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VPD-based models of dead fine fuel moisture provide best estimates in a global dataset

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ABSTRACT

Dead fine fuel moisture content (FM) is one of the most important determinants of fire behavior. Fire scientists have attempted to effectively estimate FM for nearly a century, but we are still lacking broad scale evaluations of the different approaches for prediction. Here we tackle this problem by taking advantage or a recently compiled global fire behavior database (BONFIRE) gathering 1603 records of 1h (i.e., <6 mm diameter or thickness) dead fuel moisture content from measurements before experimental fires. We compared the results of models routinely used by different agencies worldwide, empirical models, semi-mechanistic models and also non-linear and machine learning approaches based on either temperature and relative humidity or vapor pressure deficit (VPD). A semi-mechanistic model based on VPD showed the best performance across all FM ranges and a historical model developed in Australia (MK5) was additionally recommended for low fuel moisture estimations. We also observed significant differences in FM dynamics between vegetation types with FM in grasslands more responsive to changes in atmospheric dryness than woody ecosystems. The addition of computational complexity through machine learning is not recommended since the gain in model fit is small relative to the increase in complexity. Future research efforts should concentrate on predictions at low FM (<10 %) as this is the range most significant for fire behavior and where the poorest model performance was observed. Model predictions are available from https://hcfm.shinyapps.io/shinyfmd/.

1. Introduction

Dead fuel moisture content (FM) is a key driver of fire ignition, behavior and risk (Cruz et al., 2014; Nolan et al., 2016). Low fuel moisture content enhances ignition while fostering fire propagation and intensity, hence increasing potential exposure and vulnerability to wildfires. The spatial-temporal patterns of FM are strongly tied to atmospheric conditions, fluctuating in parallel with surface temperature and relative humidity and additionally affected by processes like rain, solar radiation or soil moisture (Matthews, 2014; Resco de Dios et al., 2015). Understanding how to model FM has proven to be a vexed problem in fire science for a very long time (Byram and Jemison, 1943). In principle, modeling water exchange processes from inert material should be straightforward, at least in comparison to live fuel where physiological, phenological and anatomical regulations operate. However, the hygroscopic nature of dead fuels, where water is gained through condensation, adsorption or precipitation, and water losses occur through desorption and evaporation (Viney, 1991), have led to FM modelling becoming a significant challenge.

FM values are of crucial importance in fire management operations overall. For instance, fire behavior models and systems require FM as an indirect (Forestry Canada Fire Danger Group, 1992) or direct (e.g.,

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Rothermel, 1972) input to predict fire-spread rate. FM can be used to define thresholds for fire-use by the population, it is key to prepare burn prescriptions (Fernandes, 2018), and is the basis to predict fuel consumption (Prichard et al., 2017). FM is additionally important as an overall indicator of fire danger (Cruz et al., 2014). However, FM cannot be easily measured *in situ* as it requires specialized equipment based on either time-domain reflectometry (e.g., CS-506, Campbell Sci, Logan, UT) or electrical resistance (Chatto and Tolhurst, 1997). Consequently, we are in need of FM models that are based on simple atmospheric variables like temperature, relative humidity or wind speed. To this end, while models of daily variation in FM suffice for fire danger rating, modeling hourly or sub-hourly variation is required to predict fire behavior for operational decision-making in the use or suppression of fire. Modeling daily FM serves a broad array of purposes, such as hindcasting analyses (Nolan et al., 2016) of the relationships between FM and fire activity and broad spatial scales, or other modeling exercises (Venevsky et al., 2019).

One of the factors potentially affecting FM is the generic vegetation type. For example, FM may differ between grassland or woody fuels owing to physical differences in fuel particles and fuel beds and in microclimate between open and forested ecosystems (Biddulph and Kellman, 1998; Ray et al., 2005; Tanskanen et al., 2006). Some of the early FM models presented different formulations for forests and grasslands (Noble et al., 1980). However, it is more common to use a single equation across vegetation types. To which extent do differences between vegetation types affect FM modeling has not been extensively studied.

Early fuel moisture assessment was based on tables, graphs or nomographs, while the equations were not given until computers became more accessible (Viney, 1991). Some examples include the models used by fire managers in Australia (FM_{MK5} and $FM_{McArthur}$; McArthur; Noble et al., 1980), the Canadian Forest Fire Weather Index ($FM_{vanWagner}$; Van Wagner, 1987) and the US National Fire Danger Rating System (FM_{Nelson} and FM_{Simard}; Nelson 1984; Simard, 1968). Over time, models of FM became more sophisticated, and changed from being empirical to more mechanistic approaches such as those based on vapor pressure deficit (Resco de Dios et al., 2015), equilibrium moisture (Simard, 1968) or very simple scaling indexes like the FMI (Sharples and McRae, 2011). A common approach in these models has been to develop separate calibrations across vegetation types, specially to separate between litter and grassy fuelbeds. Recent developments in complex algorithms, such as Generalized Additive Modelling (GAM) or machine learning, provide new avenues for predicting FM (Matthews, 2014).

In this study we seek to resolve the long-standing question of which approach is most effective for modelling FM. To this end, we evaluate current approaches and more complex algorithms to estimate FM using a global dataset of gravimetric moisture measurements. We compare the models across a range of moisture values, but with specific focus on situations of low FMC conducive to extreme wildfire behavior (below 10 %; Flannigan et al., 2013; Wotton et al., 2017). Additionally, we also wanted to test whether more complex algorithms would perform better than traditional approaches. We calibrated a model using GAM splines and two models based on machine learning approaches (random forests; RF) and support vector machines (SVMs). Finally, we addressed possible differences across vegetation types (grassland, woodland, and forest). We also explored the potential of Linear Mixed models with random effects in the intercepts as a function of vegetation type.

