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Estimation of live fuel moisture content of shrubland using MODIS and Sentinel-2 images

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Abstract

Live fuel moisture content (LFMC) is a critical parameter affecting vegetation flammability and fire behaviour. Reliable and updated estimations of LFMC are needed by fire managers for operational wildfire risk assessment. However, detailed and constant monitoring of LFMC in the field is costly and time-consuming. Remote sensing technologies are an important source of geospatial data that can provide spectral information related to LFMC at different temporal and spatial resolution. In this study, we used a database of LFMC monitoring sampled during 2016 and 2017 (n=81) in a monospecific *Cistus ladanifer* L. shrubland in Madrid region (Central Spain). *C. ladanifer* is a representative shrub species commonly found in Mediterranean fire-prone areas, and has been already identified as an indicator species for wildfire risk assessment by different regional fire services. A set of spectral indices (SI) derived from MODIS images (MOD09GA) were calculated at 500 m resolution and compared with field data. We also used Sentinel-2 images for SI retrieval at 20 m resolution with the aim of addressing the scale problem between field sampling site and the low spatial resolution of MODIS data. The same SI were calculated adapting formulations to Sentinel-2 spectral resolution. The timelag between images and field sampling date was limited to a maximum of 2 days for operational purposes. Multiple linear regression analysis was used to assess the potential of SI for LFMC estimation, comparing results for both type of images. Most of the SI tested showed a significant correlation with LFMC data derived from MODIS (n=62) and Sentinel-2 (n=35). For MODIS, the best indices were EVI, VARI, and VIGREEN (R^2=0.82, MAE=12%), followed by NDVI and SAVI (R^2=0.76, MAE=14%). For Sentinel-2, the best indices were VARI (R^2=0.72, MAE=13%), EVI (R^2=0.71, MAE=13%), VIGREEN (R^2=0.67, MAE=14%) and NDVI (R^2=0.62, MAE=14%). In both cases, a significant multivariate model was found including NDVI and VARI, with a slight increase in prediction accuracy compared to simple regression models (R^2=0.85 with MAE=11% for MODIS, and R^2=0.76, MAE=12% for Sentinel-2). Our findings indicate that MODIS and Sentinel-2 images provide similar results for the SI tested, and that both satellites can be used for near real-time estimation of LFMC in *C. ladanifer* shrubland. The proposed models can be used to improve monitoring of the variability of LFMC during the year, as well as helping the integration of remote sensing data on wildfire danger rating systems.

Keywords: Live fuel moisture content; MODIS; Sentinel-2; remote sensing; *Cistus ladanifer*

1. Introduction

Live fuel moisture content (LFMC) is a critical parameter affecting vegetation flammability and fire behaviour (Denisson and Moritz 2009, Marino *et al.* 2012). Moisture of both live and dead components of vegetation are often required as input to predict fire behaviour in wildfire simulation models. Reliable and updated estimations of LFMC are also needed by fire managers for wildfire danger rating (Chuvieco *et al.* 2014).

Extreme weather is becoming more frequent due to climate change thus extending the fire season in most Mediterranean areas (Ruffault *et al.* 2018), where fire regimes have shifted from fuel-limited to drougth-driven in the last decades (Pausas and Fernández-Múñoz, 2012). Dead fuel moisture, especially fine fuels, is generally more easily determined from weather variables as it relies on fuel size, local atmospheric conditions and precipitation (Viney *et al.* 1991, Nolan *et al.* 2016). Conversely, LFMC is more difficult to estimate as it strongly depends on physiological and phenological characteristics of each species that may be mostly driven by medium-term meteorological conditions (Yebra *et al.* 2013). Fire management services are spending important amount of resources on sampling vegetation for LFMC estimation to be used in pre-fire alert system and fire-fighting operations. However, detailed and constant monitoring of LFMC in the field is costly and time-consuming. Therefore, fire management services often focus on indicator species that are relevant for wildfire prevention systems.

