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Fire danger ratings inform the community and fire managing agencies of fire risk. Fire danger ratings are currently primarily based on fire danger indices (FDIs) calculated using methods that were developed many decades ago. The challenges and issues with these methods are well documented. We aimed to develop a more objective and observation-based approach to fire danger assessment that considers spatial data on the occurrence of actual fires as well as on fire factors that are already routinely produced every day for Australia. A preliminary assessment suggested a very good potential of the methodology to formally and objectively incorporate any new fire danger predictors. The method can be combined with forecasted rather than observed weather and fuel conditions to produce forward predictions of expected FDI.

Towards comprehensive characterisation of flammability and fire danger

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Introduction

Fire danger ratings are used to prepare the community and fire management agencies for the relative likelihood of fire occurrence, and the likely rate of spread and difficulty of suppressing fires once they occur. They can trigger fire bans and operational fire preparations, and affect activities such as prescribed burning. Fire danger ratings are currently primarily based on fire danger indices (FDIs) calculated using methods that were developed many decades ago, such as the McArthur Forest and Grassland Fire Danger Meters (McArthur 1966; 1967) and algorithms since fitted to those meters (Noble et al. 1980) to routinely calculate Forest and Grassland FDIs (FFDI and GFDI, respectively). The issues with the McArthur approach have been well-documented over the years and are manifold. Most limiting, perhaps, is that much-improved data are now available on weather and fuel variables that affect fire danger, such as the moisture content of the soil, litter and live fuel. However, there is no straightforward way to retrofit the McArthur framework to these new observations (Holgate et al. 2017). Further issues are that the FFDI and GFDI were developed from a small database of fires in a narrow range of vegetation types, and are not representative for the full range of weather types and fuel types and condition encountered across Australia. Unfortunately, beyond the personal experience of users who have applied the indices more broadly, there is no generic and formal possibility to consider such variations and adapt to them.

This research was motivated by the desire to develop a more objective approach to fire danger assessment, considering spatial data on the occurrence of fires as well as on fire danger factors – weather and fuel factors that influence fire occurrence and behaviour - that are now routinely produced every day. We do not propose that the methodology developed here can meet all requirements of the new Australian Fire Danger Rating System that is currently in development. However, the approach developed here may contribute to those developments by demonstrating how multiple data sources can be combined in a statistical prediction framework. Our general approach is predicated on the use of satellite-based fire detections as an observational data set of fire occurrence. We considered a set of eight predictor variables relating to fire weather and fuel condition that are derived daily from satellite remote sensing, station data interpolation or modelling. For each Australian Fire Weather Area, for each of three broad land cover types (‘forest’,’grass’ and ‘shrub’), and for each predictor variable, we calculated the conditional probability of fire occurrence at different predictor values. We fit a statistical distribution function to these probabilities and combine the eight factor-probability predictions into a single combined Fire Danger Index.

Data

Fire occurrence data are available for 2003 onwards from the Geoscience Australia Sentinel Hotspots fire detection system (Geoscience Australia 2014). The fire detections are based on detecting anomalously high surface temperatures in thermal imagery obtained by multiple satellite instruments, dominated by the two MODIS instruments in the first part of the record.

Several caveats apply to the observations: the MODIS thermal sensor footprint and accuracy is ca. 2.5 km, which means that small and low-intensity fires may not be detected and that the exact location may not always be known. The two MODIS instruments cover the surface approximately four times each day, and therefore, there is a possibility that fires are not detected. Conversely, detected fires do not only include unplanned bushfires but also planned burns (e.g., savanna, crop residue and fuel control burning and gas flares).

A list of detected fires and their inferred temperature is downloaded annually and resampled to daily grids at 0.025° (~2.5 km) resolution as part of ANU’s Australia’s Environment report. The data are made available for visualization or download through Australia’s Environment Explorer (www.ausenv.online). Here, the maximum daily fire intensity for each pixel was transformed to binary data on fire occurrence by assuming any fire with a temperature of >80 °C could be considered a fire event.

GIS data on the location of 134 Fire Weather Areas (FWAs) across Australia was combined with data on fuel type from the Australian Flammability Monitoring System (AFMS, www.anuwald.science/afms), where three broad fuel types are distinguished: ‘grass’, ‘shrub’, and ‘forest’. This classification was developed by Yebra et al. (2018) in deriving satellite-based Live Fuel Moisture Content (LFMC) estimates available in the AFMS, based on an amalgamation of classes in NASA’s MODIS land cover product (Friedl et al., 2010). The stratification by FWA and fuel type was done to account for regional differences in fire regime, fuel type and other fire factors. Any alternative definition of regions would be possible, however (e.g., fire climate classification).

