Proceedings for the 6th International Fire Behavior and Fuels Conference
April 29 – May 3, 2019, Sydney, Australia
Published by the International Association of Wildland Fire, Missoula, Montana, USA

Towards seamless predictions across scales for fire weather

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Introduction

Spatio-temporal variations in fire weather conditions are considered here based on observations, reanalysis data and climate model output for regions throughout Australia. The ability to produce datasets and practical guidance products that are consistent over different times scales is explored in this paper, including for the long-term historical climate, current climate and projected future climate. A quantile matching method is detailed here, designed for use in producing fire weather indices based on climate model data matched to observations. Examples are presented of how this method can be applied to help produce guidance information that is more consistent with observations as used by fire agencies and emergency management authorities. The analysis presented also examines the factors influencing predictability of fire weather variations at seasonal time scales, including the role of large-scale atmospheric and oceanic drivers on fire weather conditions. A more seamless service for providing fire weather information across different time scales, including covering historical, current climate and future climate periods, is intended to help enhance operational fire management, planning and policy development, as well as climate adaptation efforts.

Data and methods

Fire Weather Indices

The McArthur Forest Fire Danger Index, FFDI (McArthur 1967), is a common measure used in many regions of Australia for examining the influence of near-surface weather conditions on fire behaviour. Daily values of FFDI are used for this study throughout the time period from 1950 to 2016. This dataset, as detailed in Dowdy (2018), is primarily based on a gridded analysis of observations from the Australian Water Availability Project, AWAP (Jones et al. 2009), with a grid of 0.05° in both latitude and longitude throughout Australia. This includes daily maximum temperatures, as well as vapour pressure at 1500 Local Time (used here together with temperature to calculate relative humidity near the time of maximum temperature) and daily-accumulated precipitation totals for the 24-hour period to 0900 Local Time each day. Wind speed at 0600 UT is used (representing mid-afternoon conditions over the longitude range spanned by Australia) based on the NCEP/NCAR reanalysis (Kalnay et al. 1996), with bias correction subsequently applied to provide a better match to the wind speeds used for issuing forecasts of the FFDI by the Bureau of Meteorology.

Modelling

Global climate model (GCM) data are available in conjunction with the Intergovernmental Panel on Climate Change (IPCC), based on a set of GCM experiments: the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor et al. 2012). The direct output from the GFDL-ESM2M model, as part of the CMIP5 ensemble, is used here to examine weather conditions commonly used as input to fire weather indices, including the FFDI. This GCM was selected for presentation here as a general representative example from the broader set of CMIP5 GCMs. A high emission pathway is considered here (RCP8.5, with no stabilization this century leading to about 1370 ppm CO2 equivalent by 2100) to examine the influence of increased greenhouse gas concentrations. The direct output from GCMs is not well-suited for calculating the FFDI, including given that the wind speeds may represent mean values for a relatively large region and time period (e.g., 6-hourly average values), whereas 10-minute average wind speeds are required for the FFDI calculation. Examples such as this indicate the considerable improvements that could potentially be obtained from bias correction.

Long-range model predictions (at multi-week to seasonal lead times) are produced in Australia for weather conditions such as temperature and rainfall based on output from ACCESS-S, the Bureau of Meteorology's seasonal forecasting model. Hindcast model runs of ACCESS-S are available from 1990-2012, with real-time models runs also available for predictions out to several months ahead. Research efforts in recent years have calculated the FFDI using output from ACCESS-S, finding that although there was reasonable accuracy for the long-range predictions, the FFDI values were systematically low as compared to the observations-based FFDI dataset (Dowdy 2018), highlighting the need for bias correction.

Results

Quantile-matching

There are various different approaches that can be used for bias correction, with the method selected here based on matching model data to observations or reanalysis data using individual quantile values (i.e., a ranking-based approach known as quantile matching). This is done for each of the four input variables of the FFDI: daily maximum temperature, daily rainfall, afternoon relative humidity and afternoon wind speed. The bias correction approach uses the following steps to train the method.

1. Create probability density functions (PDFs) of weather variable data. This can be done based on model output (as is done here using GCMs and the ACCESS-S seasonal prediction model), as well as based on observations (as is done here using the input weather variables of the FFDI dataset described by Dowdy (2018)). This is done for each individual grid location, based on a historical data period (1975-2017 used for GCMs to provide a long time period that includes some extreme events, and 1990-2012 used for ACCESS-S representing its complete period of data availability for historical hindcasts).