2. Materials and methods

2.1. The BONFIRE database

Our analyses used the BONFIRE database, a comprehensive compilation of fire behavior-related data collected from experimental fires, prescribed burns and wildfires around the world (Fernandes et al., 2020). We considered only the experimental fires in the database and retained 1603 records of one-hour (1 h, i.e., fine fuels, <6 mm diameter or thickness) FM measurements for which weather variables were concurrently available. The nature of the BONFIRE database, resulting from numerous sources and various experimental protocols, implies variable FM sampling and weather acquisition procedures. The upper (top 5–20 mm) litter and/or the slash, grass and shrub profiles, which can be contiguous or elevated in relation to the litter, are the target of dead fine FM sampling in fire behavior experiments, given their dominating role in fire spread (Cheney, 1990). In treeless environments we considered only the FM of samples taken from the elevated, often the only, component of the grass or shrub fuel profile. Forest and woodland studies report the dead fine FM of each fuel layer or, more commonly, a composite FM content; in the former case we averaged the individual FM contents, weighted by their respective fuel loads. FM is sampled just before lighting the fire or, less frequently, also immediately after fire-spread cessation. The number of FM replicates varies, from one larger sample comprising material from different locations within or nearby the burn plot, to several (seldom more than five) smaller samples. The manually collected samples are sealed in bags or tins and in the laboratory are weighed, dried in an oven (typically at >80 °C for at least 8 h), and reweighed. FM content is expressed as a percentage of the dry weight. Records with FM higher than 35 % were left out as that is the saturation point (Berry and Roderick, 2005).

The BONFIRE database features field measurements of basic weather parameters, namely in-stand surface (1.5–2 m) air temperature (T), relative humidity (RH), and vapor pressure deficit (calculated from RH and T), as well as wind speed (WS) at variable heights (1-2, 6 and 10 m); WS was not available at all sites and it was subsequently discarded. Weather data was continuously collected during the fire or, less often, just before ignition or just before and just after the fire experiment. The database also comprises ancillary data such as the Köppen-Geiger climate codes (Beck et al., 2018), average temperature and annual rainfall (retrieved from the Wordclim 2 dataset; Fick and Hijmans, 2017), the type of vegetation community (Bonan, 1996) and some fuel bed characteristics (height and load). As of December 2022, the database features 153 experiments spanning from 1970 to 2020, covering 21 countries, with data from all terrestrial biomes except the tundra and the tropical rainforest (Fig. 1).

2.2. Data subsetting for model calibration and validation

To adequately assess the predictive ability of the numerous modeling tools and techniques presented in this study, a data partitioning strategy is required to optimize model hyperparameters (i.e., the set of variables/parameters that a given model requires to be specified) and test their performance with an independent set of observations. Several studies show that performance estimates reported by a regular random test subset are often biased if the spatial structure is disregarded (Meyer et al., 2018; Schratz et al., 2019). That is, model performance estimates are often overly optimistic (e.g., smaller MAE) due to spatial overfitting leading to information redundancy. Therefore, a spatial clustering approach is required to partition the data into calibration and validation subsets (Airola et al., 2019).

We applied the spatial resampling method described in Meyer et al. (2018) to prevent model misspecification due to underlying spatial autocorrelation. Our method implements a k-fold cross-validation where data is divided into k equally sized folds subsequently sampled using a leave-location-out procedure (LLO). In this way, we achieved more realistic performance yields and results, avoiding overoptimistic outcomes due to spatial overfitting and, thus, redundancy in the data (Meyer et al., 2018). As we only needed one common test subset to compare all models, we kept the partition closest to the desired CAL-VAL proportion in number of sampled records. We explored several proportional splits in terms of k, namely $k = 2$ is 50/50, $k = 3$ is 66/33, $k = 4$ is 75/25, and so on. Furthermore, the LLO was conducted following a stratified sampling scheme using the vegetation type field to ensure a

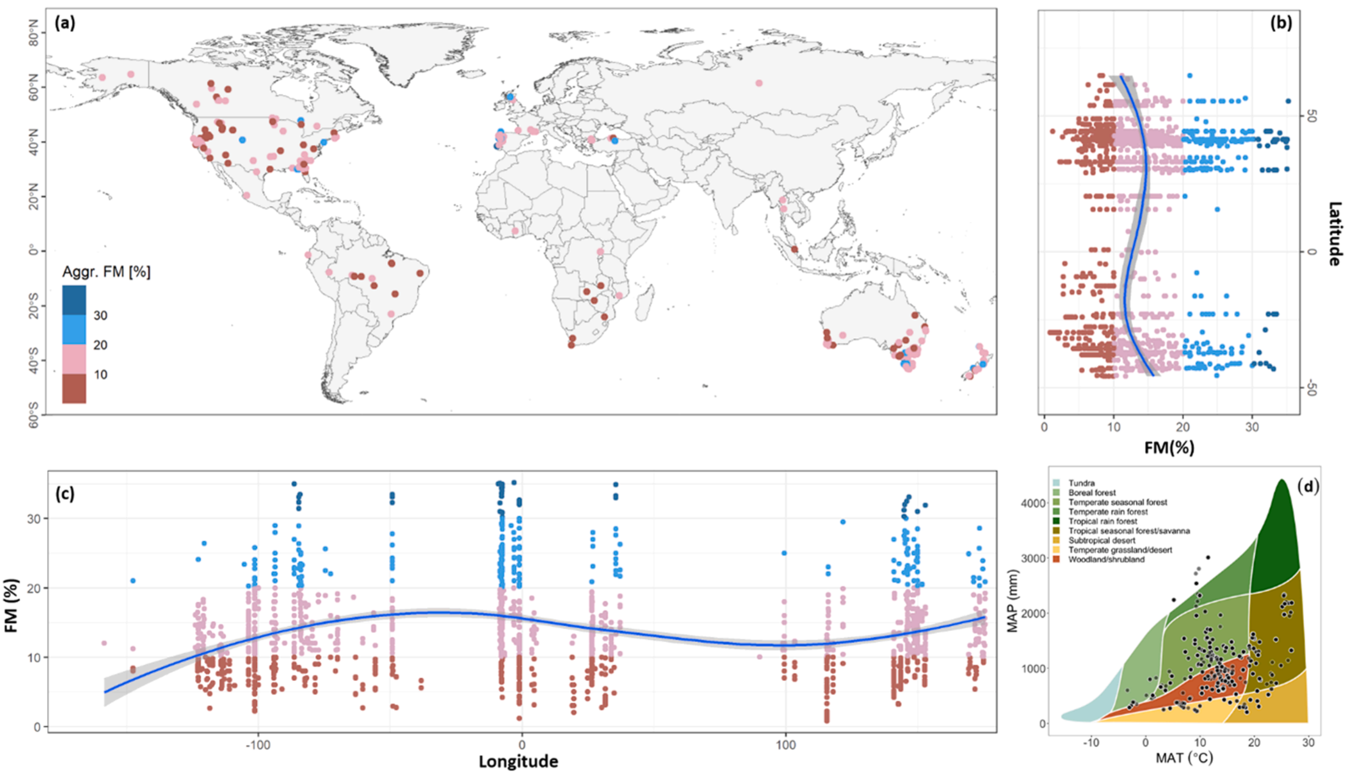

Fig. 1. Overview of the BONFIRE database selected records. (a) geographical distribution of measurement sites; (b) latitudinal trend in FM; (c) longitudinal trend in FM; (d) Whittaker biomes plot.

