuel load evaluation

For the purposes of model evaluation a separate CABLE simulation was run, forced by the MERRA reanalysis (Rienecke et al. 2011) instead of the NARCliM ensemble. The modelled fuel load values were evaluated over 31 Interim Biogeographic Regions of Australia (bioregions) in southeast Australia (Figure 3a; Hutchinson et al., 2005). Bioregions define zones of similar geology, landform and biota. Given their spatial extent and variety of vegetation types, the bioregion-based observations from Price et al. (2015) likely represent the best available validation data for our model. A second evaluation was conducted using the empirical model of Thomas et al. (2014), which links fuel in four tree-dominated vegetation types in NSW with observed gradients of temperature and rainfall.

3 Results

Our model tends to underestimate fuel amount but fits the observations reasonably well ($r^2 = 0.75$; Figure 3b). For example, while observed maximum fuel loads in forested bioregions range from 11 to 19 t ha^{-1}, modelled values range from 5.8 to 10.3 t ha^{-1} (Table 1). Our model strongly underestimated empirically-derived fuel load estimates in wet sclerophyll forest but performed reasonably in dry sclerophyll forest, rainforest and grassy woodland (Online Resource 3). Overall the model performs acceptably given our aim of exploring broad spatiotemporal trends in fuel load.

Based on this model, mean continental fine litter is projected to increase 0.35 to 0.56 t ha^{-1} (11% to 20%) by 2060-2078 (Figure 4a), with more fine litter in the lowest future ensemble member (3.28 t ha^{-1}) than the highest present ensemble member (3.22 t ha^{-1}). The spread in continental mean annual fine litter depends strongly on choice of GCM and RCM. Those models simulating the lower (higher) values of fine litter in the present remain the lower (higher) models in the future. RCM3 consistently simulates the highest litter amounts, illustrating the importance of RCM physics settings.

The sign and magnitude of changes in continental mean annual cumulative FFDI (Figure 4b) are strongly model dependent, in contrast to Figure 4a. Ensemble members driven by the 'wetting' CCCMA3.1 and MIROC3.2 (Online Resource 1) show little change and occasionally small decreases. Ensemble members driven by the drying ECHAM5 and CSIRO-Mk3.0 project large increases in FFDI. Overall ensemble mean FFDI increases from 5274 to 5816 (10%). Selecting only ECHAM5 and CSIRO-Mk3.0, the range of increases is 10 to 23%, while selecting only CCCMA3.1 and MIROC3.2 gives a range of -2 to 15% (excluding outlier MIROC3.2/RCM3 gives a range of -2 to 2%). These results highlight the dangers of using a single GCM for estimating future changes in FFDI. RCM3 is consistently at the lower end of ensemble simulated FFDI (in contrast to its placement at the upper end of simulated litter), again demonstrating the importance of RCM physics settings.

The spatial patterns of projected changes in mean annual fine litter are very similar between models, regardless of the degree of change (Figure 5a-b; see Online Resource 4 for all 12 ensemble members). All models show increases in fine litter in the southeast and northeast of Australia, particularly along the coast. Overall, our results consistently show increasing equilibrium fuel loads (i.e. fine litter) in the future.

In contrast, the overall pattern of change in annual cumulative FFDI is strongly divergent, with ensemble members forming two groups, some with substantial increases and others with modest decreases (Figure 5c-d). In the lowest ensemble member, little change in FFDI is projected across the continent. The highest ensemble member projects increases ranging from 200 to 600 in the southeast and extending along the coast to the northeast, to over 1800 over parts of northwest Australia. Again, this highlights the dangers of using single GCMs for estimating future FFDI since the choice of model determines the sign and magnitude of the overall change. The overall spatial pattern of change in FFDI is most strongly dictated by GCM, with RCMs modulating the magnitude of these changes (Online Resource 5).

There are strong seasonal patterns in projected changes in fine litter and FFDI. Increases in fine litter are projected every month in temperate, grassland and subtropical zones, with the highest increases in mid to late spring (Figure 6a-c; actual values in Online Resources 6). In contrast to the fuel load results, monthly values of mean daily FFDI show both decreases and increases in all three zones (Figure 6d-f; actual values in Online Resource 7). However, the magnitude of increases in FFDI is much greater than that of decreases. As with fine litter, in all three climate zones the largest projected increases in FFDI are projected to occur in mid to late spring (October and November). Where decreases in FFDI are projected, they are greatest from late summer to early autumn. While our focus is on mean FFDI, the strongly divergent projections also apply to extreme values. For instance, the projected change to the number of days each year where FFDI exceeds 50 varies widely in temperate (0.2-1.9), grassland (0.5-10.0) and subtropical (0.0 to 1.8) areas.

