FINDINGS

The study explores the live fuel moisture – soil moisture relationship at a national scale and suggests an approach to predict live fuel moisture content.

Predicting live fuel moisture content using soil moisture

Vinodkumar[1,2], Imtiaz Dharssi[1,2], Marta Yebra[1,3] , Paul Fox-Hughes[1,4]

[1] Bushfire and Natural Hazards CRC, Victoria
[2] Bureau of Meteorology, Melbourne, Victoria
[3] Australian National University, Canberra, ACT
[4] Bureau of Meteorology, Hobart, Tasmania

Introduction

- Live fuel moisture content (LFMC) critically affects fire ignition and fire propagation.
- Soil Moisture (SM) is found to be a key factor that influences LFMC.
- Both LFMC and SM have recently become available at continental scale through BNHCRC projects.
- LFMC is derived from satellite data and SM is provided by the JULES based Australian Soil Moisture Information (JASMIN). Both datasets are available from the Australian Flammability Monitoring System (AFMS, http://anuwald.science/afms).
- We conducted a preliminary investigation of the suitability of SM as a predictor for LFMC:
  - What is the strength of the SM-LFMC relationship over the Australian landscape?
  - Can a simple model be developed to predict LFMC using SM estimates?

Methods

- The modelling strategy assumes that the LFMC departures from its annual cycle can be predicted using SM departures from its own annual cycle.
- Therefore, at each grid point, annual cycle models were constructed for both LFMC and SM, and residuals from these models were used in the prediction model.
- 0-35cm SM from JASMIN ($SMC_{0\text{-}35cm}$) is used to develop the LFMC predictive model.
- Annual cycle models for $SMC_{0\text{-}35cm}$ and LFMC are based on trigonometric functions.
- Ordinary least-squares regression model with residual $SMC_{0\text{-}35cm}$ as the independent variable was developed for each grid point to predict daily changes in LFMC.

Results

- Figure 1 presents lag-correlation analysis conducted between LFMC and SM over selected 60 locations corresponding to the CosmOz, OzFlux, and OzNet SM networks combined.
- Average (over all sites) maximum lag-correlations observed for grasslands, woodlands, forests and croplands between LFMC and $SMC_{0\text{-}35cm}$ are 0.71, 0.69, 0.47 and 0.5, respectively, with corresponding average lag 14.28, 64.54, 218.91 and 16.85 days.
- A lag of 14 days for all sites returned a reasonable skill (site average $R^2 = 0.64$).
- The model was extended for the whole country with a constant lag of 14 days at all grid points (at 5 km resolution).
- Figure 2 depicts the correlation and normalized root mean squared difference (NRMSD)obtained from comparing the model and original (AFMS) LFMC products.
- Figure 3 shows the comparison of original and predicted LFMC over locations where a fire is detected (using MODIS FRP data). For the AFMS dataset, the mean±standard deviation of LFMC over grassland, cropland, woody savannas, and evergreen broadleaf forests locations are 40.7±30.2, 78.4±36.1, 53.9±14.1, and 101.5±20.3, respectively. The corresponding scores from the predictive model are 46.2±28.9, 82.4±30.9, 58.5±13.3, and 102.3±17.6, respectively.

Discussion

- The results indicate that SM is a leading indicator of LFMC.
- This has significant operational implications as daily variations in LFMC can be predicted using SM information from JASMIN on a national scale.
- JASMIN is currently a research prototype but can be extended to run both at real-time and in forecast mode, providing SM forecasts for up to 10 days. Thus, from the above results, a 24 day-day lead-time forecast for LFMC is possible from a 10-day SM forecast.