balanced representativeness of the surveyed vegetation communities. The process was repeated 30 times, comparing the spatial (LLO) and non-spatial (random k-fold sampling) split methods, assessing the FM estimates from the BONFIRE database as described in Section 2.3.1.

Fig. A1 shows the average (points) and the 5th and 95th percentile range (bars) of the MAE from calibration and validation estimates of FM derived from the 30 data split repetitions. Spatial overfitting must be suspected if the difference in terms of model performance between random data splitting (lower error estimates) and stratified-LLO (higher error estimates) is high, though this is not the case. Random subset validation generally showed lower variance (that is, repeated sampling produces different values) in MAE because locations used for the validation are used for training. In the stratified-LLO we see higher variance in MAE either in CAL and VAL, which suggests dependence in a particular data partition. As we can see in Fig. A2 a proportion of 66/33 (k = 3) achieved a good balance between bias-variance and a high correlation between CAL and VAL performance estimates. Furthermore, the number of samples in CAL (n = 1049) were sufficient for training those models that required hyperparameters to be optimized (GAM, RF and SVM algorithms). For the final selection (that is, stratified-LLO and k = 3), we examined whether the distribution of the response in VAL (n = 551) was similar to the distribution of CAL dataset either in FM or vegetation type representativeness Fig. A2).

The performance of the models was evaluated according to the mean absolute error (MAE), the mean biased error (MBE) and the root mean square error (RMSE) calculated from the difference between observed (O) and predicted (P) data in the test sample. We further explored model performance by fitting the regression line of observed against predicted FM. This enabled calculating the coefficient of determination while providing more insightful estimates through the intercept (β_0) and slope (β_1) of the O-P relationship (Piñeiro et al., 2008). Complementarily, model performance was addressed using the subset of observations with FM < 10 % to provide insights into the most hazardous weather conditions (Flannigan et al., 2013; Wotton et al., 2017). In this way, we tested the capability of the approaches to forecast low fuel moisture conditions that would potentially foster extreme wildfire behavior (Cruz et al., 2014). All analyses were carried out using the R Language for Statistical computing (R Core Team, 2023).

2.3. Modeling approaches

We investigated the adequacy of different indices and modeling strategies to estimate FM. We calculated FM using the main mechanistic approaches leveraging temperature (T), relative humidity (RH) and vapor pressure deficit (D) measurements from the calibration dataset (Sections 2.3.1 and 0). In turn, we regressed T, RH and D into FM exploring multiple modeling alternatives (sections 0 and 0). All models were implemented using the R Language for Statistical computing (R Core Team, 2023). Table 1 summarizes the modeling approaches calibrated and compared in this work.

2.3.1. Current modeling approaches

A first iteration of models was based on existing empirical methods to estimate dead fuel moisture content based on relative humidity and air temperature. These included:

The equilibrium fuel moisture model of Simard (1968):

$$FM_{Simard} = \begin{cases} 0.03 + 0.2626\,RH - 0.00104\,RH\,T; RH < 10\% \\ 1.76 + 0.1601\,RH - 0.02660\,RH\,T; RH \geq 10\%\ \ RH < 50\% \\ 21.06 - 0.4944\,RH^2 - 0.00063\,RH\,T; RH \geq 50\% \end{cases} \tag{1}$$

where RH is relative air humidity (%) and T temperature (°C).

The equilibrium fuel moisture model of Van Wagner (1972), currently implemented in the Canadian Forest Fire Weather Index (Van Wagner, 1987). This model considers the hysteresis in the drying (d) or wetting (w) cycles:

Table 1
Summary of models calibrated for predicting FM. Asterisk denotes models also calibrated including the vegetation type as dummy variable (*_veg). RH, relative humidity; T, air temperature; VPD, vapor pressure deficit; veg, vegetation type.

	Model	Predictors	Acronym	Source
Current modeling approaches	Equilibrium model of Simard	RH, T	FM_{Simard}	Simard (1968)
	Equilibrium model of Van Wagner	RH, T	$FM_{Wagner,d/w}$	Van Wagner (1987, 1972)
	Equilibrium model of Nelson*	RH, T	FM_{Nelson}	Nelson (1984)
	Fuel moisture index by Sharples	RH, T	FMI	Sharples et al. (2009):
	McArthur's forest fire danger index	RH, T	$FM_{McArthur}$	McArthur (1967); Viney (1991)
	Semi-mechanistic approach by Resco de Dios*	VPD	FM_D	Resco de Dios et al. (2015)
	McArthur's forest fire danger index MK5	RH, T	FM_{MK5}	Noble et al. (1980)
Alternative modeling approaches	Empirical model based on RH*	RH, T	EMP_{RH}	Custom model
	Empirical model based on VPD*	VPD	EMP_D	Custom model
Linear mixed models	Linear mixed model based on RH	RH, veg	LMM_{RH}	Faraway (2016), West et al. (2014)
	Linear mixed model based on VPD	VPD, veg	LMM_{VPD}	Faraway (2016), West et al. (2014)
Non-linear models	Generalized additive model using Gibbs index	Gibbs index,	GAM_G	Hastie and Tibshirani (1986)
	Generalized additive model using VPD	VPD	GAM_{VPD}	Hastie and Tibshirani (1986)
	Support Vector Machines	RH, T, VPD, veg	SVM_{veg}	Cortes and Vapnik (1995)
	Random Forest	RH, T, VPD, veg	RF_{veg}	Breiman (2001)

$$FM_{Wagner,d} = 0.942\,RH^{0.679} + 0.000499e^{0.1\,RH} + 0.18\,(21.1 - \mathrm{T})\left(1 - e^{-0.115\,\mathrm{RH}}\right)$$
$$FM_{Wagner,w} = 0.618\,RH^{0.753} + 0.00049954 + 0.18\,(21.1 - \mathrm{T})\left(1 - e^{-0.115\,\mathrm{RH}}\right) \tag{2}$$

Because here we could not know the phase, we fitted both models (d and w) separately.

