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A seven-day ahead bushfire fuel moisture forecasting system integrating an automated fuel sensor network, weather forecasts and a machine learning model

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Abstract: Accurate and timely forecasting of forest fuel moisture is crucial for decision-making related to bushfire risk and prescribed burning. Moisture content in forest fuels affects ignition probability, the success of fuel hazard reduction burns, and plays a critical role in fire behaviour. Currently, climate-based indices are typically used as proxies representative of the dryness state of forests. However, these indices have significant drawbacks as they fail to consider the canopy effect as a moisture buffer, do not account for all climate variables, and often constitute unverifiable and non-quantitative metrics of dryness. Over the last two decades, monitoring of in-situ dead fuel moisture content (DFMC) has significantly improved with the increased rollout and validation of automated fuelsticks that serve as proxies for different sizes of fuel components. However, forecasting using these fuelsticks has been limited so far, as traditional process-based models require precise understanding of micro-climate conditions to accurately model the DFMC. Recently, machine learning models have demonstrated better performance than process-based models on open sites, using micro-climate equivalent observations. However, these models have not been tested extensively in a diverse range of below-canopy conditions using above-canopy weather observations or in a forecasting capacity. This research aims to develop and validate a below canopy, 7-day-ahead forecasting system of daily minimum forest fuel dryness (in the form of 10-h DFMC) that integrates an automated fuel sensor network, gridded weather forecasts, landscape attributes and a machine learning model (gradient boosting algorithm; LightGBM). The study area was established across a diverse range of 28 sites in south-eastern Australia. Fuel moisture was measured hourly using 10-hour automated fuel sticks, with five years of measurements for eight sites and 1.5 years for the remaining 20. The modelling system aims to integrate daily seven-day continent-scale gridded weather forecasts, in-situ fuel moisture observations, and site variables. The model's performance was evaluated based on its ability to successfully predict the minimum daily 10-hour DFMC, and to detect events within the burnable range for fuel reduction burning (9% – 16% DFMC) and bushfire risk (<9% DFMC). The sites with long-term data outperformed those with shorter-term data. Addition of a seasonal DFMC term significantly improved short-term site forecast accuracy. Combining the two datasets did not improve the overall results. The system's performance for the daily minimum DFMC produced mean R^2 and RMSE values on day one forecasts of 0.90 and 4.76% for long-term sites, 0.90 and 5.57% for short-term sites, and 0.90 and 5.54% for the integrated combination of site datasets. The day seven forecast results were 0.67 and 9.31% for long-term sites, 0.58 and 12.21% for short-term sites, and 0.58 and 12.35% for the integrated system. The results demonstrate that accurate DFMC forecasts can be achieved by integrating sensor data, weather forecasts, landscape information, and data-driven modelling approaches. The proposed integrated system has the potential to be applied in any wildland fire setting where weather forecasts are available. This system's adaptation will greatly enhance the decision-making capabilities of fire managers across a diverse range of forests.

Keywords: *Wildfire, fuelstick, fuel dryness, gradient boosting*