





LIVE FUEL MOISTURE CONTENT MODELING **USING SPECTRAL**, **METEOROLOGICAL AND TOPOGRAPHIC** DATA IN THE VALENCIAN REGION

María Alicia Arcos Villacís (maar12m@topo.upv.es)

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INTRODUCTION

Wildfire is one of the most impactful natural disasters that can occur in any forested area. In recent years, the **frequency and intensity** of wildfires **have increased** significantly due to climate change, human activities, and natural factors. One of the most important factors to consider in **relation** to **forest fires** is the live fuel moisture content (**LFMC**). It is a crucial parameter for fire managers to **estimate** the fire danger level, **predict** fire behavior, and **plan** fire suppression activities.

STUDY AREA AND FIELD DATA





June 2020 -November 2021



Number of study **plots:** 88



Data collection radius: 10 m



Total number of observations per species and plot: 36



Location of the study plots in Cortes de Pallas

- Main fuel types considered: SH4, SH5 and TU2, TU3. They correspond to shrubland and woodland, correspondingly.
- Elevation: between 175 and 1050 masl.
- **Slope:** 1.34° 36.1°
- The most representative species considered for the measurement of LFMC were *Pinus halepensis, Pinus pinaster, Quercus coccifera, Quercus ilex, Juniperus oxycedrus, Ulex parviflorus, Rosmarinus officinalis* and *Cistus albidus.*
- Indicator parameter for the LFMC estimations: weighted average of all the species from each plot and the LFMC of *Rosmarinus officinalis*.



PREDICTOR VARIABLES



* before to data collection in the field

METHODOLOGIES



GAM - Generalized Additive

Models

An extension of linear models that allows for nonlinear relationships through smooth functions

Random Forest

An ensemble learning method that constructs multiple decision trees and merges them to improve prediction accuracy.







A generalized phenology model based on meteorology that allows studying the duration and intensity of the vegetation growing season and better understanding this cycle and its relationship with climatic conditions.





RESULTS



Linear Models

G ¹	Ft ²	Sp ³	Formula	Coef ⁴	P value	R ² adj ⁵	RMSE ⁶	MAE ⁷	MBE ⁸	# sites
						(%)				
M-M ⁹	Sh ¹⁰	Ro ¹¹	Intercept	32.9	0.03	52.1	22.9	18.5	-0.02	15
			Vgreen_10mS	68.9	0.0004					
			NMDI_10mS	198.2	2.5e-10					
			DOY_SIN	-23.4	<2e-16					
			p60	0.1	8.5e-10					
			slope	-1.3	5.5e-11					









¹ G: group; ² Ft: fuel type; ³ Sp: species; ⁴ Coef: model coefficients; ⁵ R² adj: adjusted R²; ⁶ RMSE: Root Mean Square Error; ⁷ MAE: Mean Absolute Error; ⁸ MBE: Mean Bias Error; ⁹ M-M: Meso-Mediterranean Zone; ¹⁰ Sh: shrub; ¹¹ Ro: LFMC of *Rosmarinus officinalis*.



A: SH4 plot, B: TU2 plot, Credits: Generalitat Valenciana, "Fuel Types", Province Valencia

GAM - Generalized Additive Models

Ft ¹	Sp ²	Formulation	Parameters ³	P value	⁴ R² adj. (%)	RMSE	MAE	MBE⁵
Sh ⁶	Ro ⁷	LFMC=f(a,	a = 4.62	<2e-16	65.0	19.7	15.3	0.023
		s(Vgreen_10mS),	s(Vgreen_10mS)	0.0069				
		s(NMDI_10mS),	s(NMDI_10mS)	5.6e-05				
		s(doy),	s(doy)	<2e-16				
		s(p60),	s(p60)	<2e-16				
		s(Zone code),	s(Zone code)	<2e-16				
		s(Xcoord,Ycoord))	s(Xcoord,Ycoord)	<2e-16				
					Plat 20			
	200	y = 0.54 + x	190 -		1 101 20		- 190	- Incor
		R2 = 0.663 RMSE = 18.867	170 Va	riables LFMC_Observed	٨		- 170	functi
	ខ្ល 150		150	LFMC_Predicted Upper Limit Lower Limit	E A		150	predic

- Incorporates smooth functions (e.g., splines) of predictors.
- Requires careful selection of smoothing parameters.

130

110

90

70

50

10/12/21

¹ Ft: fuel type; ² Sp: specie; ³ Parameters: model coefficients; ⁴R² adj: adjusted R²; ⁵ MBE: Mean Bias Error; ⁶ Sh: Shrub; ⁷ Ro: LFMC of *Rosmarinus officinalis*

130

110

90

70

50

200

150

LFMC Predicted

100

10/06/20

10/09/20

10/12/20

10/03/21

Date

10/06/21

10/09/21

LFMC Observ

Random Forest Models

Variables of the model to estimate LFMC of Rosmarinus officinalis in SH4 plots



¹ Ft: fuel type; ² Sp: specie; ³ Sh: Shrub; ⁴ Ro: LFMC of *Rosmarinus officinalis*; ⁵ TCARI_OSAVI: TCARI/OSAVI



Growing Season Index





LFMC of Rosmarinus	officinalis;	Cluster:	13; R ² : 71.25%
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This method needs daily meteorological values of variables such as **temperature**, **precipitation**, **relative humidity**, **vapor pressure deficit**, **and photoperiod**. Through these and a series of calculations, GSI values are obtained, which are then transformed into LFMC values. Based on these results, the respective prediction models are built for the different study areas, which in this case are the municipal terms where the LFMC data were collected.

Temporal evolution of field observed values (red line) and predicted values of *Rosmarinus officinalis* LFMC (blue line)

Parameter	Value
alfa_temp	-20
beta_temp	0
alfa_vpd	1000
beta_vpd	5000
alfa_photo	30500
beta_photo	36000
alfa_prcp	20
beta_prcp	40
Greenup	
GU	0.0
Max_LFMC	200
Min_LFMC	60

- CONCLUSIONS
- Spectral variables are able to represent LFMC changes at spatial and temporal levels, but in order to improve the fit it is convenient to use information related to precipitation, temperature, relative humidity, topography and seasonal factors (DOY_SIN, DOY_COS).
- According to the results obtained, each model has advantages and disadvantages that must be taken into account prior to implementation:
 - Best Overall: Random Forest. It is versatile, handles complex data well, and is robust to overfitting and noise. However, it requires significant computational resources and tuning.
 - Best for Interpretability and Simplicity: Multiple Linear Regression. It is easy to interpret and implement, but limited to linear relationships and sensitive to assumptions, (something that we want to avoid in the estimation of the LFMC).
 - Best for Flexible Modeling: Generalized Additive Models. These offered flexibility in capturing nonlinear relationships but can be complex to tune and interpret.
- The GSI methodology has begun to be implemented in the Valencian region and is currently being worked on.

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THANKS!

DO YOU HAVE ANY **QUESTIONS?** maar12m@doctor.upv.es https://cgat.webs.upv.es/