Previous studies demonstrate the ability of remote sensing data for LFMC estimation (Chuvieco *et al.* 2004, Garcia *et al.* 2008, Yebra *et al.* 2008). Different espectral, spatial and temporal resolutions are available depending on the type of sensor used. MODIS is one of most commonly used optical sensors due to its high temporal resolution. Empirical models were proposed by many authors to estimate LFMC from a combination of different espectral indices derived from MODIS images (Dennison *et al*. 2005, Stow *et al.* 2006, Peterson *et al.* 2008, Caccamo *et al.* 2012). Other authors used radiative transfer models (RTM), a more complex method based on physical approaches from simulations that can provide more robust LFMC estimations independent of site specificities (Hao and Qu 2007, Yebra *et al.* 2008, 2013, Yebra and Chuvieco 2009, Jurdao *et al.* 2013). Both methods applied on MODIS images provide spectral information at a coarse spatial resolution, which may limit its use in small scale sampling areas or heterogenenous vegetation. More recently, some authors assessed the potential of microwave remote sensing as an alternative for LFMC estimation, obtaining moderate results compared to optical indices derived from MODIS (Tanase *et al.* 2015, Fan *et al.* 2018). Hence, further research is still needed to provide fire managers with operational models and tools for accurate LFMC prediction that could be included in operational fire danger rating systems (Yebra *et al.* 2013). The new generation of Sentinel-2 sensors provide similar spectral information to MODIS images but at higher spatial resolution, which offers an opportunity to improve LFMC estimations for operational purposes.

The objetive of this work was to compare the ability of two different type of satellites, MODIS and Sentinel-2, for LFMC estimation. Research is focused on monospecific *Cistus ladanifer* shrubland. *C. ladanifer* is a representative shrub species commonly found in Mediterranean fire-prone areas, and has been already identified as an indicator species for wildfire risk assessment by different regional fire services.

2. Methods

2.1. Field samples and laboratory protocol

A database of LFMC monitored in *C. ladanifer* shrubland was used as reference data. The study area is a 45 ha of monospecific shrubland located in Madrid region (Central Spain) where samples of *C. ladanifer* were systematically collected during 2016 and 2017 (n=81). Samples of live fine fuels, including leaves and terminal twigs, were collected according to a field protocol defined by INIA forest fire laboratory. Sampling frequency varied along the year, starting in spring 2016, with an increased frequency of up to three days during the summer, weekly during spring and autum, and biweekly in winter.

Field samples were immediately conducted to INIA forest fire laboratory in sealed plastic pots to prevent moisture losses after cutting. Fresh samples were weighted daily and then oven-dried (24h, 100º) for moisture content estimation. LFMC was calculated as the percentage of water content of vegetation on a dry-weight basis following the equation:

$$LFMC = \left(\frac{W_f - W_d}{W_d}\right) \times 100$$

where W_f is the fresh weight and W_d the dry weight of each sample.

2.2. Remote sensing data

2.2.1. Image selection and preprocessing

Images from two different type of sensors were used: MODIS and Sentinel-2. Terra MODIS images corresponded to MOD09GA, a daily product available at 500 m and 1000 m resolution. Sentinel-2 images corresponded to both satellites 2A and 2B, providing information from 10 m to 60 m depending on the spectral band.

Time series from april 2016 to october 2017 were used in this study for both types of images. Since MODIS and Sentinel-2 products used are 1-day images, i.e. not composite products, the timelag between images and sampling date was limited to a maximum of 2 days in order to compare available images with field data. A total of 62 cloud-free MODIS images were selected for 2016-2017. As Sentinel-2 is a more recent satellite, only 8 images were available for 2016 compared to 27 for 2017, resulting in a total of 35 for the study period.

The MOD09GA product obtained by the Terra MODIS satellite corresponded to atmospherically corrected surface reflectance. The images were downloaded from the NASA Land Processess Distributed Active Archive Center (LP DAAC, https://lpdaac.usgs.gov/).

Level 1C Sentinel-2 imagery was downloaded from the European Space Agency (ESA) and preprocessed with Sen2Cor software (Louis *et al.* 2016) developed by ESA. This software performs the tasks of Atmospheric Correction and Scene Classification of Level 1C input data. Level 2A outputs are Bottom-Of-Atmosphere (BOA) corrected reflectance images.