The eight predictor variables include the LFMC data, as well as indicators of soil moisture availability that correlate with live fuel and dead litter fuel, and fire weather variables (temperature, wind speed and humidity). The LFMC (in % water mass / dry leaf mass) from the AFMS is derived from MODIS satellite instrument observations and updated every four days at 500-m resolution (Yebra et al. 2018). As indicators of soil moisture, we used the daily updated 0.05° (~5-km) resolution outputs from the Bureau of Meteorology’s Australian Landscape Water Balance website (www.bom.gov.au/water/landscape). The Australian Water Resources Assessment model (Frost et al. 2016; Van Dijk 2010) that underpins this data service produces estimates of the relative moisture availability (0–1, scaled to a fraction of plant available water) in the topsoil (w0, 0–10 cm), shallow soil (ws, 0.1–1m) and deep soil (wd, 1–6m). While these are simulated separately for shallow- and deep-rooted vegetation, we used the publicly available grid-cell average values here. The fire weather variables were also derived from gridded data provided by the Bureau of Meteorology, including 0.05° (~5-km) daily climate grids of maximum daily temperature (Tmax, °C) and 3pm vapour pressure (VP15, hPa) and mean daily wind speed (Uavg, m/s) that are based on interpolation of station data (Jones et al., 2007). The VP15 values were not used directly but combined with Tmax and an assumed standard surface pressure to calculate relative humidity (RH, %) and vapour pressure deficit (VPD, Pa) using standard methods. All eight predictors (LFMC, w0, ws, wd, Tmax, Uavg, RH, and VPD) were resampled from their original resolution to the 0.025° and daily resolution of the fire observations. The analysis period was 2003-2017, where the start year is limited by the fire observations, and the end year by the readily available wind speed data. However, all data are updated daily, and therefore, a repeat of the methodology in future can rely on an extended dataset.

Methods

The steps to predict the composite Fire Danger Index from the eight predictor variables are detailed below.

1) Extraction x-y data pairs: First, all occurrences of a predictor variable x (e.g., LFMC) over time for each grid cell corresponding to an FWA region and a fuel type of interest were recorded. In addition, it was also recorded whether a fire event occurred on that grid cell and day. Only 0.025° grid cells dominated by one fuel type (>80% cover fraction) were considered. For cases where the total number of fire events was <30, the sample was considered too small, and no further processing was undertaken.

2) Calculate conditional probabilities P(Y|X>xi): The calculation is explained here for the case where fire danger is expected negatively related to x (where it expected positively related, the same logic was applied). For each value xi in a series with small intervals, the total number of records (N) and the number of fire events (Ne) corresponding to x>xi was calculated. From these, the conditional probability of fire was calculated as P(Y|X>xi)=Ne/N. The resulting values were rescaled by dividing by the marginal (or ‘unconditional’) fire probability P(Y). An example is shown in Figure 1. Note that while not a desirable feature, rescaled probabilities for intermediate x values can exceed unity, if the frequency of fires in the sample exceeds the frequency for the entire population.

