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How well do meteorological drought indices predict live fuel moisture content (LFMC)? An assessment for wildfire research and operations in Mediterranean ecosystems

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ABSTRACT

Live Fuel Moisture Content (LFMC) is a critical variable affecting fire ignition, behavior and severity in many ecosystems. Although the use of meteorological drought indices as proxies for LFMC is a straightforward and widespread approach, it is largely unknown whether it can provide reliable estimates of LFMC, either for local or spatial applications. We address this issue by evaluating the capacity of drought indices to predict LFMC quantitative variations and critical values. LFMC observations used for reference were measured on six different Mediterranean shrub species for 15 years in 20 different sites in Southern France. Six drought indices were evaluated: the Duff Moisture Code (DMC) and Drought Code (DC) of the Canadian Forest Fire Weather Index System, the Keetch-Byram Drought Index (KBDI), the Nesterov Index (NI) and the Relative Water Content (RWC) of the soil derived from a forest water balance model for low (80 mm) and high (160 mm) field capacities. The species were classified in two groups according to their seasonal variability: high and low responding species. We found large differences in the capacity of drought indices to predict LFMC, with indices that simulate long-term drought dynamics (DC, RWC and KBDI) generally performing better than others (NI and DMC). Once calibrated at stand scale, drought indices showed a good potential for predicting LFMC of high responding species, although large variations between sites were observed. In contrast, spatial predictability was limited with a RMSE and R^2 on the order of 20% and 0.3, respectively (for high responding species). Our results suggest that drought indices should therefore be used with caution for spatial applications in wildfire research and operational fire management. Because they can explicitly consider environmental (soil, climate) and biological (species traits related to dehydration) factors, mechanistic indices have a great potential to improve LFMC predictions.

1. Introduction

Live Fuel Moisture Content (LFMC), the mass of water contained within living vegetation in relation to the dry mass, is a critical variable affecting fire interactions with fuel (Chandler et al., 1983). In a number of fuel types present in the Mediterranean biomes, fire spreads through living plants and LFMC has been identified as a determinant factor of fire ignition, behavior and severity in these ecosystems (Dennison and Moritz, 2009; Chuvieco et al., 2009; Nolan et al., 2016; Ruffault et al., 2018). Recent experimentsconfirm this importance in laboratory, showing that there is no difference between the effect of LFMC and dead fuel moisture content (DFMC) on the fire rate of spread (Marino et al., 2012; Rossa and Fernandes, 2017). Accordingly, LFMC is incorporated in some widely-used fire behavior models (Jolly, 2007; Andrews et al., 2008) and is also monitored during the fire season by some fire agencies (such as the French Forest Service) to adjust fire hazard levels for fire suppression planning and resource allocation (Weise et al., 1998; Martin-StPaul et al., 2018; Yebra et al., 2018). The response of LFMC to increasing drought conditions is also one of the key factors of future fire regime in a context of climate changes (Abatzoglou and Williams, 2016).

Despite a growing need for reliable LFMC estimations in wildfire research and management, obtaining comprehensive and reliable time series of LFMC remains problematic. One main reason for this difficulty is that the dynamics of moisture in live fuels remains poorly understood and predicted, in particular when compared to DFMC. Indeed, DFMC is essentially determined by the short-term weather conditions (Resco de Dios et al., 2015), whereas LMFC is driven by dynamic and nonlinear interactions between weather conditions, soil properties and plant physiological processes, the latter including plant response to drought

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and dry mass changes associated with phenology (Jolly et al., 2014; Fares et al., 2017; Jolly and Johnson, 2018). As a consequence, field measurement remains a reference method to provide reliable LFMC point estimations. This method, however, requires the collection of multiple vegetation samples that must be weighed fresh, oven-dried during several hours and weighed dry (Countryman and Dean, 1979). Besides, its extension to landscape or regional scales is not feasible, particularly in areas where climatic and/or land cover heterogeneity are important such as the Mediterranean. Alternatively, remotely sensed data provide LFMC estimations over large areas (Dennison et al., 2003; Chuvieco et al., 2004a,b; Peterson et al., 2008; Caccamo et al., 2012; Jurdao et al., 2012; Fan et al., 2018; Yebra et al., 2018), but this method require extensive calibration and validation (see a review in Yebra et al., 2018) and its application, which is limited by the availability of spectral indices, is restricted to LFMC monitoring and to mid-term historical reconstructions.