2.2.2. Spectral indices

A set of spectral indices (SI) derived from MODIS images were calculated at 500 m resolution (Table 1), including Normalized Difference Vegetation Index (NDVI), Normalized Difference Infrared Index with band 6 and 7 (NDII6, NDII7), Global Vegetation Moisture Index (GVMI), Normalized Difference Water Index (NDWI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), Visible Atmospherically Resistant Index (VARI), Vegetation Index — Green, or Normalized Green Red Difference (VIGREEN).

The Sentinel-2 satellites include a high-resolution optical sensor that operates in 13 bands between the visible and the SWIR. Spatial resolution is 10 m for visible and NIR bands, 20 m for red-edge and SWIR bands, and 60 m for atmospheric bands. The same MODIS indices (except GVMI and NDWI) were calculated for Sentinel-2 images at a 20 m pixel resolution, adapting formulation to the spectral resolution of Sentinel-2 when needed.

For MODIS images, SI values corresponded to the weighted mean of pixel values according to each pixel surface inside the sampling area. For Sentinel-2, SI values were the average values of the pixels completely included inside the sampling area.

Table 1 - Spectral indices used to estimate LFMC from MODIS data. ρ_x is reflectance in MODIS band x.

Index	Formulation	Reference
Normalized Difference Vegetation Index	$NDVI = \frac{\rho_2 - \rho_1}{\rho_2 + \rho_1}$	Rouse *et al.* (1974)
Normalized Difference Infrared Index (band 6)	$NDII6 = \frac{\rho_2 - \rho_6}{\rho_2 + \rho_6}$	Hardisky *et al.* (1983)
Normalized Difference Infrared Index (band 7)	$NDII7 = \frac{\rho_2 - \rho_7}{\rho_2 + \rho_7}$	Hardisky *et al.* (1983)
Global Vegetation Moisture Index	$GVMI = \frac{(\rho_2 + 0.1) - (\rho_6 + 0.02)}{(\rho_2 + 0.1) + (\rho_6 + 0.02)}$	Ceccato *et al.* (2002)
Normalized Difference Water Index	$NDWI = \frac{\rho_2 - \rho_5}{\rho_2 + \rho_5}$	Gao (1996)
Enhanced Vegetation Index	$EVI = \frac{2.5 \times (\rho_2 - \rho_1)}{(\rho_2 + 6 \times \rho_1 - 7.5 \times \rho_3 + 1)}$	Huete *et al.* (2002)
Soil Adjusted Vegetation Index	$SAVI = (1 + 0.5)\frac{(\rho_2 - \rho_1)}{(\rho_2 + \rho_1 + 0.5)}$	Huete (1988)
Visible Atmospherically Resistant Index	$VARI = \frac{\rho_4 - \rho_1}{\rho_4 + \rho_1 - \rho_3}$	Gitelson *et al.* (2002)
Vegetation Index — Green	$VIGREEN = \frac{\rho_4 - \rho_1}{\rho_4 + \rho_1}$	Tucker (1979)

2.3. Statistical analysis

The temporal variability of LFMC monitored during the field sampling was assessed and compared with the temporal profiles of the SI derived from satellites images. Linear regression was used to assess the potential of each SI for LFMC estimation, analysing the perfomance of spectral information derived from MODIS and Sentinel-2 independently.

In addition, multiple regression models combining different SI were assessed, comparing the results obtained from both sensors. Colinearity was checked, rejecting models with variance inflation factor (VIF) > 5 for any variable included in the model. Evaluation metrics included coefficiente of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The adjusted R^2 value was used in order to compared goodness-of-fit between models with different number of input variables.

3. Results

3.1. MODIS images

Most of the SI derived from MODIS (n=62) showed a significant correlation with LFMC data (Table 2). The best indices were EVI, VARI, and VIGREEN (R^2=0.83, MAE=12%, RMSE=15%), followed by NDVI and SAVI (R^2=0.76, MAE=14%, RMSE=18%). NDWI showed a moderate correlation with field data (R^2=0.61, MAE=17%, RMSE=22%), whereas NDII6, NDII7 and GVMI had the lower correlation and higher errors (R^2 < 0.56, MAE > 20%, RMSE>24%).

A significant multivariate model was found including NDVI and VARI, with a slight increase in prediction accuracy compared to simple regression models (R^2=0.85 with MAE=11% and RMSE=14%).