The equilibrium fuel moisture model of Nelson (1984):

$$FM_{Nelson} = a + b\ ln\left(\frac{-R\ T}{M\ ln\left(\frac{RH}{100}\right)}\right) \tag{3}$$

where a and b are fitting parameters (calibrated using linear least-squares fitting), and R and M are the universal gas constant and the molar mass of water, respectively.

The fuel moisture index (FMI) by Sharples et al. (2009):

$$FMI = a - b(T - RH) \tag{4}$$

where c and d are model coefficients (calibrated using linear least-squares fitting). It is important to not that FMI is not a fuel moisture model as such, but an index providing an equivalent scale for dead fuel moisture content.

Fuel moisture for the McArthur's forest fire danger index (McArthur, 1967) using Viney's parameterization (Viney, 1991):

$$FM_{McArthur} = 5.658 + 0.04651\ RH + 0.0003151\left(\frac{RH}{T}\right) - 0.1854\ T^{0.77} \tag{5}$$

The semi-mechanistic approach (FM_D) by Resco de Dios et al. (2015):

$$FM_D = FM_0 + FM_1\ e^{-mD} \tag{6}$$

where D is vapor pressure deficit (kPa), FM_0 is the minimum FM in the dataset (a measured value), FM_0+FM_1 indicate the maximum fuel moisture and m indicates the rate of FM decay with D. FM_1 and m were obtained through non-linear squares fitting.

The McArthur's forest fire danger index using MK5 parameterization (Noble et al., 1980):

$$FM_{MK5} = \frac{97.7 + 4.06\ RH}{T + 6} - 0.00854\ RH \tag{7}$$

2.3.2. Alternative modeling approaches

We have also developed custom models based on specific parameterizations and grouping strategies using dummy variables (categorical variables acting as grouping factor in a model) and model splitting accounting for vegetation types, i.e., fitting separate models per vegetation type. We built two empirical models based on linear regression. The first model (EMP_{RH}, Eq. (8)) is based on RH and temperature and the second (EMP_D, Eq. (9)) is on vapor pressure deficit (D):

$$EMP_{RH} = a + b\ T + c\ RH \tag{8}$$

$$EMP_D = a + b\ \log(D) \tag{9}$$

where a, b and c are the parameters to be calibrated.

We considered the effect of vegetation classes in FM predictions (Bonan, 1996), namely forest (deciduous, needleleaf evergreen and mixed forests), shrubland (deciduous, evergreen and open shrubland), grassland and woodland. We reworked all models susceptible of being calibrated (FM_{Nelson}, FMI, FM_D, EMP_{RH} and EMP_D) including the vegetation type as dummy variable (*_veg). The values of the calibration coefficients are available in Table A2.

2.3.3. Linear mixed models

A final set of models was calibrated using linear mixed models (LMMs). LMMs are particularly suitable when repeated measurements of a given variable are taken at one location or to account for possible differences between experiments (Breslow and Clayton, 1993). Experiment reference and location were considered as random factors, and only random effects associated with the intercept were evaluated. Because some sites encompass several studies, we did not consider nested random factors. We used either RH (LMM_{RH}) or D (LMM_D). We followed the guidelines of West et al. (2014) and Faraway (2016) to perform LMM analyses. We performed $\chi 2$-tests, F-tests, and the Kenward–Roger method (described in Faraway et al., 2016) to evaluate the significance of fixed-effect parameters. LMMs were calibrated and evaluated using the *lme4* (Bates et al., 2015), *lmerTest* (Kuznetsova et al., 2017) and *pbkrtest* (Halekoh and Højsgaard, 2014) R package packages (R Core Team, 2023). We also compared models by means of likelihood ratio tests (LRT) via anova (with ML and REML estimations), as well as the *exactRLRT* function from the *RLRsim* package (Scheipl et al., 2008), which uses bootstrap simulations to calculate exact LRT (Faraway, 2016).

2.3.4. Generalized additive models and machine learning approaches

Following the recommendations by Masinda et al. (2021) and Lee et al. (2020), we investigated the predictive ability of more complex modeling algorithms enabling non-linear responses in the relationships between FM, RH, T and VDP. We tested Generalized Additive Models with splines (GAM; Hastie and Tibshirani, 1986), Random Forests (RF; Breiman, 2001) and Support Vector Machines (SVM; Cortes and Vapnik, 1995).

We fitted two univariate GAM models using VPD (GAM_D) and the Gibbs index (GAM_G), separately. The smoothing parameter was optimized using a 10-fold leave-one-out cross-validation and 5 repetitions with the calibration subset. In the case of RF and SVM, we leaned towards multivariate models, also introducing the vegetation class as covariate (RF_{veg} and SVM_{veg}). RF was optimized in terms of the number of trees and number of variables at each split. With SVM, we sought to minimize the effect of outliers or highly influential observations on the regression equations (Kuhn and Johnson, 2013). After an initial evaluation, we discarded SVM with polynomial and radial kernel functions because they showed some artifacts in the prediction, hence we focused solely on the linear function approach. For SVM linear, we assessed different values of the cost hyperparameter (the single one involved in the linear kernel function) and model formulations and here we report only the results from the best combination.

