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A forest fuel dryness forecasting system that integrates an automated fuel sensor network, gridded weather, landscape attributes and machine learning models

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Keywords

Fuel moisture content; Landscape forecasting; Machine learning; Forest management; Weather forecasting

Abstract

Accurate and timely forecasting of forest fuel moisture is critical for decision making in the context of bushfire risk and prescribed burning. The moisture content in forest fuels is a driver of ignition probability and contributes to the success of fuel hazard reduction burns. Forecasting capacity is extremely limited because traditional modelling approaches have not kept pace with rapid technological developments of field sensors, weather forecasting and data-driven modelling approaches. This research aims to develop and test a 7-day-ahead forecasting system for forest fuel dryness that integrates an automated fuel sensor network, gridded weather, landscape attributes and machine learning models. The integrated system was established across a diverse range of 30 sites in south-eastern Australia. Fuel moisture was measured hourly using 10-hour automated fuel sticks. A subset of long-term sites (5 years of data) was used to evaluate the relative performance of a selection of machine learning (Light Gradient Boosting Machine (LightGBM) and Recurrent Neural Network (RNN) based Long-Short Term Memory (LSTM)), statistical (VARMAX) and process-based models. The best performing models were evaluated at all 30 sites where data availability was more limited, demonstrating the models' performance in a real-world scenario on operational sites prone to data limitations. The models were driven by daily 7-day continent-scale gridded weather forecasts, in-situ fuel moisture observation and site variables. The model performance was evaluated based on the capacity to successfully predict minimum daily fuel dryness within the burnable range for fuel reduction (11 – 16%) and bushfire risk (<11%). The sites with long-term data performed favourably using the LightGBM model. Producing average probability of detection (POD; probability of detecting an event in the specified range) prediction results 1-days out, 5-days out and the average across all seven days of 0.92, 0.81 and 0.80 (<11%), and 0.71, 0.54 and 0.53 (11 – 16%); with R2's of 0.77, 0.59 and 0.55. The machine learning models performed favourably compared to the statistical and process-based models. This demonstrates that accurate, real-time operational fuel moisture forecasting can be achieved by integrating sensor data, weather forecasts, landscape information, and data-driven modelling approaches. The proposed system has the potential to be applied in any wildland fire setting where weather forecasts are available, and the adaptation of this system will greatly enhance the decision-making capabilities of fire managers.

1. Introduction

Bushfires as a natural disaster are the cause of hundreds of fatalities in Australia and across the globe (Blanchi et al., 2014; Haynes et al., 2010, 2019). An important component of bushfire risk is the dead fuel moisture content (DFMC). This is partially due to the ignition probability of fuels having a non-linear relationship, with a significant increase in ignition risk once the fuels reach a threshold moisture content (Ellis, 2015). In productive forests, fuel moisture is also an important variable which controls the risk of bushfire ignition and spread, with the fuel loads being high enough to maintain a fire once started (Cawson et al., 2018). Fuel moisture also makes planned burning extremely difficult (Slijepcevic et al., 2015). Due to this being able to predict the DFMC into the future would allow for better risk identification and fuel management planning.

Modelling of DFMC has been attempted using processes-based methods which input temperature, relative humidity, solar radiation, and precipitation. With the model proposed by Nelson (2000) being widely used. Recently this model has been surpassed by more mechanistic (Van Der Kamp, 2017) or data driven (Lee et al., 2020; Shmuel et al., 2022) approaches which improve the representation and accuracy of FMC predictions. These methods utilise a larger number of input variables which aim to improve the modelling accuracy by more detailed representation of the physical processes, or through determining the relationships through statistical, data driven techniques (e.g. random forest, neural networks). These methods have not been explored in predictive modelling under varying forest canopies (key driver of FMC (Brown et al., 2021)), forecasting fuel moisture multiple days in advance using forecast data. A forecasting system would be another valuable tool to assist fire managers in early warning risk detection systems or allow fuel reduction burn operations to be moved to a day which will optimise the likelihood of achieving a successful burn.

The overall aim of this study was to develop an automatic fuel moisture monitoring system, capable of forecasting 10-hour fuel moisture. This system is aimed at capturing the change in fuel moisture under varying forest types, located across a large spatial and climatic range. The system integrates advancements in the ability to forecast short-term climate conditions and utilise the ever-expanding, continuous dataset which the automatic fuelsticks provide. For this system to produce the highest accuracy predictions, two specific research questions arose, these being:

1. If you have a high quality and quantity of data how do machine learning models compare with statistical (VARMAX) and process-based models, and which model is likely to be the most reliable in a real-world scenario?
2. How well does the best performing methods in question forecast across a larger network with smaller datasets and varying data quality?