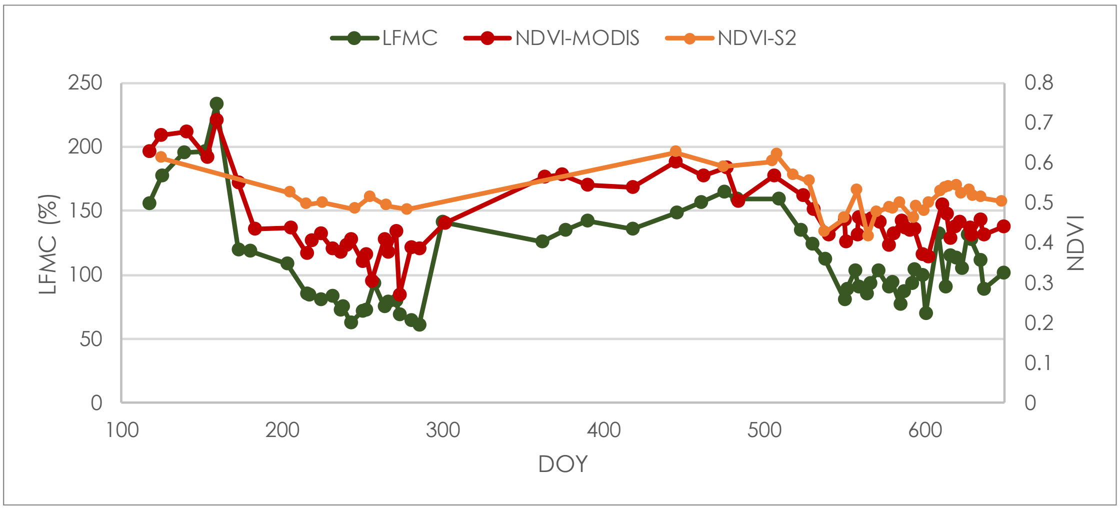
Table 2 - Results of the most significant linear regression models to estimate LFMC from MODIS and Sentinel-2 data. MAE, mean absolute error; RMSE, root mean square error.

Sensor	Model	R^2 (adjusted)	p-value	MAE (%)	RMSE (%)
MODIS	NDVI	0.756	<0.0001	14.190	17.816
	NDII6	0.553	<0.0001	20.356	24.142
	NDII7	0.469	<0.0001	22.286	26.314
	GVMI	0.553	<0.0001	20.356	24.142
	NDWI	0.611	<0.0001	17.218	22.509
	EVI	0.823	<0.0001	12.611	15.202
	SAVI	0.756	<0.0001	14.190	17.816
	VARI	0.832	<0.0001	12.220	14.799
	VIGREEN	0.823	<0.0001	12.477	15.179
	NDVI, VARI	0.847	<0.0001	11.283	13.987
Sentinel-2	NDVI	0.619	<0.0001	14.457	18.119
	NDII6	0.565	<0.0001	15.302	19.362
	EVI	0.712	<0.0001	12.539	15.758
	SAVI	0.588	<0.0001	14.897	18.840
	VARI	0.717	<0.0001	13.433	15.616
	VIGREEN	0.670	<0.0001	14.144	16.864
	NDVI, VARI	0.764	<0.0001	12.045	14.054

3.2. Sentinel-2 images

For Sentinel-2 (n=35), the best indices were VARI (R^2=0.72, MAE=13%, RMSE=16%), EVI (R^2=0.71, MAE=13%, RMSE=16%), VIGREEN (R^2=0.67, MAE=14%, RMSE=17%) and NDVI (R^2=0.62, MAE=14%, RMSE=18%). The lower correlations were found for NDII6 and SAVI (R^2<0.59, MAE=15%, RMSE=19%).

Similarly to MODIS data, the combination of NDVI and VARI resulted in a significant multivariate model that increased the performance of simple regression models (R^2=0.76, MAE=12%, RMSE=14%). Figure 1 depicts NDVI and VARI values derived from both satellites compared to LFMC during the study period.