2. Using the rankings of values in these PDFs, a given value of a weather variable for the model data is matched to the corresponding value for the observations-based data, with the matched values having equal rankings in their respective distributions.

3. Values outside of the historical range in the PDFs from Step 1 are possible, particularly when applied for future climate projections, as well as for seasonal prediction applications. Consequently, the 5 most extreme values are used to calculate the mean difference between the model and the observations-based data, with this mean difference used for the bias correction applied to values outside of the historical range of occurrence. This is calculated individually for the 5 extreme high values, as well as for the 5 extreme low values. This approach allows extreme values of this order to be represented in the model data after bias correction, while also helping avoid a potentially strong influence in some rare cases from outliers (e.g., if a 1 in 500 year event occurred during the historical training period).

The above steps were applied individually for different seasons (December to February, March to May, June to August and September to November), noting that different weather systems can preferentially occur around a particular time of year and that models can vary in their ability to represent some types of weather phenomena. Additionally, it was found when applying this quantile-matching method to temperature projections towards the end of this century (using a high emissions scenario) that the large-scale shift in the overall PDF is important to consider. Consequently, a 40-year running mean anomaly (as compared to the mean value for the historical training period used in Step 1) is subtracted from the future projections of temperature prior to applying the quantile matching method described in the above steps. After the quantile matching has been applied, the 40-year mean anomaly is added back into the data. These steps as described above result in an improved representation of the model data as compared to the observations-based data, as shown in Figure 1.