2. Methods

2.1. Overview - Fuel moisture monitoring forecasting system

The Forest Fuel Moisture Forecasting System (FFMFS) comprises four components that come together to allow fuel moisture to be forecast for up to seven days. The conceptual diagram shown in Figure 1 illustrates how these key components are integrated for a continuously retrained spatial/temporal forecast model (gridded weather forecast, gridded landscape attributes, live on ground sensor network, daily re-trained ML model). It integrates spatially forecast climate variables, with the significant advancements in continuous in-situ forest fuel moisture monitoring (Automated fuel moisture sticks), and in remote sensing datasets. These different streams of data and information were brought together in a machine learning algorithm which predicts the minimum, maximum and mean fuel moisture content across the landscape at a daily timescale, seven days in advance. The system was developed in consultation with the Department of Environments, Land, Water and Planning (DELWP, Victorian Government, Australia), this was to ensure that it could be replicated within the government organisation, with the potential to be used in risk and management planning.

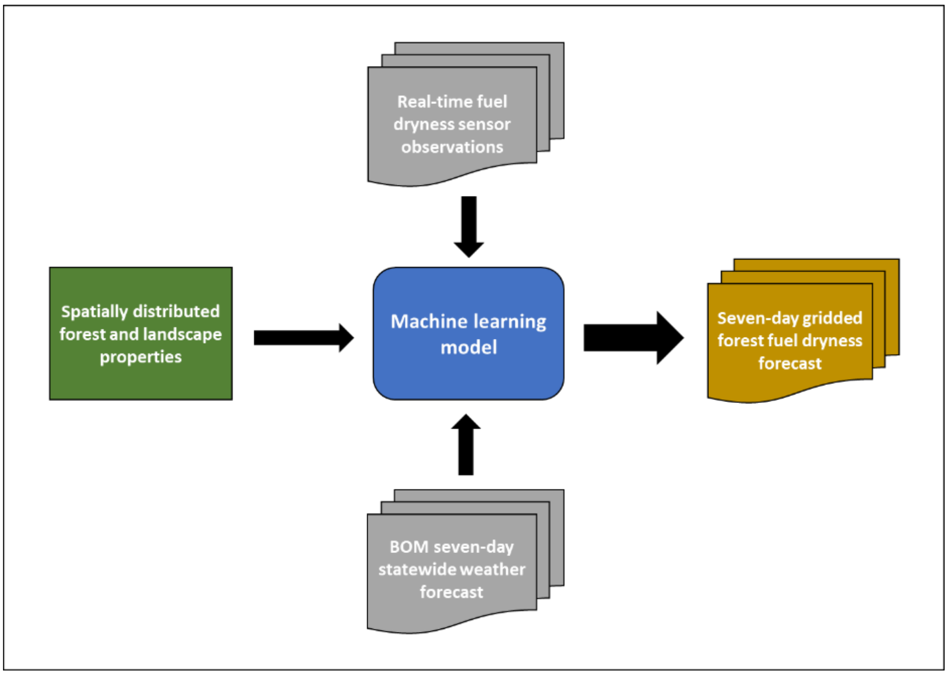

Figure 1- The components of the forest fuel moisture monitoring system

2.2. Study area

The study area was located across Victoria, Australia (Figure 2). On the traditional lands of the First Nations peoples (Victorian Aboriginal Heritage Council Victoria's Current Registered Aboriginal Parties (RAP), 2022). The study comprised of 30 field sites which captured a wide range of physical and environmental variables throughout the region. The long-term climatic conditions vary significantly across the sites, with aridity indexes from 1.13 to 5.90. The study area also covers a range of vegetation types and forest structures, from tall eucalyptus forests to sparse woodlands with shrubs and minimal vertical structural complexity. The sites aimed to capture both open and closed forest conditions.

