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Spatio-temporal dynamics of live fuel moisture content using Sentinel-2 and MODIS data †

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Abstract: Live fuel moisture content (LFMC) is a crucial factor that influences fire behaviour, rendering its precise estimation indispensable for effective fire risk assessment and management. However, LFMC estimation remains a significant challenge, especially given the dynamic nature of live forest fuels. The aim of this study was to establish a robust method for estimating and monitoring LFMC by employing spatio-temporal modelling with a universal kriging approach, integrating remote sensing data and field measurements. This research was conducted in the Sierra Morena region of Andalusia, Spain, focusing on *Cistus ladanifer* shrub patches, which are well-known for their high fire risk. A total of 38 sampling plots were established to monitor LFMC over a 15-month period. Vegetation indices derived from Sentinel-2 and MODIS products were incorporated as auxiliary information in the universal kriging model to predict LFMC. The results showed a RMSE (Root Mean Squared Error) score of 12.35% for Sentinel-2 EVI and 12.34% for MODIS GVMI indices. These findings have practical implications for forest fuel modelling, fire risk evaluation, and operational decision-making concerning fire prevention and management.

Keywords: *Cistus ladanifer*; fire management; geostatistical modelling; remote sensing; Sierra Morena; universal kriging

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1. Introduction

The live moisture content of forest fuels (LFMC) plays an essential role in fire behaviour and hence in wildfire risk models. Accurately estimating LFMC over large areas remains a challenge, which is being addressed by diverse research groups worldwide, including some in Spain[1–3] and Europe [4].

One promising technique for LFMC estimation over large areas is Universal Kriging (UK), an interpolation technique that leverages spatial autocorrelation to increase accuracy, considering trends from auxiliary variables. However, to our knowledge, there is a notable gap in the research when it comes to applying UK interpolation to the study of LFMC.

Various satellite data sources can be harnessed either individually or in combination with other source variables to predict LFMC [5], though their strengths and limitations need careful exploration due to differing spatial and temporal resolutions. Correlating satellite data with field measurements presents challenges due to varying vegetation types within the same pixel, each responding differently to environmental conditions [6]. Shrubs, for instance, are more weather-dependent than forests as their roots cannot penetrate deeper layers of soils, meanwhile, grasslands convert live fuel moisture into dead fuel moisture (DFM) over time due to senescence. Some studies have focused on monospecific stands for model refinement [1,7], while others weight LFMC values based on the cover fraction [5].

Furthermore, the escalating implications of global warming have raised significant alarm regarding wildfires, with rising temperatures and changing precipitation patterns affecting fuel moisture content [8]. Understanding the LFMC-environmental interactions becomes crucial for wildfire prediction and management as the climate evolves.

The primary objective of this study was to devise a multitemporal analytical approach for LFMC estimation, facilitating the assessment of vegetation burn likelihood and operational calculation of fire hazard by means of a novel approach. This methodology holds practical significance for temporal fire risk planning and identifying burn windows for prescribed fire plans.

2. Methods

The study was conducted over an area containing a great concentration of *Cistus ladanifer L.* shrub patches in Sierra Morena, in the west of the province of Cordoba (Andalusia, South of Spain) (Figure 1). In total, 38 sampling plots of 10x10 m were established. To ensure data representativeness, samples from at least 5 individuals were collected in each plot to measure the LFMC, avoiding repetition of the same individual in consecutive field campaigns.