4 Discussion

Our results suggest that projected changes in climate and atmospheric CO_2 will increase fuel load in both forested and grassland areas of Australia by the latter part of the 21^{st} century, independent of model choice. In contrast, changes in fire weather are more model-dependent. The high end of ensemble projections represents substantial increases in fire weather conditions, while the lower end represents little change. These results suggest that FFDI projections are strongly dependent on the choice of GCM, with RCM choice modulating these effects. Across all ensemble members, the biggest increases in fire weather conditions are projected to occur in late spring, suggesting a longer (stronger) fire season in areas where spring is shoulder (peak) season. However, the impact of these changes will strongly depend on the relative importance of fuel and weather in regional fire regimes. Projections of increasing fuel load are potentially more significant in grassland regions, where fire incidence tends to be load-limited, while increases in fire weather conditions may be more significant in forested areas, where fire incidence is limited more by weather conditions that dry fuel out enough for it to burn (Bradstock 2010; King et al. 2013). Where both fire weather and fuel load increase, rate of fire spread can also be expected to increase (McArthur 1967).

These fire weather projections, particular in temperate areas, are in broad agreement with a range of previous studies which have projected increased wildfire risk from weather, particularly in spring (Cai et al. 2009; Hasson et al. 2009; Matthews et al. 2012; Fox-Hughes et al. 2014). While our study focuses on average conditions, similar changes occur at the upper end of the FFDI distribution, when fires that occur are most difficult to control (Clarke et al. 2012). Perhaps surprisingly, fire weather is often projected to remain stable or increase modestly in a subset of regions, seasons and models (Flannigan et al. 2009) – even in temperate areas (Clarke et al. 2011; Lucas et al. 2007). Unlike most studies, we intentionally maximised the range of plausible future changes in temperature and precipitation, hence our spread of FFDI values is not unexpected. One exception is CSIRO & Bureau of Meteorology (2015), which used three GCMs but found virtually no decreases in FFDI, possibly because none of these GCMs showed substantial increases in precipitation.

Our projections of uniform and widespread increases in fuel load differ from previous assessments for Australia. King et al. (2012) projected mostly decreases in grassy fuel load in southeast Australia, with CO_2 fertilisation insufficient to compensate for changing temperature and rainfall. Matthews et al. (2012) and Penman and York (2010) projected decreases in forest fuel load at two forested sites in southeast Australia, although the decreases reported by Penman and York (2010) were not significantly different to present values. Neither of these studies factored in CO_2

fertilization. However, all three studies used GCMs projecting an overall decrease in rainfall, in contrast to our ensemble of GCMs spanning both increases and decreases in rainfall.

Improving certainty in regional rainfall projections may not clarify all vegetation trends, due to differences in the response of major vegetation types to precipitation (Thomas et al. 2014; Gibson et al. 2014). The complex relationships observed between climate and vegetation type contrast with the near uniform changes in vegetation amount projected in our study. A possible reason is the CO_2 fertilisation effect in land surface models, which has elsewhere been found to be the major cause of modelled increases in gross primary productivity (NPP plus autotrophic respiration), strongly above rainfall or temperature and regardless of climate zone (Raupach et al. 2013). However, modelled CO_2 fertilisation effects still require validation in mature Australian native vegetation and the degree to which plant growth is nutrient-limited, rather than CO_2 limited, is a major question (Norby and Zak 2011). A further caveat is that plant functional type distribution in our model cannot respond to climate change (e.g. Gibson et al., 2014). Nevertheless, the model captures observed variation across multiple fuel types and climatic zones, albeit with consistent underestimates. This may relate to biases in BIOS2, which we used to link NPP with fine litter and which underpredicts fine litter in cool temperate and several forested ecosystems (Haverd et al., 2013).