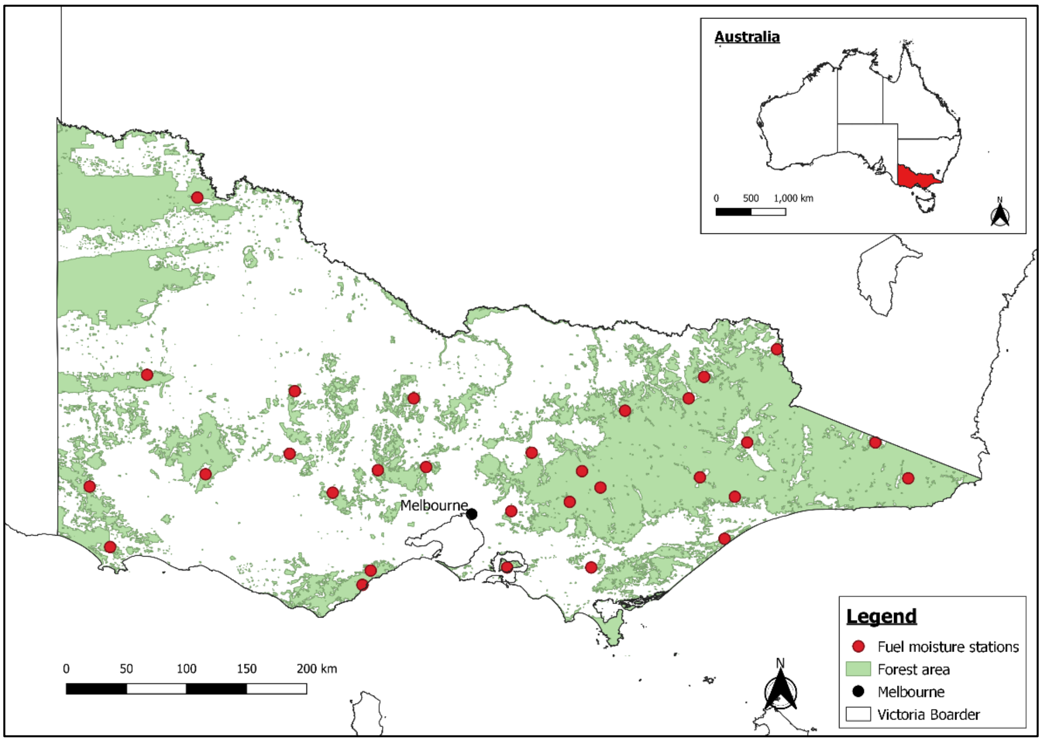

Figure 2- Study area spatial extent across Victoria, Australia.

2.3. Site instrumentation and data collection

The data collection period was from April 2014 to August 2021, with seven sites installed throughout 2014 and 23 in 2019. The sites had fuel moisture content readings collected half hourly using fuel sticks (CS506, Campbell Scientific, Inc., Logan, USA). The fuel moisture sticks were installed 10 - 30cm above the ground to represent elevated ground fuels. Site variables used to represent the vegetation and climate signature includes elevation, slope, aspect, aridity index, long term annual rainfall and vegetation cover fraction. The weather forecast variables were from the Australian Digital Forecast Database (Australian Bureau of Meteorology, 2022). This is a gridded seven day forecast across Victoria, producing daily to sub-daily predictions at ~3km resolution. The daily climate variables used in the model were: Temperature, precipitation, relative humidity, skyview factor, Keetch–Byram Drought Index (Keetch & Byram, 1968), wind direction (predominant) and wind speed (max).

2.4. Modelling

Time Series prediction models fall into three broad categories: Autoregressive, Statistical/machine learning, and process-based/mechanistic. In this study a comparison of these methods for DFMC forecasting is presented.

Autoregressive (AR) models are often the simplest to implement with time series predictions. These models attempt to forecast from the existing dataset using recent values as independent variables. They use linear models with previous values, or residuals from the rolling average of previous values. In addition to recent variables, they may also account for seasonal and long-term trends estimated from time series decomposition, and other independent variables. This study uses an Autoregressive integrated moving average (ARIMA) variation VARMAX as the baseline autoregressive model to determine whether fuel dryness can be predicted using past time series data alone.

The two machine learning methods used were, a boosted regression tree random forest (BRT-RF) model (Breiman, 1998; Elith et al., 2008) and a long short term memory recurrent neural network (LSTM-RNN) model. Boosted regression trees train an ensemble of models (i.e. Random Forest regression models), on subsets of data iteratively to create a decision tree algorithm to predict the response variable. We used the LightGBM python package (Ke et al., 2017) to build and train the random forest model. In addition to BRT's, Neural Networks have also been used effectively for time series forecasting (Fan & He, 2021). We used a Long Short Term Memory Recurrent Neural Networks (LSTM-RNN) to compare ML approaches.

The process–based (PB) model used as a comparison was the model proposed by Van Der Kamp (2017). The model only requires four inputs: temperature, relative humidity, precipitation and radiation. The fuelstick model proposed by Van Der Kamp is an improved version of the Nelson model (2000), representing the radiation loading on the fuelstick in more detail. The original Nelson model has been used operationally in the U.S. National Fire Danger Rating System (NFDRS 2016 version; US National Wildfire Coordinating Group, 2021), as well as in fire behaviour models such as FARSITE and FlamMap.