3. Results

3.1. Links between FM, weather and vegetation type

FM showed a clear association with RH, T and D. As expected, FM increased with RH and decreased with T, D, logD (Pearson's $R = 0.52$, $R = -0.49$ and -0.56, respectively; Fig. 2). The strongest association was found with RH and log D, following a quasilinear profile. This linear

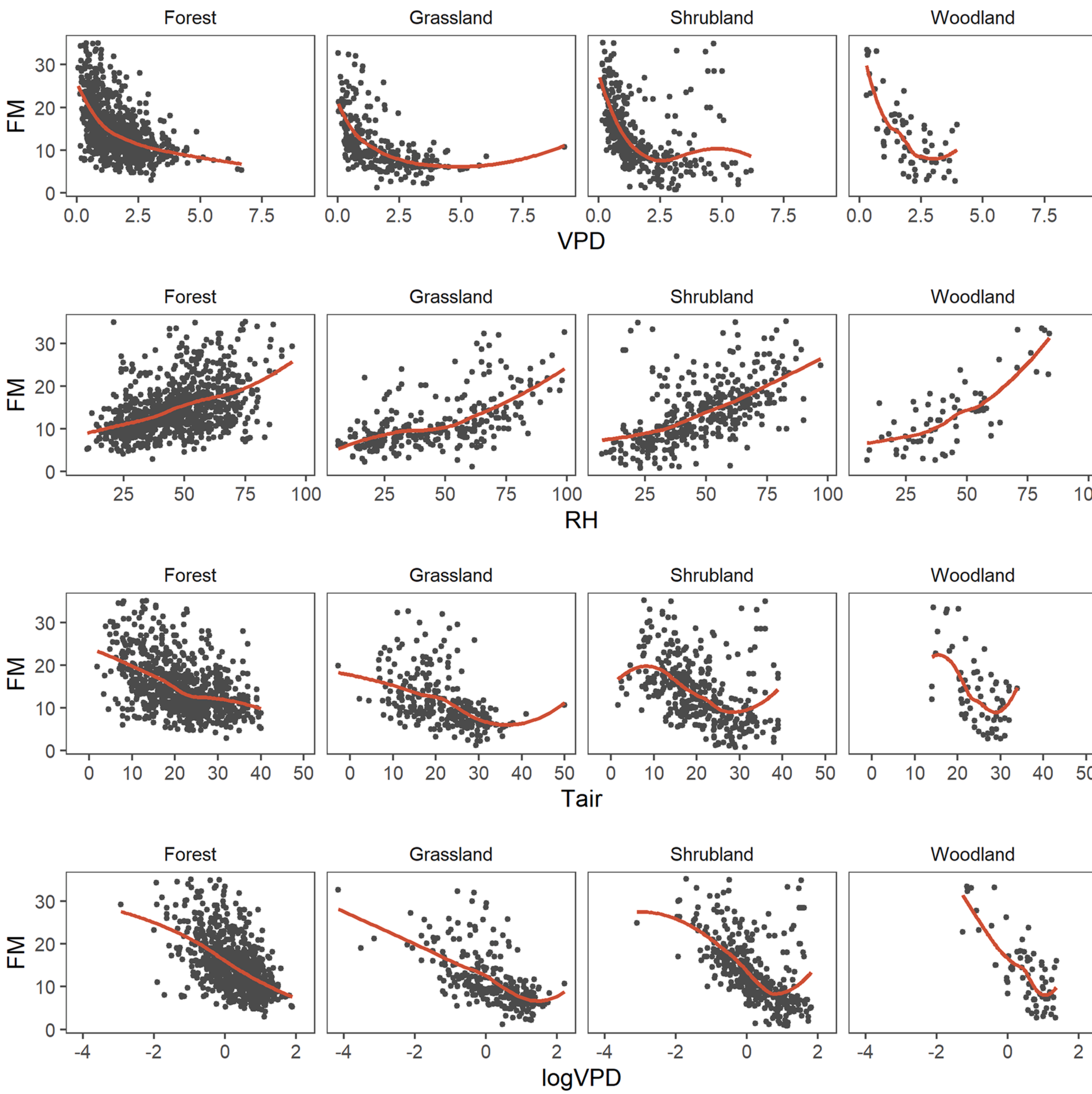

Fig. 2. Relationship between FM and the explanatory variables per vegetation type. The red line shows the LOESS smoothed profiles.

pattern was consistently observed across vegetation types. However, the marginal distribution of FM per vegetation type suggested significantly lower ($p < 0.05$) moisture content in grassland communities, with the remaining woody vegetation types displaying similar FM percent content. Median FM was approximately 5 % lower in grassland communities (FM ≈ 14 %), compared to forest, shrubland or woodland vegetation types (FM ≈ 9.5 %).

3.2. Model performance

Predictions' accuracy was moderate among the candidate models when considering the full range of FM with R^2 and MAE ranging between 0.24–0.44 and 3.85–6.05, respectively. Noticeably, performance dropped considerably when focusing on FM below 10 %, with the best model standing at an R^2 of 0.16.

Among the current approaches, empirical models (EMP_{RH} and EMP_D) showed the best performance on testing data (Fig. 3). The linear mixed model based on RH (LMM_{RH}; MAE = 3.8, MBE = -0.7, R^2 = 0.43) and the empirical models based on RH (EMP_{RH_veg}; MAE = 4.0, MBE = -0.3, R^2 = 0.41) performed slightly better than the recalibrations of FMI ($FMI_{\_veg}$; MAE = 4.0, MBE = -0.3, R^2 = 0.40) and FM_D (FM_{D_veg}; MAE = 4.1, MBE = -0.2, R^2 = 0.40). Most models tend to underestimate FM (slope > 1 and negative MBE) when considering the entire range of moisture content (from 4 to 35 %). Machine learning (RF and SVM) approaches and LMM, all of them including the effect of vegetation as a dummy variable, provided small improvements relative to traditional