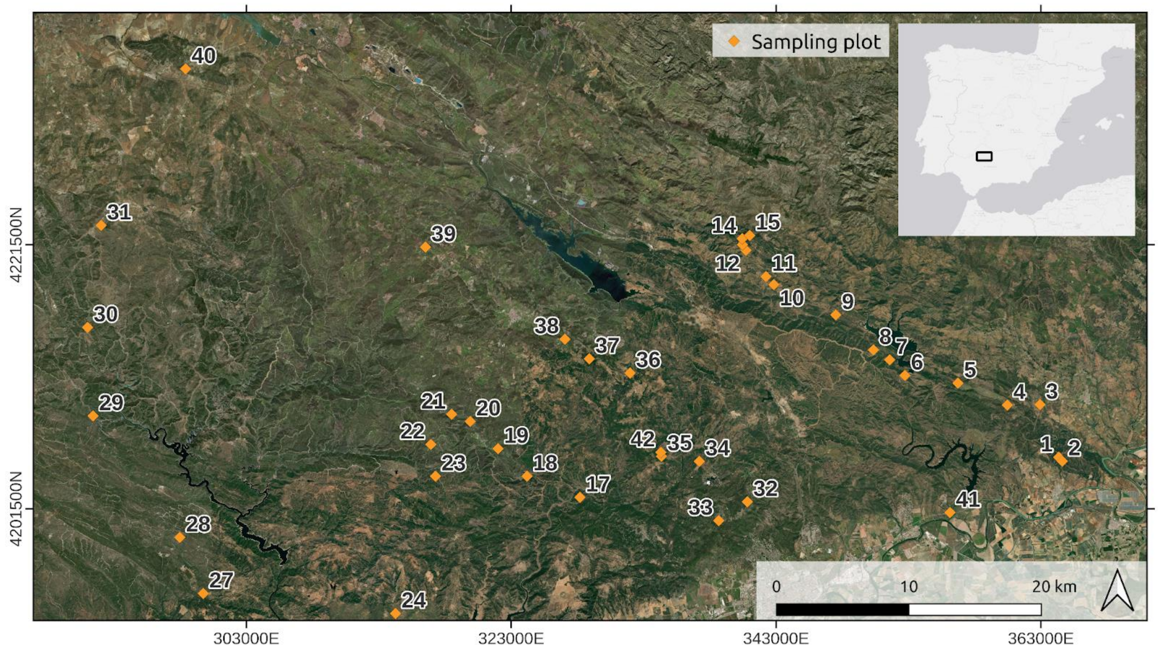


Figure 1. Sampling plots overlaid on orthophoto. Made with QGIS. Orthophoto credits: Bing Satellite. Microsoft product screenshot reprinted with permission from Microsoft Corporation. Situation basemap credits: Esri, DeLorme, HERE, MapmyIndia.

After some collections, sampling plots 39 and 33 were transferred to other locations, plots 41 and 42 respectively, due to optimization of the route. The sampling was conducted roughly once a month for 16 months, between June 2021 and September 2022, making a total of 15 field campaigns. Altogether, 570 samples were collected.

The destructive sampling technique for determining the LFMC, proposed by the Forest Fire Laboratory of the Spanish National Institute for Agricultural and Food Research and Technology (INIA) [1] was applied. The LFMC was calculated as

$$LFMC(\%) = \frac{Mf - Md}{Md}100, \tag{1}$$

being Mf the mass of the fresh collected sample and Md the oven-dried mass at 100 ºC for 24 h of the same sample.

Several vegetation indices were derived from the S2MSI2A product from Sentinel-2 Multi-Spectral Instrument and the MCD43A4 v061 product from Moderate Resolution Imaging Spectroradiometer (MODIS). Sentinel-2 imagery free of clouds and acquired on the closest date to the field-work campaigns were selected. Similarly, MCD43A4 matching the field campaign dates were selected. MCD43A4 product is a composite image of the best available pixels, including cloudiness-free criterion, within a 16-day period.

Calculation of the spectral indices was performed by the graph processing tool (GPT) from the Sentinel application platform (SNAP) software from ESA, Version 9.0.0.

Most indices were selected based on [1], as their study assessed the suitability of Sentinel-2 and MODIS data for estimating LFMC through empirical modelling in *C. ladanifer* shrubs. A correlation analysis was executed in order to decide which variable or set of variables will be used in both the Sentinel-2 and MODIS models.

Universal kriging (UK) model was used for LFMC prediction. In UK, the target variable (LFMC) is compounded by a trend function that depends on the vegetation indices (auxiliary variables) and a residual that shows spatial and temporal autocorrelation. The Iterated Reweighted Least Squares (IRWLS) method was applied for adjusting the variogram parameters and trend function coefficients, taking the ordinary kriging variogram parameters as the starting point [9,10].