2.4.1. Long-term climate trends

Time Series Forecasting of environmental systems is a problem in that it typically needs to account for long term trends, seasonal cyclicity, antecedent conditions and lag response to controlling processes (Cheng et al., 2015). Time series data often contain patterns of trend and seasonality that can be extracted to improve predictive capability. To do this, Time Series Decomposition (TSD) is used to split a time series dataset into long term trends, seasonal cycles, and residual error. We use the Facebook prophet python package (Taylor & Letham, 2018), which uses an additive method to decompose the time series. This was used to create a seasonal term for input into the BRT-RF and LSTM-RNN models.

2.5. Model validation and performance metrics

All models were evaluated on the seven original sites installed in 2014. To determine which method performed best with the most high-quality data available. The training dataset was from 2014 to September 2020. The validation dataset was from May 2020 – May 2021. The BRT-RF and PB models were then assessed across the entire range of sites, with the additional sites installed in 2019 having a lesser quality of data. These real-world operational sites, which are centrally managed do not always have the same data quality as research-based sites. Each daily forecast had R^2, RMSE, NSE and MAE calculated, as well as the event-based metrics of the probability of detection (POD) and false alarm ratio (FAR). These event-based metrics predict how the model performs predicting specific fuel moisture ranges (events), within levels relevant to planned burning (Slijepcevic et al., 2015).

3. Results

The RBT-RF results from the seven long-term sites are presented in Table 1. These results show an overall decrease in the accuracy across the seven days. There was high variability between the sites, with Dimboola, Bendigo and St. Arnaud performing well across all the metrics, while Alexandra and Daylesford performed poorly. The event-based metrics (Figure 3) showed the models performed best at low FMC (<11%), while as the higher two ranges performing worse. The "Patchy Burn" range had the highest FAR, making this range the most unreliable in predictions.

Table 1 – BRT-RF model performance across the seven long term sites from 2014 – 2021.

	R^2				**NSE**				**MAE**				**RMSE**			
Site	**1-D**	**3-D**	**5-D**	**7-D**	**1-D**	**3-D**	**5-D**	**7-D**	**1-D**	**3-D**	**5-D**	**7-D**	**1-D**	**3-D**	**5-D**	**7-D**
Dimboola	0.87	0.73	0.69	0.65	0.86	0.61	0.61	0.23	1.17	1.98	1.97	2.63	1.67	2.79	2.93	3.87
Hattah	0.88	0.74	0.68	0.63	0.84	0.56	0.55	0.35	0.79	1.23	1.39	1.62	1.27	2.11	2.43	2.59
Bendigo	0.87	0.68	0.74	0.65	0.85	0.45	0.69	0.28	1.32	2.39	1.99	2.69	1.87	3.56	2.77	4.04
St. Arnaud	0.79	0.72	0.74	0.63	0.71	0.53	0.49	0.42	1.74	2.39	2.86	2.85	2.71	3.42	3.81	3.80
Casterton	0.73	0.64	0.66	0.56	0.37	-0.82	-0.96	-1.43	3.13	6.20	5.99	7.27	4.70	798	8.00	9.37
Daylesford	0.56	0.17	0.20	0.18	-0.03	-6.10	-7.95	-5.53	2.70	7.35	8.55	7.23	3.95	10.4	11.6	9.95
Alexandra	0.69	0.50	0.47	0.55	0.60	-0.17	-0.17	0.11	1.76	2.69	3.09	2.68	2.45	4.18	4.20	3.64
Overall mean	***0.77***	***0.59***	***0.59***	***0.55***	***0.60***	***-0.70***	***-0.67***	***-0.80***	***1.80***	***3.46***	***3.65***	***3.85***	***2.66***	***4.92***	***4.94***	***5.32***