In conclusion, we have provided the first regional assessment of the combined effects of climate change and increasing CO_2 on fuel load levels and fire weather conditions in Australia. In the forests of temperate and subtropical climate zones, where fuel moisture is a greater limit of overall fire activity, our results suggest the possibility of both little change and strong increases in wildfire risk, due to the wide spread in fire weather projections. In contrast, fuel load is consistently projected to increase, which could increase wildfire risk in grasslands and other areas where fuel amount tends to limit fire incidence. Refining this simple model to better reflect the complexities of Australian vegetation types, particularly in northern Australia, and improving regional-scale rainfall predictions will lead to a better understanding of long-term changes in Australian fuel load and fire weather.

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Figure captions

Fig 1 Summary of methodology. FFDI is calculated from a regional climate model ensemble spanning present (1990-2008) and future (2060-2078) periods. The same ensemble supplies the meteorological forcing to CABLE, yielding NPP. Based on the relationship between fine litter and NPP in BIOS2, fine litter is calculated from NPP in CABLE.

Fig 2 Köppen classification major climate zones

Fig 3 a) Southeast Australian bioregions b) Modelled fuel load compared to observations in 31 bioregions shown in 3a.

Fig 4 Ensemble mean annual continental (a) fine litter and (b) cumulative FFDI for present and future periods. Whiskers show the ensemble range, box shows the quartiles. Individual GCM/RCM combinations are represented by marker (GCM) and colour (RCM).

Fig 5 Change in mean annual (a) fine litter and (b) cumulative FFDI from the lowest and highest ensemble members, calculated from the average of all grid cell changes

Fig 6 Change in mean monthly (a) fine litter load and (b) FFDI in temperate, grassland and subtropical climate zones. Unbroken line shows multimodel mean, dotted lines show ensemble minimum and maximum values.

Electronic supplementary material (ESM) captions

ESM 1 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).

ESM 2 Scatterplots of BIOS2 mean annual NPP and mean annual fine litter from the same year (left) and the next year (right), in each climate zone.

ESM 3 Modelled fuel load compared to empirical estimates for tree-dominated vegetation types in NSW.

ESM 4 Change in mean annual fine litter from each ensemble member

ESM 5 Change in mean annual cumulative FFDI from each ensemble member

ESM 6 Present and future mean monthly fine litter (a-c) and FFDI (d-f) in temperate, grassland and subtropical climate zones. Unbroken line shows multimodel mean, dotted lines show ensemble minimum and maximum values.

References

Abramowitz G, Leuning R, Clark M, Pitman AJ (2008) Evaluating the performance of land surface models. J Climate 21:5468–5481

Archibald S, Roy D, Van Wilgen B, Scholes R (2009) What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Biology 15:613–630

Bedia J, Herrera S, Martín D et al (2013) Robust projections of Fire Weather Index in the Mediterranean using statistical downscaling. Climatic Chang 120(1–2):229–247

Bishop CH, Abramowitz G (2013) Climate model dependence and the replicate Earth paradigm. Clim Dynam 41:885–900

Bradstock RA (2010) A biogeographic model of fire regimes in Australia: contemporary and future implications. Global Ecology and Biogeography 19:145–158

Cai W, Cowan T, Raupach M (2009) Positive Indian Ocean Dipole events precondition southeast Australia bushfires. Geophys Res Lett 36:L19710

Clarke H, Smith PL, Pitman AJ (2011) Regional signatures of future fire weather over eastern Australia from global climate models. Int J Wildland Fire 20:550-562

Clarke H, Lucas C, Smith P (2012) Changes in Australian fire weather between 1973 and 2010. International Journal of Climatology 33:931–944

Clarke H, Evans JP, Pitman AJ (2013) Fire weather simulation skill by the Weather Research and Forecasting (WRF) model over south-east Australia from 1985 to 2009. Int J Wildland Fire 22:739–756

CSIRO and Bureau of Meteorology 2015, Climate Change in Australia Information for Australia’s Natural Resource Management Regions: Technical Report, CSIRO and Bureau of Meteorology, Australia

Donohue RJ, Roderick ML, McVicar TR, Farquhar GD (2013) Impact of CO2 fertilization on maximum foliage cover across the globe’s warm, arid environments. Geophys Res Lett 40:3031-3035

Eliseev AV, Mokhov II, Chernokulsky AV (2014) An ensemble approach to simulate CO_2 emissions from natural fires. Biogeosciences 11:3205-3223