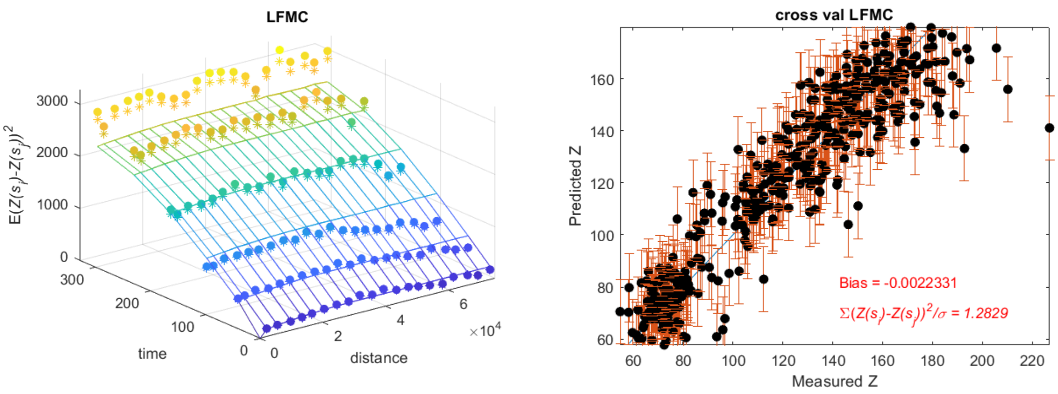
For each set of auxiliary variables, the p-values were derived and leave-one-out cross-validation was conducted to test the model performance through the bias (mean value of the residuals) and the root mean square error (RMSE), calculated as the mean value of the quotient between the square of the residuals and the variance of the prediction. Model selection was based on p-values, bias and RMSE.

Then prediction maps were obtained for monospecific stands of *C. ladanifer* in the study area by fitting the models to Sentinel-2 and MODIS images. Analyses were performed with Geostat software, developed in Matlab® by the authors.

3. Results and Discussion

The LFMC values determined in the field decreased gradually, as expected, between June and July and then sharply in August, in both 2021 and 2022, denoting a sharp seasonality.

The variogram was fitted and a cross-validation was done in all the selected models. When using Sentinel-2 derived auxiliary data, the results pointed out EVI as the best predictor for the model (Figure 2), with a p-value of 0.003, skew of -0.003 and RMSE of 12.35%, although the other auxiliary variables showed very similar results.



(**a**) (**b**)

Figure 2. Model results when using EVI index from Sentinel-2 as auxiliary variable. (**a**) Fitted spatio-temporal variogram; (**b**) cross-validation of LFMC values predicted by fitting the model.

The range of autocorrelation in the fitted variogram was approximately 27 km and 6 months, which means that out of these ranges the results may be not accurate due to unaccounted sources of variability.

In terms of the LFMC variability accounted for by the model, 80.15% of the variability was explained by the temporal autocorrelation, 4.24% of the variability by spatial autocorrelation and the auxiliary variable, in this case, the EVI index, absorbed 9.12% of the variability. This high temporal autocorrelation, which can be attributed to a strong seasonality, suggests that changes in LFMC over time are strongly correlated and significantly impact the model's performance. On the other hand, spatial autocorrelation explained a smaller portion of the variability, indicating that the spatial patterns of LFMC were less important for prediction. It must be considered that samples were measured within the same area and in the same habitat (shrubs), hence this result aligns with expectations.

The EVI index had a moderate impact on explaining variability, although it plays a meaningful role in explaining LFMC fluctuations, as indicated by the low p-value (0.003). The variability unexplained by the model was 6.50%, which could be related to factors not considered by the model or additional sources of randomness.

It is important to highlight the well-founded choice of employing the UK in our study. This method excels in capturing spatio-temporal information, which is essential given the intrinsic connection between LFMC and site-specific, climatic, and ecological processes, leading to high autocorrelation. Additionally, our dataset covers an entire year and includes 38 sampling points, providing adequate data for kriging. These conditions are crucial in the development of an effective kriging model.

The MODIS vegetation index which performed better as auxiliary variable was the GVMI index, with a p-value=0.009. The model resulted in a bias=0.001 and a RMSE=12.34%.

Future research includes the addition of meteorological information as auxiliary variables to improve the model, in view of the fact that LFMC is related to weather conditions, especially in shrublands, and is spatially autocorrelated. For instance, the Canadian Forest Fire Weather Index (FWI) System based on the moisture content of forest fuel is daily updated from weather readings [11]. [5] demonstrated a potential improvement in the LFMC prediction in their models based on spectral indices when adding meteorological variables during fire season in mixed Mediterranean vegetation areas. Hence, we expect this addition to raise the impact on the auxiliary variable and to lower the variability unexplained by the model.