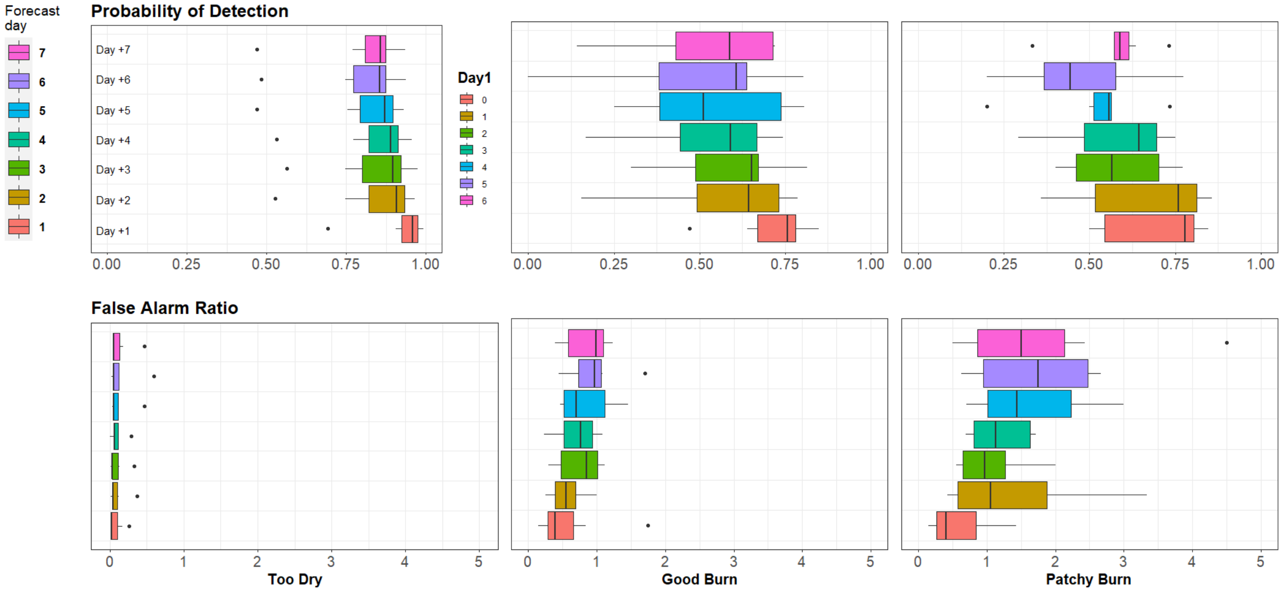

Figure 3 – Event based performance of the BRT-RF model for the daily minimum DFMC forecasts within the range of 11 – 16%, for the seven long term sites. (Top) Probability of detection, (Bottom) false alarm ratios. Left, middle and right columns representing planned burn outcoms proposed in Slijepcevic et al (2015) based on FMC ranges.(left) Too dry and higher risk of burn escaping (0 – 11% FMC); (middle) Good burn representing the FMC range that will sustain a burn but less likely to escape (11 – 16% FMC); and, a Patchy burn due to the FMC being too high and the burn not self sustaining (16 – 21% FMC)

4. Discussion

The BRT-RF managed to incorporate information traditional processed-based modelling cannot, determining how this information relates to the DFMC. The decay in the accuracy, decreasing POD and increasing FAR across the seven days highlights the increased uncertainty associated with the weather forecast. However, the use of event-based performance metrics showed that although the model decreased in accuracy, it remained within the ranges to predict critical DFMC relevant to planned burning (Slijepcevic et al., 2015). This is critical as while traditional statistics highlight the accuracy in models, they don't reflect the important range for land and fire managers. The results demonstrated that a fuel moisture monitoring forecast system could effectively predict 10-h DFMC up to seven days in advance. Linking ground-based fuel moisture monitoring stations spatially across forested terrain with gridded forecasts allows the complex sub-canopy climate variability to be accounted for in predictions. Grounding the starting DFMC in observations also proved important due to the decay rate across the seven days. If the starting DFMC was incorrect, then adding this uncertainty to the decay rate would decrease the reliability of the forecasts. Lastly, incorporating site variables assisted in the model's ability to account for the transfer of climate relationships from above the canopy to below. The ability to incorporate canopy and landscape variables also has the potential to expand the point-based forecasts into a spatial forecast.

The proposed system differs from previous DFMC forecasting as it incorporates live continuous below canopy measurements with above canopy weather, machine learning techniques and a seasonal rolling term. The assembled dataset represents the largest below canopy comparison of continuous DFMC forecasting using machine learning to our knowledge, across the largest range of forest types. The performance of the model validates the use of ML for predicting DFMC below canopy in closed forests, this being highlighted as an area of limited research by Shmuel et al. (2022). Early results from the other traditional models indicate that the machine learning model performed favourably in comparison, highlighting the value of ML techniques for below canopy moisture forecasting.

5. Conclusion

The proposed Forest Fuel Moisture Forecasting System has demonstrated the ability to incorporate advancements in ML techniques, weather forecasting, ground-based sensors, and remote sensing into a theoretically operational system for land managers. The ability to predict forest fuel moisture multiple days in advance with known levels of uncertainty within relevant DFMC ranges will allow for more informed decisions and planning around fuel reduction burns and bushfire risk. While more work needs to be done on validating the effectiveness of using DFMC forecasting for decision making in bushfire risk and planned burning, the proposed system provides a tool and framework with which this research can be conducted.

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