Fine-tuning remote sensing foundation models for improved live fuel moisture content estimation

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The moisture content of living vegetation, known as live fuel moisture content (LFMC) (Yebra et al. 2013), is a primary driver of flammability and susceptibility to bushfire ignition and spread. Modelling using remote sensing data is the most cost-effective way to understand status and changes in Earth's environment on a global scale, providing a basis for mapping that is internally consistent and repeatable over time (Defries and Townshend, 1999). Therefore, LFMC estimation has a long history in the remote sensing literature, based on statistical and physically-based algorithms (commonly using radiative transfer model inversions) applied to coarse resolution imagery such as Moderate Resolution Imaging Spectroradiometer (MODIS) or Advanced Very High Resolution Radiometer (AVHRR) (Yebra et al. 2008, 2013). Empirical statistical relationships tend to be site-specific, while application of physical methods requires complex parameterisation (Yebra et al. 2013, 2018).

More recently, the derivation of LFMC estimates from remote sensing optical data has used temporally-aware deep learning models such as a temporal convolutional neural network (TempCNN) (Zhu et al. 2021, Miller et al. 2022, 2023), recurrent neural network (RNN) (Rao et al. 2020) and long short-term memory (LSTM) integrated with temporal convolutional network (TCN) (Xie et al. 2022). Including additional input data to model development such as time series meteorological data has been shown to improve LFMC estimates (e.g. Miller et al. 2022, 2023). Additionally, the inclusion of Sentinel-1 SAR data, which is sensitive to vegetation structure and water content, has shown potential to enhance LFMC estimation, improving temporal coverage by filling gaps from cloudy optical imagery and capturing structural moisture dynamics not evident in optical data alone (Rao et al. 2020; Xie et al. 2022).

Despite these advances, machine learning models in general and for LFMC in particular can remain limited in their scalability, often constrained by location, time or sensor specificity, which makes global application over long timeframes difficult (e.g. Foody et al. 2003, Yebra et al. 2013, 2018). Remote sensing foundation models, pre-trained on large collections of imagery capturing spatial and spectral features and also temporal dynamics, may provide more generalizable and adaptable tools able to be used for many different Earth Observation applications. These models can potentially perform new tasks (e.g. estimation and prediction of LFMC) with very few or no labelled examples (known as 'few-shot or zero-shot learning' respectively) reducing the need for training of large task-specific deep learning models for particular purposes.

In this study, existing foundation models are fine-tuned using ground measurements of LFMC from continental US (CONUS) (Yebra et al. 2024) and six-band (Blue, Green, Red, NIR, SWIR1, SWIR2) Harmonized Landsat and Sentinel-2 (HLS) surface reflectance data (Claverie et al. 2018) for the period 2014-2023. These data will serve as labels to generate LFMC estimates for both CONUS and Australia, which will be validated using historical in-situ LFMC measurements from 1977-2013. Model outputs will be compared to those obtained using existing approaches (e.g., Miller et al. 2022, Yebra et al. 2018) and preliminary results shared at MODSIM 2025.

This work contributes to a growing effort to evaluate the potential of foundation models for remote sensing applications, demonstrating their relevance for wildfire risk assessment, prediction and detection in an increasingly fire-prone and warming world.

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