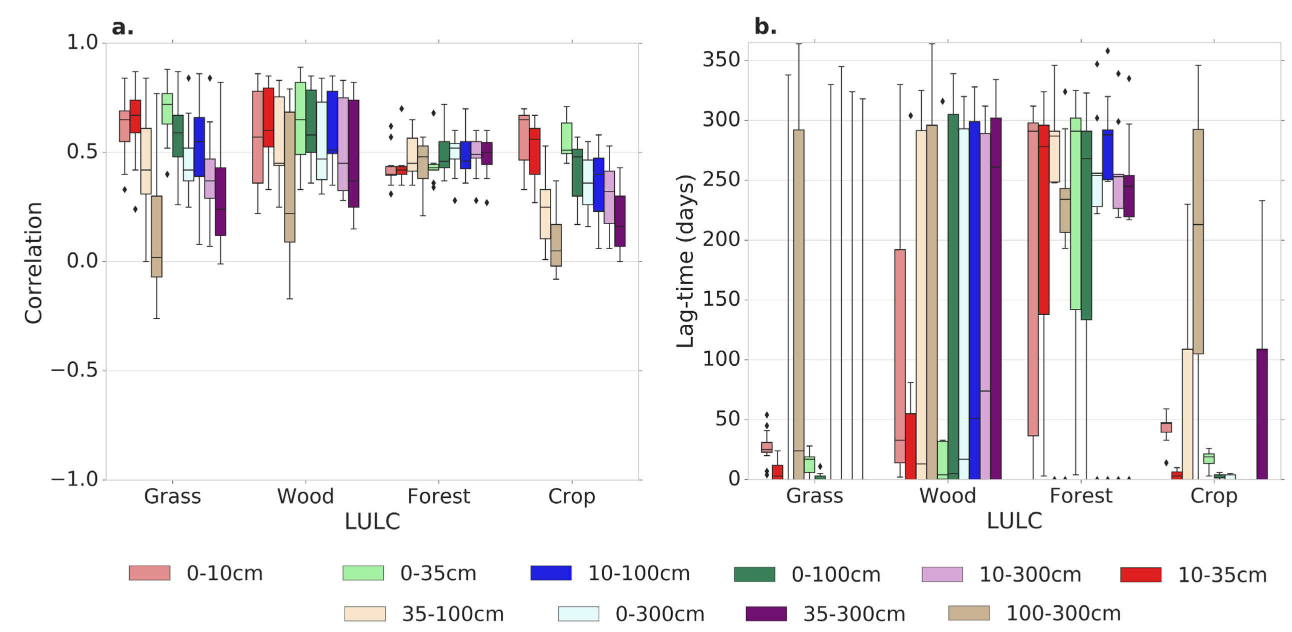

Figure 1. Box and whisker plot representing a) Lag-correlation and b) lag in days between LFMC and SM from various JASMIN native and derived layers. The scores are computed for 60 sites from the CosmOz, OzFlux, and OzNet SM networks combined. The grouping is done based on the land cover type of the observing site. The outliers are marked as diamonds.