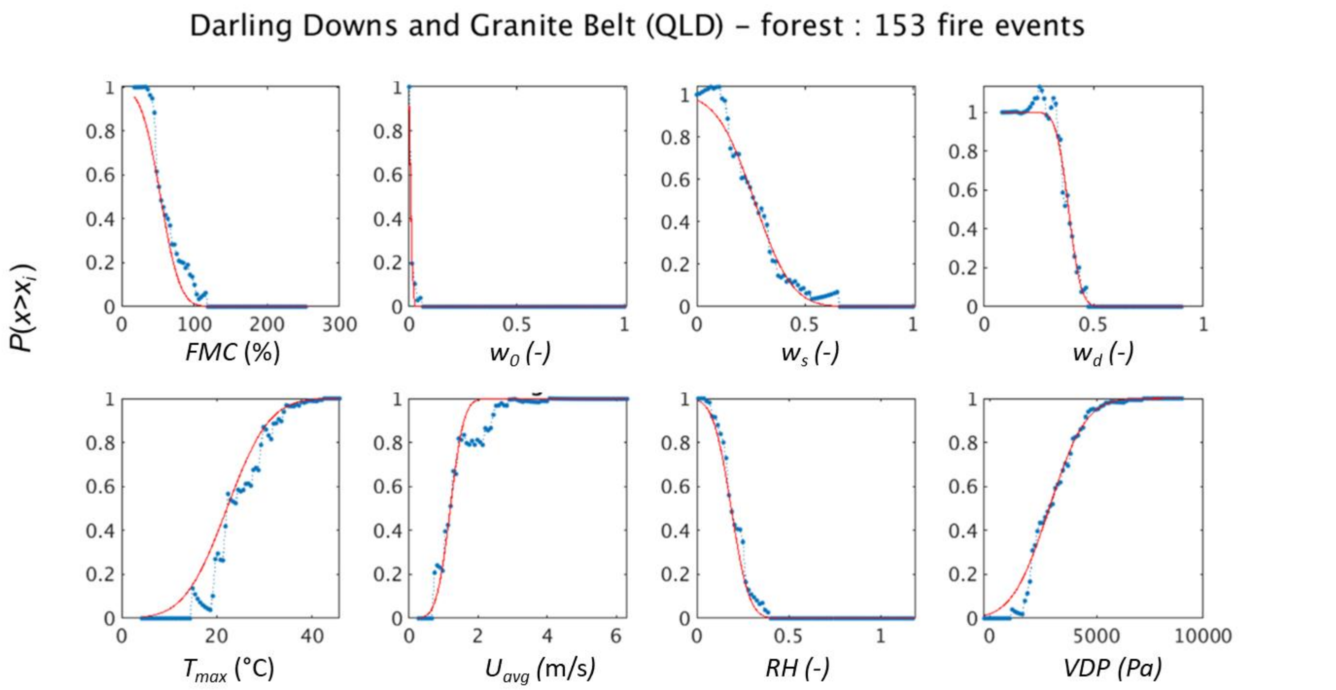

Figure 1. Example of empirical and fitted cumulative probability, rescaled to between zero and unity, for the eight fire risk predictors (see text for explanation of symbols).

3) *Fit cumulative distribution function.* A simple Gaussian Cumulative Distribution Function (CDF) was fitted to the resulting probability function (Fig. 1). The distribution requires estimation of a mean (μ) and standard deviation (σ). The mean can be interpreted as a fire danger threshold, in that fire probability increases most rapidly at this value of x, whereas σ defines the sharpness of the transition between low and high fire occurrence probabilities. For a Gaussian distribution, μ is equal to the x for which rescaled probability P exceeds 0.5 $x(P=0.5)$, whereas σ can be calculated from the inter-quartile range $IQR=|x(P=0.75) - x(P=0.25)|$ as $\sigma=IQR/1.349$.

4) *Calculate the Fire Danger Index.* For each of the eight predictors, the respective fitted CDF function (for the respective FWA and land cover type) was applied to the predictor time series. The result might be termed the The resulting FDI can be calculated for each 500-m grid cell and each day.

However, by visually comparing the predicted fire danger time series with actual fire frequency across the region and fuel type for each day, the specificity of the estimates can be interpreted, that is, the ability of the method to accurately distinguish high and low fire danger conditions Factor Component FDI (*FCF*) and represents the fire danger expected when only considering one factor. An overall composite FDI was calculated by multiplying each of the eight FCFs and raising the result to the power 1/8.

5) *Evaluation*. The entire time series of fire observations were used to calculate probabilities to maximize sample size. This precludes an independent verification.

Results

For all FWA and vegetation type combinations for which a sufficiently large number of detected fires (N>30), the parameters μ and σ of the Gaussian CDF were fitted. Generally, this produced parameter values that were near-uniform across the continent or showed a gradual transition, but local anomalies did occur (Fig. 2). Preliminary investigation of these anomalies suggests that they were often associated with a relatively small sample size (see inset in Fig. 2), suggesting that the chosen sample threshold may have been too small. Inspection of the calculated FCF and overall FDI time series indicated that the key variables that appear to control fire occurrence varied between fuel type and FWA (representing different fire regimes). For example, the predictive value of LFMC was quite strong for grasses and shrublands, as well as for open forests in (seasonally) drier FWAs, but less so for forests in humid regions (Fig. 3). All variables except deep soil moisture (w_d) appeared to provide information on fire danger, but the inclusion of such non-informative variables does not deteriorate the overall FDI predictions, as their FCF is always (near-) unity. A visual comparison between FDI and actual fire frequency generally shows good correspondence. Fires do not always occur during high FDI conditions, as may be expected, given ignition is required. Formal verification statistics have not yet been calculated, but visually, the results show a low 'false negative' rate for most FWAs.