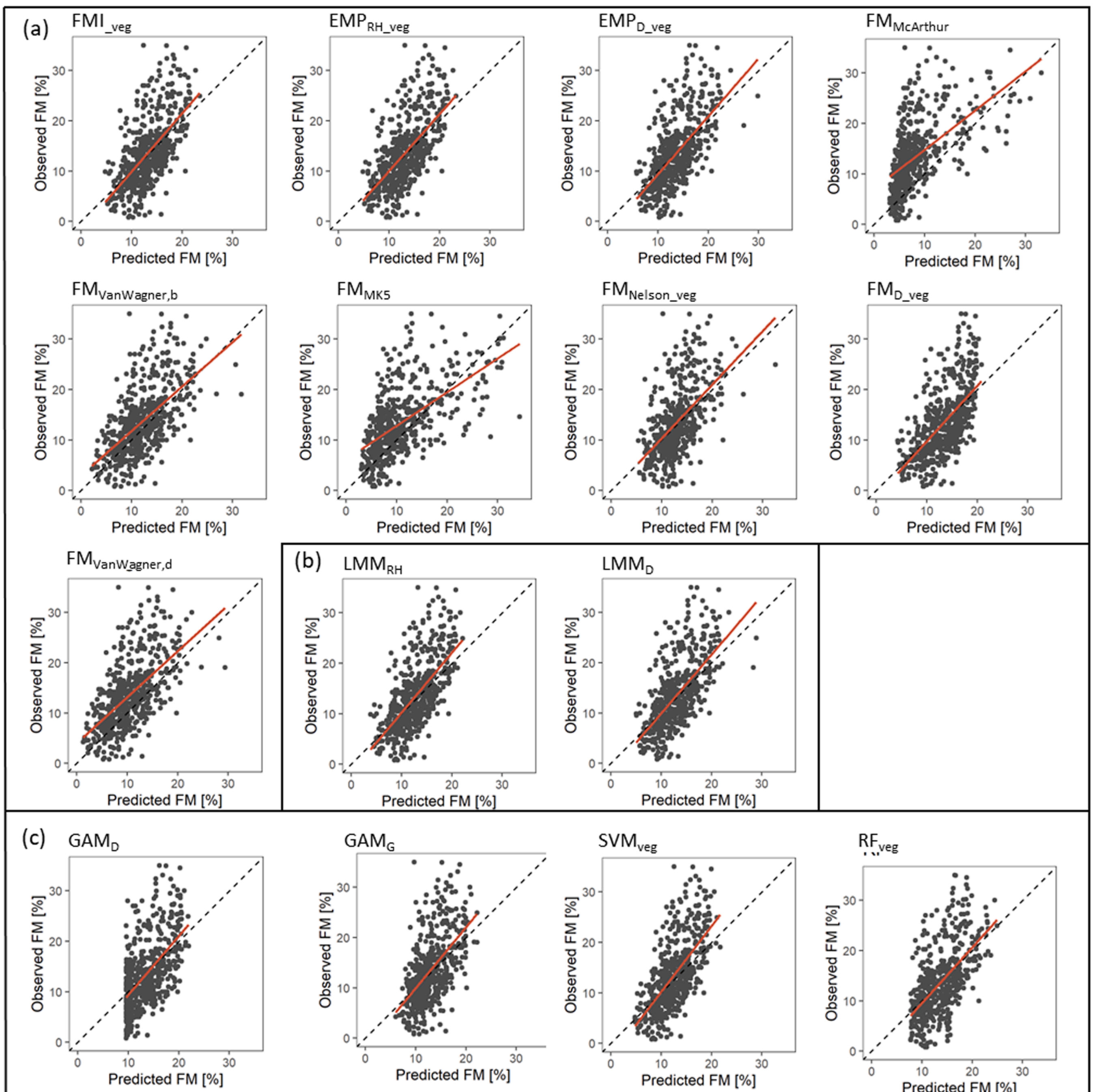

Fig. 3. Summary of the prediction performance from the validation sample. (a) current approaches; (b) linear mixed models; (c) machine learning models and GAM. The dashed line displays the axis of perfect prediction while the red solid line displays the linear relationship between predicted and observed values.

approaches. SVM_{veg} was the best alternative in global FM models (MAE = 3.89; MBE = -0.94; R^2 = 0.44). GAM models attained mid-tier performances. GAM_D was affected by some apparent outliers and showed an artifact in the predictions, saturating at 10 % FM (see Fig. A3). The GAM_G model did not show the prediction artifact and reached similar performance (MAE = 4.21; MBE = -0.94; R^2 = 0.33) than the analogous Nelson model (MAE = 4.25; MBE = -0.47; R^2 = 0.31), but with higher intercept and MBE. Hence, Nelson's models would be preferable since they are simpler.

Model performance substantially dropped when assessing the capability for predicting FM below the 10 % threshold (Fig. 4). LMM_{RH} and SVM_{veg} were the best alternative to model low FM, though still with poor performance (R^2 = 0.16;0.14, respectively). FM_{MK5} reported the lowest MAE (2.36), and it was not biased in its predictions (MBE = 0.4), but it showed high overall uncertainty (R^2 = 0.11). For FM<10 %, models based on VPD such as the empirical model and FM_D ranked among the highest in terms of R^2. It is worth noting that RH-based models were often more suitable to model FM, but when focusing on low FM, those considering vapor pressure deficit (e.g., EMP_{D_veg}, FM_{D_veg}) offered better predictions. In turn, models tend to overestimate (positive MBE) when assessing FM<10 % (Figs. 4, A5, Tables 1, 2 and Table A1).

Consideration of vegetation type contributed to improving performance in all modeling approaches ($*_{\_veg}$). Likewise, the ML, GAM and LMM models, which intrinsically accounted for vegetation type, consistently outperformed the other approaches by a narrow margin.

4. Discussion

In this paper we provide a comprehensive evaluation of current alternatives in forecasting the moisture content of dead fine fuel. An extensive global database compiling records from multiple studies, regions, biomes, climates, and vegetation types has been used to determine which modeling approach is best and to what extent moisture content can be predicted. Multiple approaches are available, with a large number of indexes and algorithms. Here, we showcase the main indices based on temperature, relative humidity or vapor pressure deficit, while investigating different improvement alternatives as well as the most widespread modeling frameworks.

4.1. Model selection

The link between relative humidity and FM is stronger when modeling the entire range of FM, but predictions under low FM conditions (FM<10 %) were more reliable (though still weak) when involving VPD. Recommending a single model for daily predictions of FM requires a suitable model for the whole range of FM as well as for low conditions. In this sense, the version of FM_D that incorporates different vegetation types (FM_{D_veg}) offers a good balance between performance and simplicity. FM_{D_veg} was the only model amongst the top best performing models for both, the entire dataset and FM<10 %, when the R^2 between observed and predicted is chosen as criteria to select the best performing model. Hence, we recommend FM_{D_veg} for a generic estimation of FM across the full data range, including when FM<10 %. Additionally, FM_{MK5} showed very low MAE when FM<10 %, indicating its suitability for predictions under low FM. The performance of the models presented in our work is close to that of previous efforts with similar approaches. In our analyses, the reformulated version (FM_{D_veg}: MAE = 4.06, R^2 = 0.40) of the Resco de Dios et al. (2015) FM index shows better performance than its original counterpart ($FM_{D:}$ MAE = 4.27, R^2 = 0.35). The performance metrics have slightly dropped compared to Resco de Dios et al. (2015), especially in the models whose target FM is less than 10 % (FM_{D_veg}: MAE = 4.23, R^2 = 0.11; FMD: MAE = 1.77, R^2 = 0.19). But it should be noted that the BONFIRE database covers a wider range of geographical and bioclimatic environments around the world, so a