Evans JP, McCabe MF (2010) Regional climate simulation over Australia's Murray–Darling basin: a multi-temporal assessment. J Geophys Res 115:D14114

Evans, J., M. Ekström, and F. Ji (2012), Evaluating the performance of a WRF physics ensemble over South-East Australia. Climate Dynamics, 39(6):1241–1258

Evans JP, Ji F, Lee C et al (2014) Design of a regional climate modeling projection ensemble experiment – NARCliM. Geoscientific Model Development 7:621-629

Flannigan MD, Krawchuk MA, De Groot WJ et al (2009) Implications of changing climate for global wildland fire. Int J Wildland Fire 18:483–507

Fox-Hughes P, Harris RMB, Lee G et al (2014) Future fire danger climatology for Tasmania, Australia, using a dynamically downscaled regional climate model. Int J Wildland Fire 23:309-321

Friedlingstein P, Andrew RM, Rogelj J et al (2014) Persistent growth of CO2 emissions and implications for reaching climate targets. Nature Geoscience 7(10):709-715

Gibson RK, Bradstock RA, Penman TD et al (2014) Changing dominance of key plant species across a Mediterranean climate region: implications for fuel types and future fire regimes. Plant Ecology 215:83-95

Griffiths D (1999) Improved formula for the drought factor in McArthur's Forest Fire Danger Meter. Australian Forestry 62: 202 – 206

Grose M, Fox-Hughes P, Harris RMB, Bindoff N (2014) Changes to the drivers of fire weather with a warming climate – a case study of southeast Tasmania. Climatic Change.

Hasson AEA, Mills GA, Timbal B, Walsh K. 2009. Assessing the impact of climate change on extreme fire weather events over Southeastern Australia. Climate Research 39:159–172

Haverd V, Cuntz M (2010) Soil-Litter-Iso A one-dimensional model for coupled transport of heat, water and stable isotopes in soil with a litter layer and root extraction. J Hydrology 388:438–455

Haverd V, Raupach MR, Briggs PR et al (2013). Multiple observation types reduce uncertainty in Australia's terrestrial carbon and water cycles. Biogeosciences 10:2011-2040

Hutchinson MF, McIntyre S, Hobbs RJ, Stein JL, Garnett S, Kinloch J (2005) Integrating a global agro-climatic classification with bioregional boundaries in Australia. Global Ecology and Biogeography, 14:197–212

Jiang X, Rauscher S, Ringler T et al (2013) Projected future changes in vegetation in western North America in the twenty-first century. J Clim 26: 3672–3687

Jones D, Wang W, Fawcett W (2009) High-quality spatial climate data-sets for Australia. Australian Meteorological Magazine 58:233–248

Kala J, Decker M, Exbrayat J-F et al (2014) Influence of Leaf Area Index Prescriptions on Simulations of Heat, Moisture, and Carbon Fluxes. Journal of Hydrometeorology 15:489-503

Keetch JJ, Byram GM (1968) A drought index for forest fire control. Research Paper SE-38. USDA Forest Service, Ashville, NC

Kindermann GE, McAllum I, Fritz S, Obersteiner M (2008) A global forest growing stock, biomass and carbon map based on FAO statistics. Silva Fennica 42:387-396

King KJ, de Ligt RM, Cary GJ (2011) Fire and carbon dynamics under climate change in south eastern Australia: insights from FullCAM and FIRESCAPE modelling. Int J Wildland Fire 20:563–577

King KJ, Cary GJ, Gill AM, Moore AD (2012) Implications of changing climate and atmospheric CO2 for grassland fire in south-east Australia: insights using the GRAZPLAN grassland simulation model. Int J Wildland Fire 21:695–708

Kloster S, Mahowald N, Randerson J, Lawrence P (2012) The impacts of climate, land use, and demography on fires during the 21st century simulated by CLM–CN. Biogeosciences 9:509– 525

Kumar SV, Peters-Lidard CD, Eastman JL, Tao W-K (2008) An integrated high- resolution hydrometeorological modeling testbed using LIS and WRF. Environmental Modelling and Software 23:169–181

Lehtonen I, Ruosteenoja K, Venäläinen A, Gregow H (2014) The projected 21st century forest fire risk in Finland under different greenhouse gas scenarios. Boreal Environ Res 19:127–139