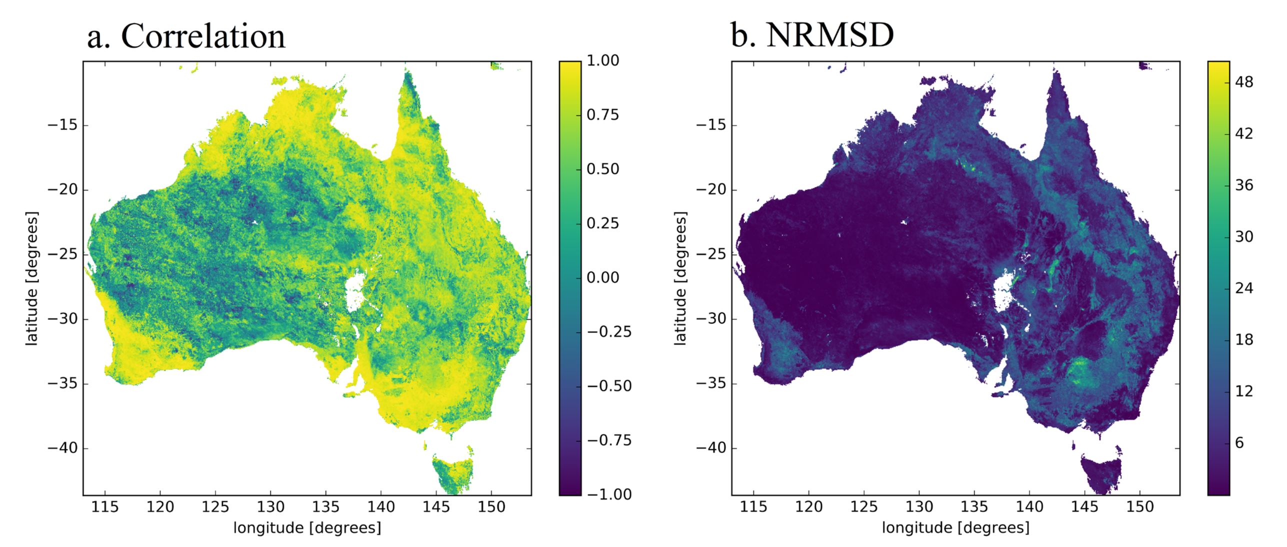

Figure 2. Validation of the LFMC predictive model: a) Pearson's product-moment correlation, and b) normalized RMSD. The validation time period is 2010-2019.

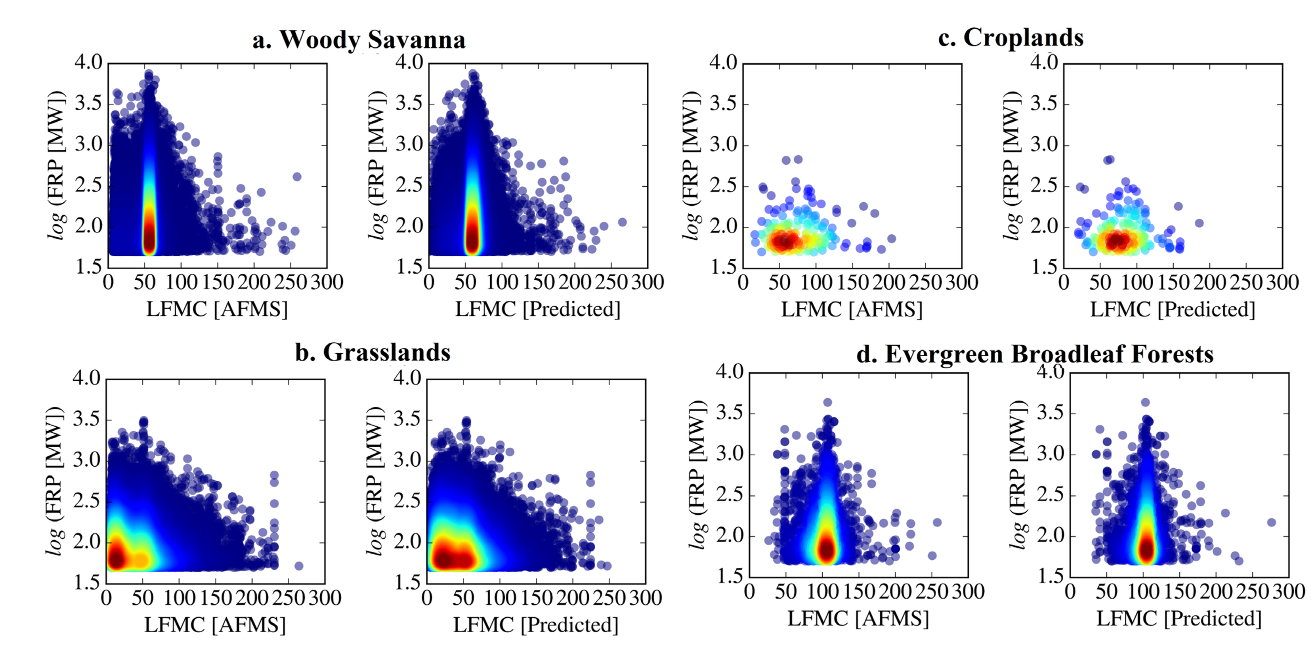

Figure 3. Scatter plot of original AFMS LFMC and predicted LFMC against the MODIS FRP. The colours depict the probability density estimated using Gaussian kernel density estimation method. The light blue colours indicate least dense locations on the plot and the dark red indicate the densest locations. The data span from 2010-2016.

End-user statement: Stuart Matthews, NSW RFS

Predicting the moisture status of live fuels is an important gap in modelling fire risk over periods of weeks to seasons. Current methods rely on persistence of observed values or subjective expert assessment of the response of fuels to forecast rainfall anomalies. Being able to link fuel moisture to predicted soil moisture has the potential to improve the skill and repeatability of fire danger predictions

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For more information, please email vinod.kumar@bom.gov.au