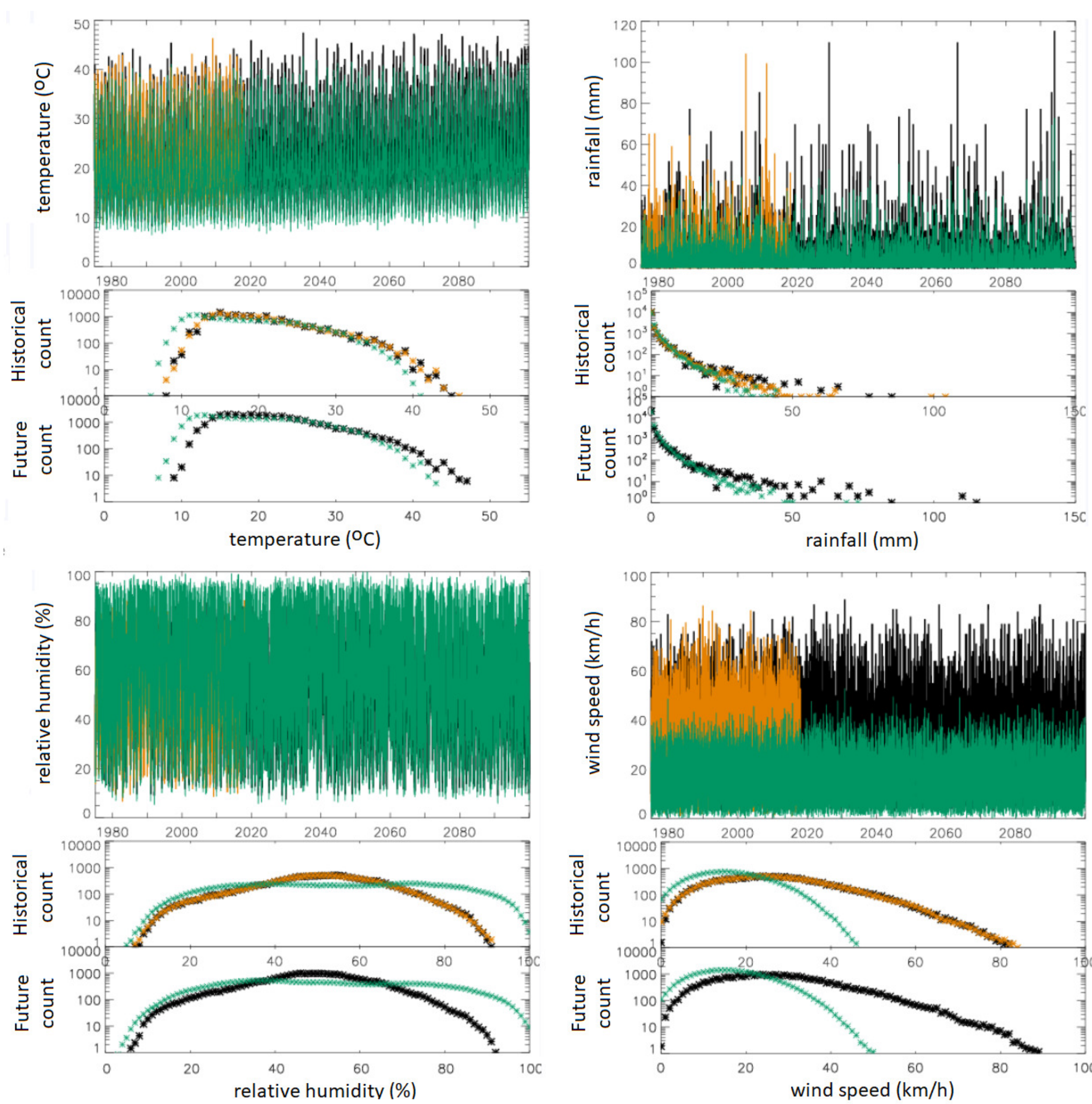

Figure 1: Daily values of maximum temperature (upper left), rainfall (upper right), relative humidity (lower left) and wind speed (lower right). Results are shown for the GFDL-ESM2M global climate model based on the direct output data from the model (green) and the bias-corrected version of these data (black), as well as based on observations

and reanalysis (orange). Time series are shown from 1975 to 2100, with PDFs for the historical training period (from 1975 to 2017) and the future projections period (from 2018 to 2100).

The results presented in Figure 1 are for the location of Melbourne in southeast Australia, based on GFDL-ESM2M data (i.e., the direct output from the GCM) matched to the data used for the observations-based FFDI dataset (Dowdy 2018). The results show that the quantile-matching method helps provide consistency between the model output and the observations-based data for these four input variables to the FFDI. Similar improvements over the raw model output are obtained for other locations around Australia. In addition to providing a reasonable match between the PDFs of the bias corrected model data and the observations-based data, as shown in Figure 1, the method also results in a reasonable representation of individual extreme values (e.g., as shown for the historical period time series in Figure 1).

The method has also recently been applied to wind speeds from the ACCESS-S seasonal prediction model, with temperature, rainfall and humidity already available with quantile matching applied for consistency with the AWAP gridded analysis of observation. The resultant FFDI values are now more similar in magnitude to the observations-based data.

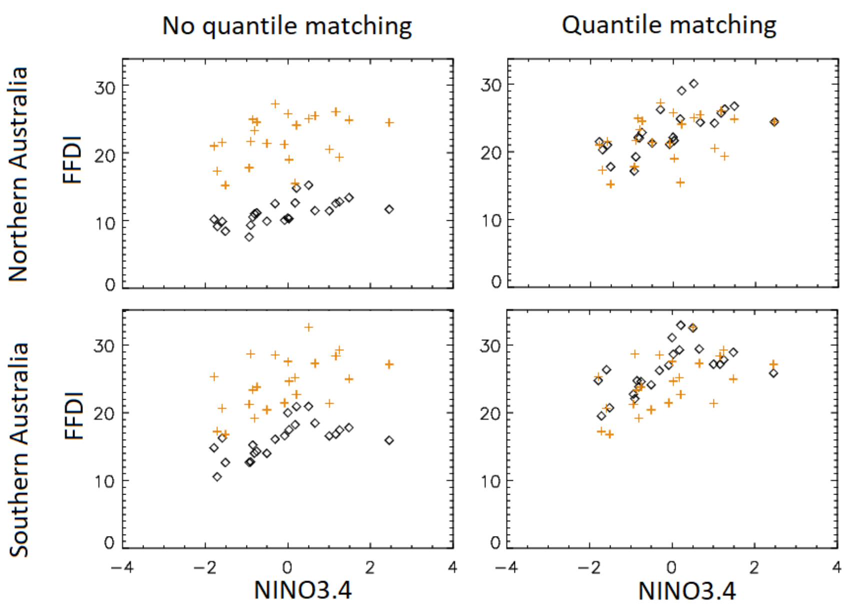

Figure 2: Daily values of FFDI based on ACCESS-S without (left) and with (right) bias correction applied, with the observations-based FFDI data also shown (orange). Results are shown for individual years from 1990-2010, averaged for the northern and southern halves of Australia during summer (December to February), using November 1 initial conditions for the model. The relationship with ENSO is also presented (using the NINO3.4 index summer average).