Loepfe L, Martinez-Vilalta J, Piñol J (2012) Management alternatives to offset climate change effects on Mediterranean fire regimes in NE Spain. Climatic Change 115:693–707

Lucas C, Hennessy K, Mills G, Bathols J (2007) Bushfire weather in south-east Australia: recent trends and projected climate change impacts. Bushfire CRC and CSIRO, Melbourne

Luke R, McArthur A (1978). Bush fires in Australia. Australian Government Publishing Service, Canberra

Lung T, Dosio A, Becker W et al (2013). Assessing the influence of climate model uncertainty on EU-wide climate change impact indicators. Climatic Change 120:211-227

Luo L, Tang Y, Zhong S et al (2013) Will Future Climate Favor More Erratic Wildfires in the Western United States? Journal of Applied Meteorology and Climatology 52:2410-2417

Matthews E (1997) Global litter production, pools, and turnover times: Estimates from measurement data and regression models. Journal of Geophysical Research 102:18771-18800

Matthews S, Sullivan AL, Watson P, Williams RJ (2012) Climate change, fuel and fire behaviour in a eucalypt forest. Global Change Biology 18:3212–3223

McArthur AG (1967) Fire behaviour in eucalypt forests. Commonwealth of Australia Forest and Timber Bureau Leaflet No. 107. Commonwealth of Australia, Canberra, Australia

Meehl GA, Covey C, Delworth T et al (2007) The WCRP CMIP3 multimodel dataset: a new era in climate change research. Bull Am Meteorol Soc 88:1383–1394

Mori AS, Johnson EA (2013) Assessing possible shifts in wildfire regimes under a changing climate in mountainous landscapes. Forest Ecology and Management 310:875-886

Noble IR, Barry GAV, Gill AM (1980). McArthur's fire danger meters expressed as equations. Australian Journal of Ecology 5:201 – 203

Norby, RJ, Zak, DR (2011) Ecological lessons from free-air CO2 enrichment (FACE) experiments. Annual Review of Ecology, Evolution and Systematics 42:181-203.

Pechony O, Shindell DT (2010) Driving forces of global wildfires over the past millennium and the forthcoming century. Proc Natl Acad Sc USA 107(45):19167–19170

Penman TD, York A (2010) Climate and recent fire history affect fuel loads in Eucalyptus forests: implications for fire management in a changing climate. Forest Ecology and Management 260:1791–1797

Price OF, Penman TD, Bradstock RA, Boer MM, Clarke H (2015) Biogeographical variation in the potential effectiveness of prescribed fire in south-eastern Australia. Journal of Biogeography 42:2234-2245

Raupach MR, Haverd V, Briggs PR (2013) Sensitivities of the Australian terrestrial water and carbon balances to climate change and variability. Agricultural and Forest Meteorology 182-183:277-291

Rienecker MM, Suarez MJ, Gelaro Ret al (2011) MERRA - NASA's Modern-Era Retrospective Analysis for Research and Applications. Journal of Climate 24:3624-3648

Roberts G, Wooster MJ, Lagoudakis E (2008) Annual and diurnal African biomass burning temporal dynamics. Biogeosciences Discussions 5:3623-3663

Skamarock WC, Klemp JB, Dudhia J et al (2008) A Description of the Advanced Research WRF Version 3, NCAR Technical Note, NCAR, Boulder, CO, USA

Stern H, de Hoedt G, Ernst J (1999). Objective classification of Australian climates. Australian Meteorological Magazaine 49:87-96

Thomas PB, Watson PJ, Bradstock RA et al (2014). Modelling surface fine fuel dynamics across climate gradients in eucalypt forests of south-eastern Australia. Ecography 37:1-11

van Wagner CE (1987) Development and Structure of the Canadian Forest Fire Weather Index System. Technical Report 35. Canadian Forestry Service, Ottawa, ON

Wang YP, Law RM, Pak B (2010) A global model of carbon, nitrogen and phosphorus cycles for the terrestrial biosphere. Biogeosciences 7:2261–2282

Wang YP, Kowalczyk E, Leuning R et al (2011) Diagnosing errors in a land surface model (CABLE) in the time and frequency domains. J Geophys Res 116:G01034

Williams AAJ, Karoly DJ, Tapper N (2001) The sensitivity of Australian fire danger to climate change. Climatic Change 49:11–191

Williamson GJ, Prior LD, Grose MR et al (2014) Projecting canopy cover change in Tasmanian eucalypt forests using dynamically downscaled regional climate models. Regional Environmental Change 14:1373-1386

Table 1 Modelled load statistics compared to southeast Australian bioregions.