The results of the spatio-temporal prediction with sentinel-2 EVI index for April, July and September 2022 are shown in Figure 3. LFMC predicted values in April ranged from

169 to 185%, in July from 70 to 95% and in September from 80 to 105%, being July the month with the lower LFMC values from the three.

Predictions from the computed model with MODIS GVMI index as auxiliary variable gave rise to similar results.

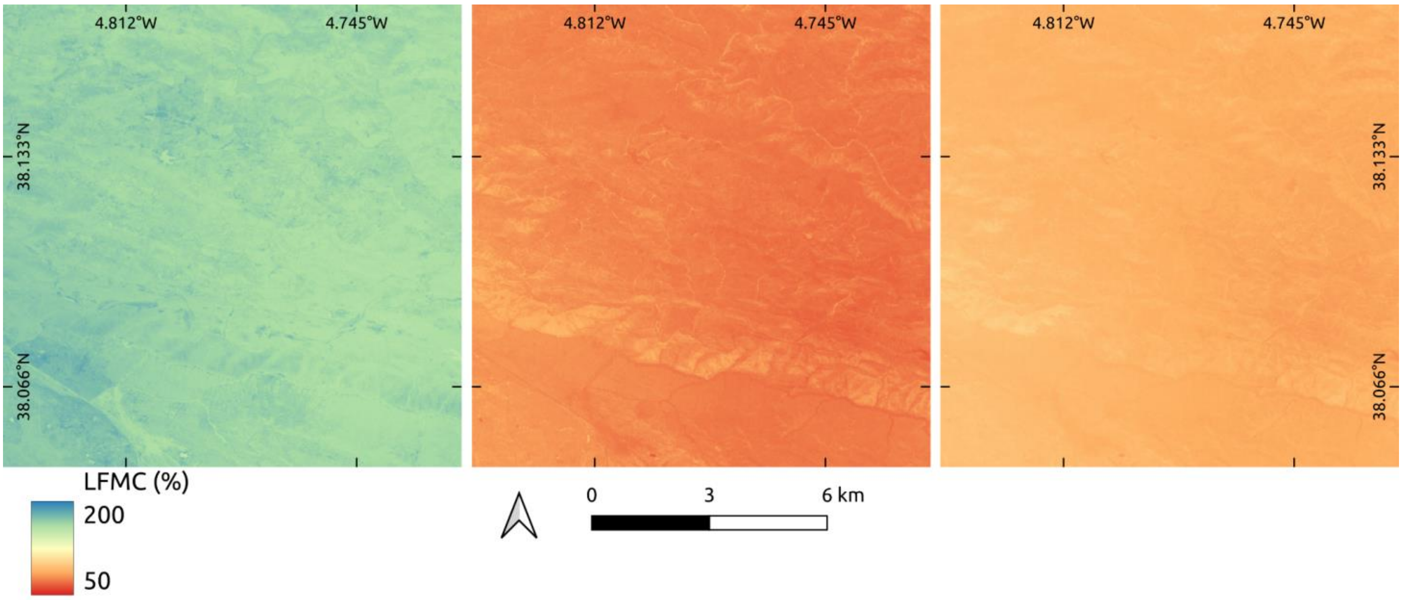


Figure 3. LFMC prediction obtained with Sentinel-2 EVI index as auxiliary variable in an inside area. From left to right April, July and September 2022. Made with QGIS.

Figure 3 reveals the potential value of dynamic modelling for monitoring changes in fuel moisture. Note that other land uses such as urban areas, water bodies or rocky soils were also included. Future research considers using a mask to apply the model only in shrublands.

4. Conclusion

Live fuel moisture content of *C. ladanifer* was successfully predicted by spatio-temporal modelling with a universal kriging (UK) model, using Sentinel-2 EVI and MODIS GVMI indices as auxiliary variables. The results showed RMSE of 12.35% and 12.34% respectively. To our knowledge, this technique has not been previously utilised for this specific purpose, marking a significant advancement in the field of forest fuel modelling and fire risk evaluation.

Moreover, while the study primarily focused on satellite-derived indices, it is essential to recognize the untapped potential of incorporating meteorological variables into such models. The inclusion of meteorological variables has the potential to enhance the performance of these models.

These findings have practical implications for forest fuel modelling, fire risk evaluation, and operational decision-making concerning fire prevention and management not only in the study area but also in potentially similar regions.

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