Drivers of predictability for the current climate

In addition to long-term climate change projections driven by increasing greenhouse gas concentrations (Taylor et al. 2012), the climate can also be predictable to some degree at shorter time scales (e.g., multi-week to seasonal) based on a range of factors. In addition to modelling methods, discussed in the previous section, the ability to predict future fire weather conditions can also be based on previous observations. In particular, the relatively slow rate of change in fuel moisture in some cases is such that current moisture content can be a useful indicator of future moisture content (and therefore also FFDI) to some degree. For example, considering the three fuel moisture codes of the Fire Weather Index System (van Wagner 1987), larger/deeper fuel have a drying rate of about 50 days for a 2/3 reduction in moisture content. The long-term historical climatology also provides some predictability of fire weather (as distinct from fire occurrence) at seasonal time scales, including based on the mean climatology of FFDI, such as the progression of the peak conditions for dangerous fire weather for different seasons through the year (Figure 3) as well as based on climate change trends that have already occurred (e.g., temperatures are more likely to be hotter now than in the past which contributes to a trend in FFDI for some regions and seasons (Dowdy 2018)).

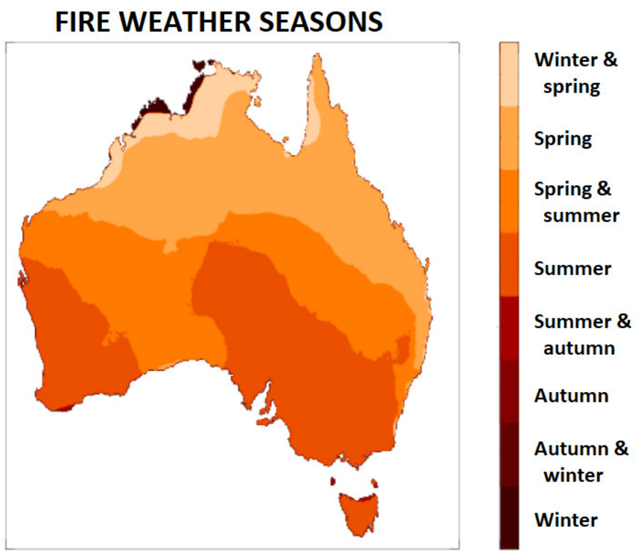

Figure 3: The season with the most dangerous weather conditions for bushfires, mapped for different regions of Australia. At each location, the season shown is the one with the highest average value of the Forest Fire Danger Index (FFDI, based on daily data from 1950 to 2016 (Dowdy 2018)).

Large-scale atmospheric and oceanic modes of variability, such as the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) can sometimes be predictable several months ahead. This can help provide an ability to accurately predict fire weather conditions in some regions, with global studies highlighting Australia as a lucky country in having relatively high accuracy of long-range predictions leading up to and during the warm season (Dowdy et al. 2016). To further examine the physical reasons for this skill, the four input variables of the FFDI are shown in Figure 4 at locations where a significant correlation occurs with the NINO3.4 index (an oceanic measure of ENSO). The sample Pearson's correlation coefficient *r* is used to examine the dependence between ENSO and fire weather conditions, based on concurrent seasonal correlations of the datasets. The 95% confidence level is used to examine the significance of the correlations, determined using a nonparametric bootstrap method based on 500 random permutations of the data.

The results show that temperature, relative humidity and rainfall in many regions of Australia are all influenced by ENSO in a broadly similar way (in the sense of more dangerous fire weather condition: i.e., higher temperatures, together with lower relative humidity and rainfall). Positive values of the NINO3.4 index (e.g., as occur for conditions associated with El Niño) are typically associated with higher temperatures and lower values of relative humidity and rainfall in many parts of Australia, with the converse generally being the case for conditions associated with La Niña. Figure 4 also shows that wind speed is notably different to the other variables in its relationship to ENSO, with the overall fire weather conditions (based on FFDI values) largely following the general pattern of the ENSO relationships for the three other weather variables.