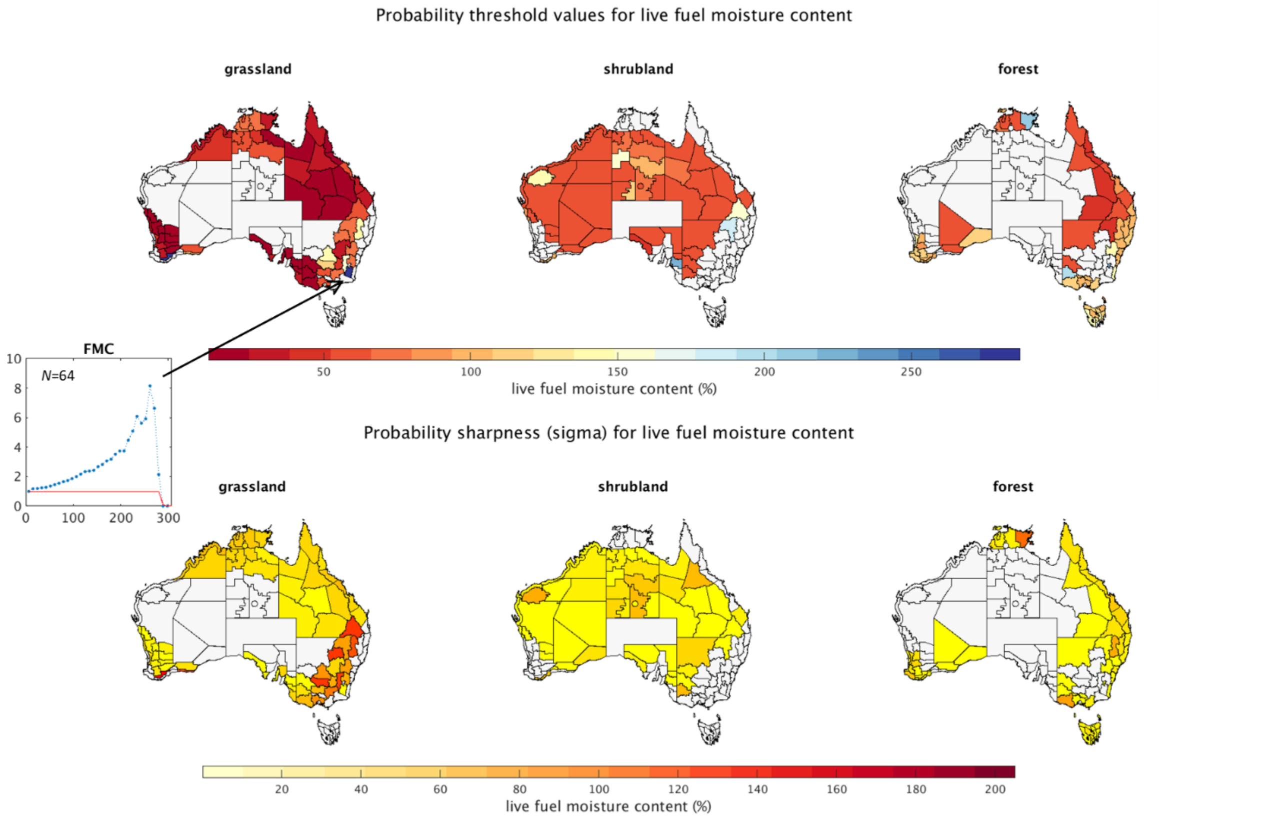

Figure 2: Regional differences in (top) threshold (μ) and (bottom) sharpness (σ) of the fitted CDF function between rescaled fire frequency and one of the eight variables (LFMC). The inset shows an example of an anomalous CDF (note the small sample size and high FMC values).

Conclusions

From these preliminary research results, we conclude that it is possible to at least partially replace the traditional McArthur FDI with an FDI that has a stronger basis in observations. We used readily available, daily updated spatial data on fire danger predictors (fuel condition and weather) to develop an FDI that translates these predictors into a combined FDI based on a database of fires detected by the satellite-based Sentinel Hotspots system. A preliminary assessment suggested a very good potential of the methodology to formally and objectively incorporate any new fire danger predictors. It is noted that the MacArthur method is used to assess the risk of fire occurrence but also fire behaviour and suppression difficulty. Further research or trials would be required to determine whether the FDI developed here has merit for that application.

are well-constrained by fire observations and the temporal variability in component factor FDIs is a strong indication of their predictive value. Further research would also be beneficial to test the merit of alternative statistical approaches (e.g., more flexible CDFs and formal joint-probability approaches) or, possibly, machine-learning approaches.