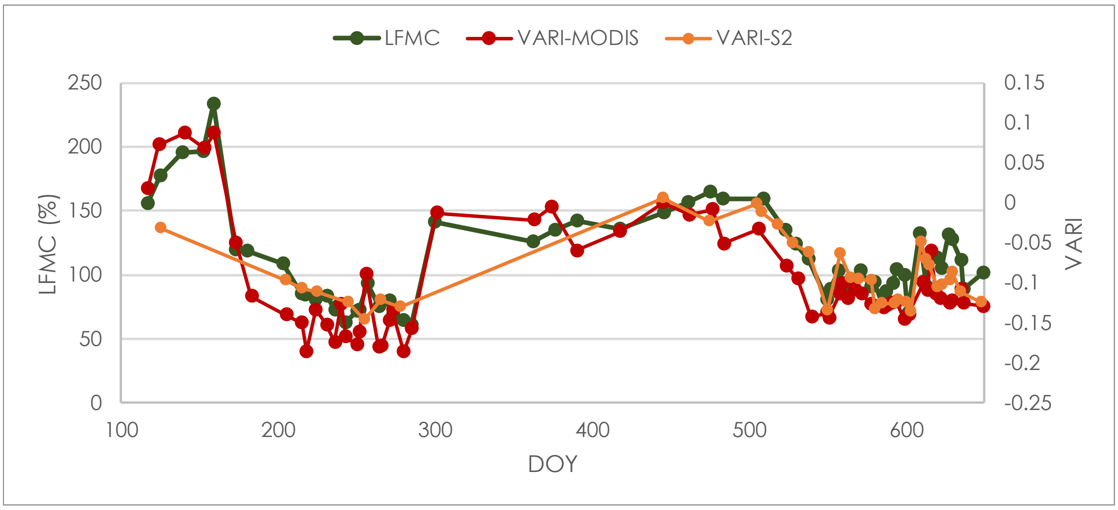
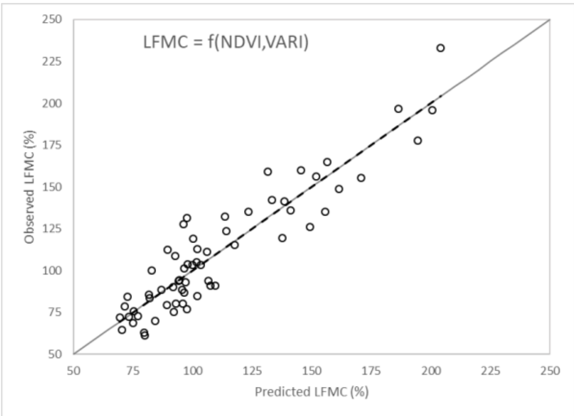


Figure 1 - Comparison of LFMC vith NDVI and VARI derived from MODIS and Sentinel-2 in Cistus ladanifer shrubland, from 24 April 2016 (DOY = 117) to 10 October 2017 (DOY = 649).



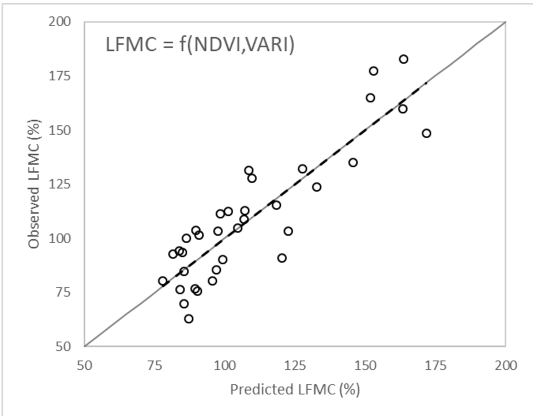


Figure 2 - Observed vs predicted values of LFMC for the best models obtained for MODIS (left, n=62) and Sentinel-2 (right, n=35) data.

4. Discussion

As reported in previous works, this study shows that spectral vegetation indices are an efficient means of obtaining empirical information related to LMFC from multispectral sensors (Yebra *et al.* 2013). Our results indicate that MODIS and Sentinel-2 images provide similar results for the SI tested (Table 2, Figure 2). The slightly better performance of most SI in the coarser resolution images could be partly due to the lower number of images available from Sentinel-2 for the study period. This limitation specially affected 2016 dataset, with only 8 cloud-free images found compared to 26 from MODIS. However, 27 images from Sentinel-2 were available in 2017 compared to 36 from MODIS. Our results suggest that longer time series may be used in future Sentinel-2 models to better account for the temporal variability of LFMC. This should not prevent the use of spectral information derived from Sentinel-2 images as, with both satellites 2A and 2B fully operational, it is currently possible to produce LFMC estimations every 5 days. However, MODIS still have higher potential in terms of temporal resolution compared to Sentinel-2, which may be a constraint when trying to achieve daily operational products at a finer spatial resolution.