Bioregion	**Vegetation Type**	**Observed fuel max (t/ha)***	**Modelled fuel mean (t/ha)**	**Bias**	**RMSE**
Australian Alps	Eucalypt Forest	19	9.6 ± 0.2	9.4	9.5
Brigalow Belt South	Eucalypt Woodland	4.7	4.0 ± 0.1	0.7	1.7
Broken Hill Complex	Chenopod	2.4	0.7 ± 0.0	1.7	1.7
Central Ranges	Acacia Woodland	4.7	1.1 ± 0.0	3.6	3.7
Channel Country	Chenopod	2.4	0.7 ± 0.0	1.7	1.7
Cobar Peneplain	Eucalypt Woodland	10	2.0 ± 0.1	8.0	8.0
Darling Riverine Plains	Eucalypt Woodland	10	2.6 ± 0.1	7.4	7.5
Eyre Yorke Block	Mallee	8.7	3.2 ± 0.1	5.5	5.7
Flinders Lofty Block	Chenopod	2.38	1.8 ± 0.1	0.6	2.0
Furneaux	Eucalypt Forest	16.4	11.0 ± 0.7	5.4	5.8
Gawler	Acacia Woodland	4.5	0.6 ± 0.0	3.9	3.9
Great Victoria Desert	Acacia Woodland	0	1.0 ± 0.0	-1.0	1.1
Kanmantoo	Eucalypt Woodland	10	7.4 ± 0.3	2.6	2.8
Mulga Lands	Acacia Woodland	4.5	1.0 ± 0.0	3.5	3.5
Murray Darling Depression	Mallee	5.8	2.4 ± 0.1	3.4	3.9
Nandewar	Eucalypt Forest	16.4	5.8 ± 0.2	10.6	10.7
Naracoorte Coastal Plain	Eucalypt Woodland	10	8.0 ± 0.3	2.0	3.3
New England Tablelands	Eucalypt Forest	16.4	10.3 ± 0.3	6.1	6.5
NSW North Coast	Eucalypt Forest	19	10.1 ± 0.2	8.9	9.1
NSW South Western Slopes	Eucalypt Woodland	4.7	6.9 ± 0.1	-2.2	2.7
Nullarbor	Chenopod	2.4	0.6 ± 0.0	1.8	1.8
Riverina	Chenopod	2.4	3.8 ± 0.1	-1.4	2.3
Simpson Strzelecki Dunefields	Hummock Grassland	10	1.0 ± 0.0	9.0	9.0
South East Coastal Plain	Eucalypt Forest	16.4	9.1 ± 0.3	7.3	7.6
South East Corner	Eucalypt Forest	16.4	9.6 ± 0.2	6.8	7.0
South Eastern Highlands	Eucalypt Forest	19	9.4 ± 0.1	9.6	9.8
South Eastern Queensland	Eucalypt Forest	11	7.8 ± 0.2	3.2	3.8
Southern Volcanic Plain	Wetlands	19	9.1 ± 0.2	9.9	10.0
Stony Plains	Chenopod	2.4	0.4 ± 0.0	2.0	2.0
Sydney Basin	Eucalypt Forest	16.4	9.7 ± 0.2	6.7	7.1
Victorian Midlands	Eucalypt Forest	16.4	8.1 ± 0.2	8.3	8.5

* values are from Price et al. (2015)

Supplementary Table 1 Modelled load statistics compared to tree-dominated vegetation types in NSW.

Vegetation type (Keith 2004)	Empirically modelled fuel max (t/ha)*	Modelled fuel mean (t/ha)	Bias	RMSE
Dry Sclerophyll Forest	10.8	8.2 ± 0.0	2.6	3.8
Wet Sclerophyll Forest	20.2	10.0 ± 0.0	10.2	10.4
Rainforest	8.1	10.0 ± 0.0	-2.0	3.0
Grassy Woodland	8.6	8.5 ± 0.0	0.1	3.0

* values are from Thomas et al. (2014) and are based on statistical models relating site-based observations to temperature and rainfall