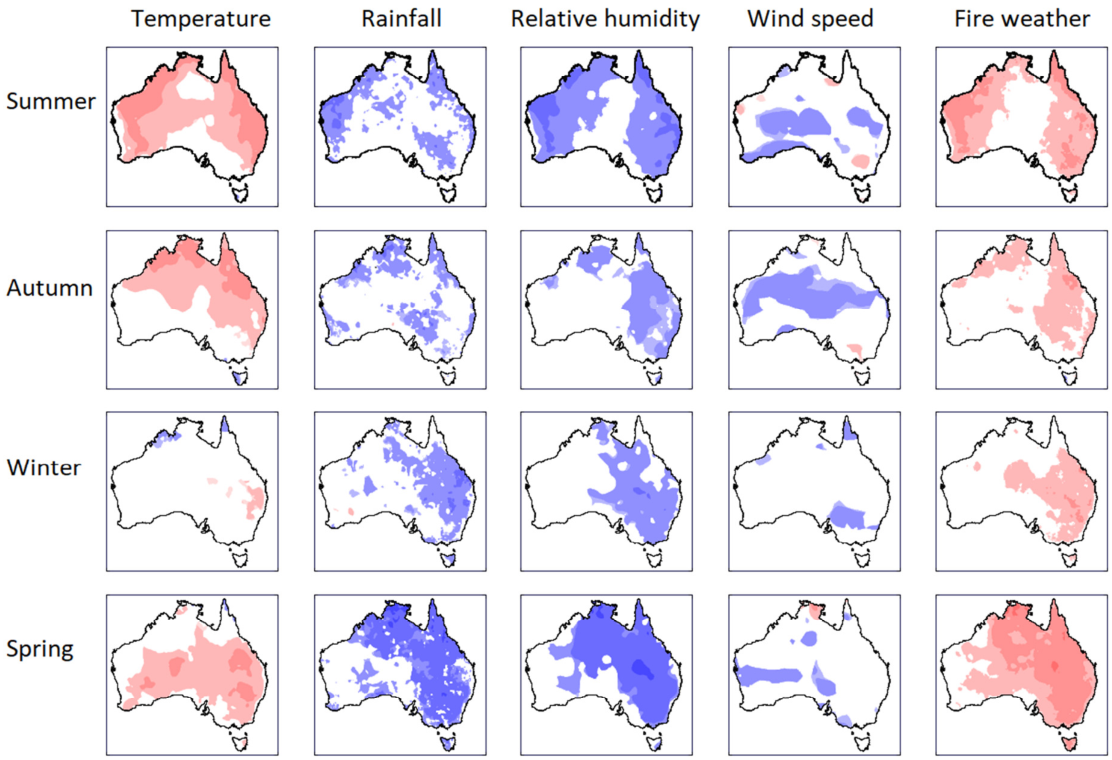

Figure 4: Correlations between seasonal values of NINO3.4 and weather condition (including the FFDI for fire weather), for the time period from 1951 to 2016. The correlations are calculated individually for DJF (a), MAM (b), JJA (c) and SON (d). The coloured regions represent locations where the magnitude of the correlation is significant at the 95% confidence level. For further details on the data see Dowdy (2018).

References

Dowdy AJ (2017) Climatological variability of fire weather in Australia. *J. Appl. Meteorol. Climatol.* **57**, doi: 10.1175/JAMC-D-17-0167.1.

Dowdy AJ, Field RD, Spessa AC (2016) Seasonal forecasting of fire weather based on a new global fire weather database. Proceedings for the 5th International Fire Behaviour and Fuels Conference April 11-15, 2016, Melbourne, Australia. Published by the *International Association of Wildland Fire*, Missoula, Montana, USA.

Jones D, Wang W, Fawcett R (2009) High-quality spatial climate datasets for Australia. *Aust. Meteorol. Mag*., **58**, 233-248

Kalnay E & Coauthors (1996) The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society*, **77**(3), 437-471.

McArthur AG (1967) Fire behaviour in eucalypt forests. *Forestry and Timber Bureau*, Canberra.

Taylor KE, Stouffer RJ, Meehl GA (2012) An Overview of CMIP5 and the experiment design. *Bull. Amer. Met. Soc.* **93**, 485-498, https://doi.org/10.1175/BAMS-D-11-00094.1.