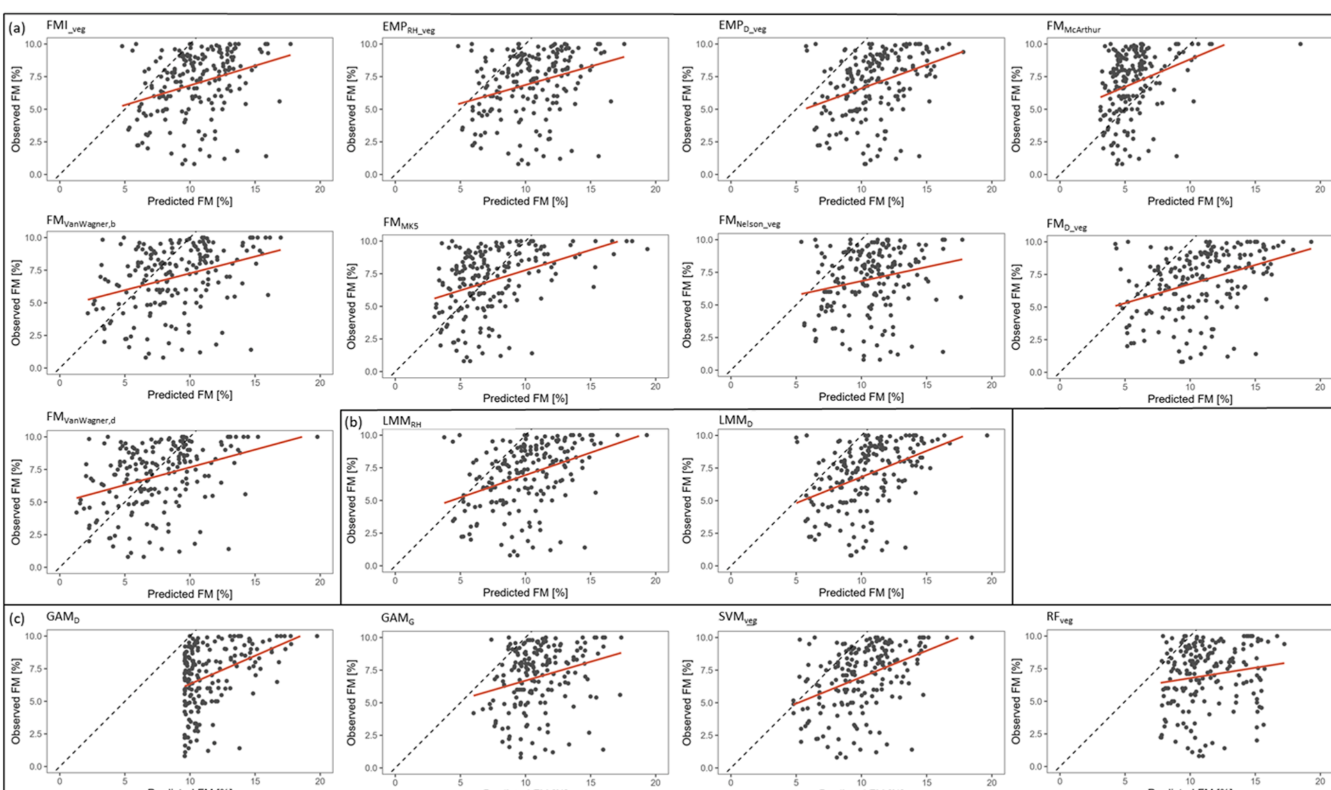

Fig. 4. Summary of the prediction performance from the validation sample for FM below 10 %. (a) current approaches; (b) linear mixed models; (c) machine learning models and GAM. The dashed line displays the axis of perfect prediction while the red solid line displays the linear relationship between predicted and observed values.

Table 2
Summary of model performance from the validation sample. MAE: mean absolute error; RMSE: root mean square error; β_0, β_1 and R^2 indicate the intercept, slope and square R of the regression line between observed-predicted.

Full range of moisture content (4–35 %)							FM < 10 %						
Model	MAE	MBE	RMSE	β_0	β_1	R^2	Model	MAE	MBE	RMSE	β_0	β_1	R^2
SVM_{veg}	3.89	-0.94	5.26	-3.02	1.32	0.44	LMM_D	3.62	3.45	4.33	2.82	0.39	0.16
LMM_{RH}	3.85	-0.72	5.17	-1.81	1.2	0.43	SVM_{veg}	3.25	3.03	4.00	3.06	0.38	0.14
EMP_{RH_veg}	3.96	-0.31	5.24	-1.98	1.17	0.41	EMP_{D_veg}	4.23	4.10	4.91	3.01	0.35	0.12
$FMI_{\_veg}$	3.97	-0.36	5.28	-1.78	1.16	0.40	FM_{MK5}	2.36	0.36	2.97	4.73	0.29	0.11
FM_{D_veg}	4.06	-0.21	5.25	-1.82	1.13	0.40	FM_{D_veg}	4.23	3.43	4.85	2.65	0.38	0.11
EMP_{D_veg}	4.07	0.08	5.25	-2.4	1.17	0.40	GAM_D	4.50	4.50	5.16	2.36	0.39	0.11
RF_{veg}	4.11	0.08	5.41	-1.72	1.12	0.36	EMP_{RH_veg}	3.78	3.58	4.60	3.93	0.28	0.09
$FM_{vanWagner,d}$	4.19	-1.55	5.59	2.83	0.89	0.37	$FM_{vanWagner,a}$	2.45	0.37	3.15	5.12	0.23	0.08
GAM_G	4.21	-0.54	5.61	-2.40	1.23	0.33	$FMI_{\_veg}$	3.76	3.55	4.60	4.10	0.26	0.08
FM_{Simard}	5.90	-5.32	7.7	4.48	1.1	0.32	$FM_{McArthur}$	2.37	-1.41	2.81	4.54	0.42	0.07
FM_{Nelson_veg}	4.20	-0.47	5.64	-0.04	1.04	0.31	FM_{Simard}	2.36	-0.91	2.89	5.37	0.24	0.04
$FM_{McArthur}$	6.05	-4.98	7.89	8.18	0.62	0.29	GAM_G	4.02	3.97	4.85	4.45	0.22	0.03
FM_{MK5}	4.93	-2.17	7.98	8.92	0.4	0.24	RF_{veg}	4.35	4.30	5.28	5.56	0.11	0.01

closer approach to regional models could lead to better performance.