We did not attempt verification against independent observations or the McArthur FDIs, and also did not undertake formal verification analysis yet; this will be the subject of further research. Nonetheless, the predictions

FDI forecasts would be of greater value than the retrospective analyses provided here, and can be produced by replacing the daily climate analysis grids with forecasts of temperature, humidity and wind speed and soil moisture from numerical weather predictions (e.g., the Bureau of Meteorology's ACCESS system and the AWRA forecasting system currently in the testing phase). Any systematic biases between the two data sources would need to be accounted for in this process. The resulting composite FDI could be produced daily as forecast at a resolution of 500m nationally and disseminated as an experimental service as part of the AFMS. In time, this could make a useful contribution to a new Australian Fire Danger Rating System.

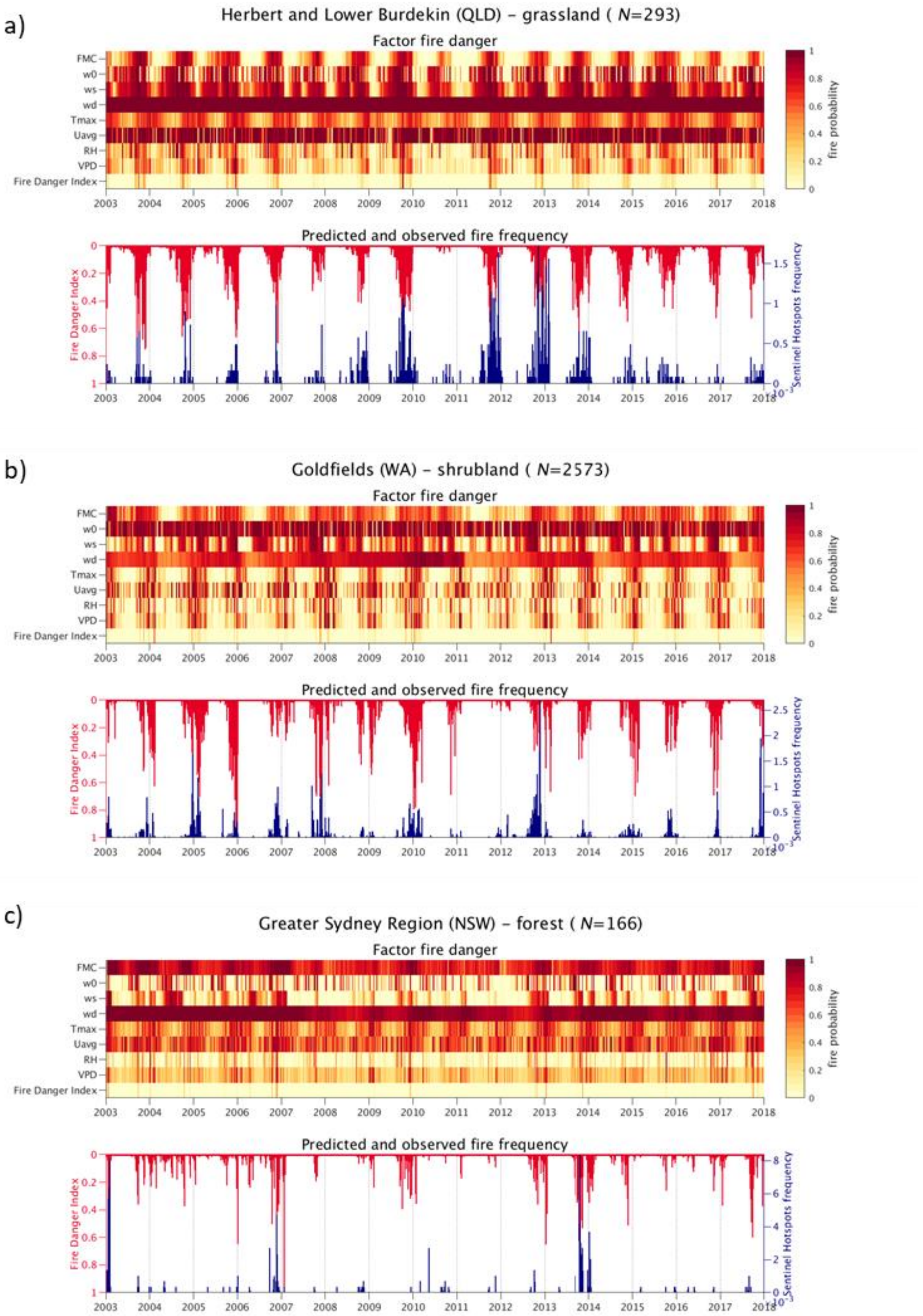

Figure 3: Example time series of (top panels) Factor Component and overall FDI for three FWAs with contrasting fire climate and fuel types, and (bottom panels) comparison of overall FDI and observed fire frequency. Time series are all calculated as averages across the vegetation type and FWA.

Acknowledgements

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