We found that VARI was the SI showing the higher correlation with field measurements of LFMC (Table 2). Regarding MODIS images, previous authors also highlight VARI as the best indicator of LFMC variability in shrubland species compared to other SI (Stow *et al.* 2006, Peterson *et al.* 2008, Caccamo *et al.* 2012, Fan *et al.* 2018). Stow *et al.* (2006) and Peterson *et al.* (2008) reported R^2 between 0.74 and 0.93 depending on the chaparral sampling site. Caccamo *et al.* (2012) found lower prediction capacity of VARI with only 0.42, but mixing different types of vegetation. Our results are in general agreement with these authors, finding R^2 of 0.83 for MODIS data. However, it should be highlighted that all these authors used MODIS composite products (generally 8-days composites) compared to the 1-day images used in the present study. Avoiding the use of a composite product in our study reduced the number of available cloud-free images to compare field data (n=81) with spectral information (n=62 for MODIS). However, this choice was deliberately done in order to test the ability of near real-time daily images (only up to two days timelag to sampling date) for LFMC estimation, which is a critical aspect for models to be include in any operational system for wildfire risk assessment.

The best multivariate models combined the same spectral indices (VARI and NDVI) in both type of images. In Australia, Caccamo *et al.* (2012) suggested NDII6 for improving performance in a multivariate model derived to estimate LFMC from MODIS in shrubland and heathland. Stow *et al.* (2006) found the best multivariate model combining VARI with NDWI in California chaparral, whereas Peterson *et al.*(2008) reported better results with VARI and VIGREEN for the same type of shrubland. In our case, VIGREEN also had a strong correlation in the simple models, but NDII6 and NDWI were among the indices with lower correlation with LFMC data. Both VARI and NDVI measure greenness variability, whereas NDWI and NDII6 directly account for water content variations. Although greenness indices do not include water absorption bands, they can be used as an indirect estimation of water content since moisture variations affect chlorophyll activity, which is the case of *C.ladanifer* (Yebra *et al.* 2008).

Despite Sentinel-2 provided a slightly lower accuracy, LFMC prediction errors were very similar in the best multivariate model, with mean absolute error of 12% compared to 11% of MODIS (Table 2). According to fire management services, these are good results taking into account that 10% errors in LFMC estimation from field measurements are generally acceptable. Nevertheless, the proposed models should be validated with 2018 data in the same sampling area, in order to assess the sensitivity of both sensors to monitor seasonal and interannual variability of LFMC. Empirical models are also known to have limitations in terms of its ability for extrapolationg accurate results to different sites compared to RTM models (Yebra *et al.* 2008). However some authors reported moderately good model results for different sites with the same type of vegetation (Stow *et al.* 2006, Peterson *et al.* 2008, Caccamo *et al.* 2012). Hence, further comparison with similar shrubland areas would be highly recommended in order to test limitations when applying these models in other monospecific *C. ladanifer* shrubland.

5. Conclusions

This work compares the capacity of empirical models for LFMC estimation in *Cistus ladanifer* shrubland from two different type of satellite sensors: MODIS and Sentinel-2. MODIS provides daily estimates at a coarser spatial resolution whereas Sentinel-2 can provide higher spatial accuracy every 5 days. Despite both sensors provide images at different spatial and temporal resolution, this study showed similar results in terms of the most relevant spectral indices and model performance. The combination of VARI and NDVI provided the best models for both sensors tested. The proposed models derived from 1-day images should be validated with indepedent datasets and with longer time series. However, results suggest that both sensors could be used for near real-time estimation of LFMC in monospecific *C. ladanifer* shrubland. This study contributes to improve monitoring of the variability of LFMC during the year based on non-composite products, helping the integration of remote sensing data on wildfire danger rating systems.

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