SVM_{veg} would be the preferred alternative for a global FM model. However, improvements in performance compared with very simple models like the recalibration of FMI (FMI_{veg}), a regression against temperature and RH (EMP_{RH_veg}) or FMD (FM_{D_veg}) were minor in terms of MAE (0.1-0.2 %) and of R^2 (<0.04). Machine learning and linear mixed models performed slightly better, but the need for optimization (e.g., SVM hyperparameters) and complexity of their interpretation (LMM) hinder their usefulness. In this sense, the FM_{D_veg} seems a suitable approach, attaining a good prediction capability overall ($R^2 = 0.40$, 0.12 when FM<10 %).

A commonality across all models was an overall limited predictive capacity towards the drier end (<10 % FM). This is a very important limitation as the response of rate of spread to fuel dryness is exponential (Rothermel, 1972). Consequently, even small FM changes of 1 % can have substantial impacts. Here we only considered meteorological drivers but additional factors alter FM. Differences in fuel bed depth could alter the relationship between FM and meteorological drivers as deep fuel beds will be more resistant to drying (Matthews, 2014; Pook and Gill, 1993). Soil moisture has sometimes been documented to affect FM (Zhao et al., 2022). These factors can be incorporated within more realistic fuel moisture models, but they require more parameters than the ones available for the sites within our dataset (Matthews, 2006). There are also species differences in anatomical attributes that alter water relations, as will be discussed in the next section. Predicting FM at the lower end should thus be at the forefront of our research efforts. But selecting a model for the drier end is more difficult. Based upon MAE, either FM_{Simard} or FM_{MK5} would be preferable as they had the lowest MAE (2.4 %). However, these models performed very poorly when using the global dataset and FM_{Simard} also showed amongst the lowest R^2 (0.04). Although we have previously recommended FM_{D_veg} due to its relatively high R^2, we must note that its MAE in the lowest FM range was 4.2 %, which is amongst the highest for all models.

One of the potential reasons underlying poor model fit lies in the limitations of using a global dataset where different sampling and measurement protocols have been used. These include different oven-drying temperatures, including the use of temperatures <105°C that have been shown to underestimate FM (Matthews, 2010), differences in the timing of sample collection as well as in topographic position and canopy cover that affect the exposure to solar radiation. Wind speed is an additional important aspect that was not considered in this study and there could also be some “contamination” by dew, recent rainfall or duff moisture (Viney 1991).

Models with a higher degree of computation intensity, such as GAM fitting or machine learning, have been gaining attention in recent years (Matthews, 2014). However, these models did not solve the issue of poor model performance under low FM. Considering the limited gains in model fitting, and the increasing complication associated with predictions and computational costs, we do not recommend these techniques for FM modeling. Finally, we acknowledge that ML approaches may have not been fairly tested here because of the few variables involved. ML approaches have the potential to integrate a wide range of response variables and may be more useful in developing gridded estimates of dead fuel moisture content. Subsequent work should address this possibility. The use of a reduced set of predictors (temperature, relative humidity and VPD) may hinder their capacity to model FM.

Vapor pressure deficit has been gaining traction as an overall indicator of fire activity globally (e.g., Clarke et al., 2022). Our results provide an additional basis to these results as we have shown how FM_D, a VPD-based fuel moisture model, was amongst the best models to use across the entire FM range. Ignitions under high VPD will be more likely to spread and will spread faster due to fuel drying and, additionally, spot fires may consequently increase under high VPD (Nolan et al., 2016; Slijepcevic et al., 2015).

4.2. Effects of vegetation

We observed significant differences in dead fuel moisture content between grasslands and the other vegetation types. This is likely showing that dead fuel moisture in grasslands reflects cured grass while dead fuel moisture in woody vegetation reflects dead leaves and twigs, either in the litter or in an elevated position (Anderson, 1990). Differences in litter accumulation rate across vegetation types, leading to differences in fuel bed depth, may have also contributed to the response (although one hour moisture is often assessed from material from the top 1-2 cm). In other words, differences in fuel traits (particle size, surface area to volume ratio, fuel bed depth and compactness) are affecting the rate of water loss. Additionally, differences in radiation transfer and aerodynamic properties between grassy and woody canopies likely led to different meteorological conditions at the surface, where dead fuels are lying, even if weather measurements were all taken at the same height (typically 1.5–2 m).

These results highlight the importance of assessing FM in grasslands and woodlands separately, the former often depicting lower moisture content. Grasslands are more directly and thoroughly exposed to solar radiation and wind speed, and they may also comprise finer materials (with a faster response). These diverging FM responses between grasslands and woody ecosystems may be one of the factors contributing to differences in fire activity between grassy and litter fuels (Boer et al., 2021). All models considering the effect of vegetation, either directly embedding it as a covariate (e.g., SVM_{veg}) or splitting models across vegetation types (e.g., FM_{D_veg}, $FMI_{\_veg}$) outperformed global approaches (Table A1).

Further work would be required to expand and complete the findings from this work. For instance, additional covariates to incorporate topographic effects or gridded datasets to replace invalid observation data (e.g., wind observations). Moreover, most of the methods used in this paper are empirical, so their parameters must be tested using regional or local samples and further evaluation is required in those regions not comprised in our database.

CRediT authorship contribution statement

Marcos Rodrigues: Conceptualization, Writing – original draft. **Víctor Resco de Dios:** Conceptualization, Formal analysis, Writing – original draft. **Ângelo Sil:** Investigation, Data curation. **Àngel Cunill Camprubí:** Formal analysis. **Paulo M. Fernandes:** Conceptualization, Investigation, Data curation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2023.109868.

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