As a result of these limitations, the use of empirical relationships between meteorological drought indices and LFMC remains a straightforward and widely-used approach. These indices are based on daily weather data (air temperature, air humidity, wind speed and precipitation) that can be easily derived from weather datasets, and therefore provide historical or projected time series of LFMC predictions at locations of interest. The most popular are the Drought Code (DC) and Duff Moisture Code (DMC) of the Fire weather index (Van Wagner, 1987) and the Keetch-Byram Drought Index (KBDI, Keetch and Byram, 1968). While none of these drought indices were initially designed to model foliage moisture, they have often been used to predict LFMC in Mediterranean ecosystems (Viegas et al., 2001; Castro et al., 2003; Dimitrakopoulos and Bemmerzouk, 2003; Pellizzaro et al., 2007). More generally, drought indices are also frequently related to various fire metrics, either by being explicitly mentioned as LFMC proxies (Ruffault and Mouillot, 2015, 2017) or used in a more indirect way, as indicators of fuel aridity or dryness as a whole (*e.g.* Thonicke et al., 2010; Pausas and Paula, 2012; Abatzoglou and Kolden, 2013; Gudmundsson et al., 2014; Ruffault et al., 2016; Littell et al., 2016).

To date, very little effort has been devoted to evaluating the genericity/generality of this approach. Yet, this question is all the more relevant that these relationships are applied for operational or research purposes in highly heterogeneous environments. One notable exception is the statistical model developed in Castro et al. (2003), that includes several climatic variables and drought indices which increase model spatial generality. This model, however, applies to a single species and was calibrated on a limited number of sites and years.

The recently published "Réseau hydrique" database (Duché et al., 2017) provides more than 20,000 multispecies and multisites LFMC measurements of several shrub species in Mediterranean France (Martin-StPaul et al., 2018). This dataset therefore offers a good opportunity to undertake a thorough evaluation of meteorological drought indices for LFMC estimation regarding both theoretical and operational purposes. In the present paper, we estimated daily values of several drought indices and compared them to LFMC measurements of a selection of species in different sites. The objectives of the study were (i) to evaluate the performance of some widespread meteorological drought indices for LFMC predictions in Mediterranean ecosystems, (ii) to discriminate the relative influence of site and species on these relationships and (iii) to suggest some improvements to improve LFMC predictions.

2. Material and methods

2.1. Background: description of drought indices

In this subsection, we describe the six drought indices that were evaluated against LFMC data in this study. All indices are based on daily temperature and precipitation and some of them also relied on additional variables, namely relative humidity and global radiation. They include carry-over effects over time, as they were designed to represent empirically the water dynamic in soil or duff reservoir.

The two first indices were the Duff Moisture Code (DMC) and the Drought Code (DC), which are both sub-components of the widespread Canadian Fire Weather Index. These indices are logarithmic functions of respectively duff and soil moisture, that differ in the quantity and depth of duff or soil layers considered (Van Wagner, 1987). The DMC was originally designed to estimate the moisture availability of a loosely-compacted-duff layer with a depth of 3 in. (76.2 mm). It combines a set of empirical functions that describe the dynamics of a single water reservoir that fills and empties according to daily rainfall, temperature, relative humidity and day length. The DC was initially developed to estimate the soil water content of deep and compacted duff (over 10 in. of soil). The DC differs from the DMC in the soil horizon considered -which is shallower in DMC- and in the more mechanistic description of the water balance, which includes a Thornthwaite-type evapotranspiration function (Turner, 1972).

The third index was the Keetch-Byram Drought Index (KBDI; Keetch and Byram, 1968). KBDI intends to describe moisture deficit in deep duff and upper soil layers. it was developed to measure the cumulative soil water deficit of forested ecosystems for a layer of 8 in. (202.3 mm) from daily temperature and precipitation. An interesting aspect of KBDI lies in the fact that it indirectly accounts for density of transpiring vegetation by weighting the daily moisture deficit by the annual rainfall of the location of interest.

The fourth index was the Nesterov index (NI, Nesterov, 1949). NI uses the mid-day and dew-point temperature, as well as the number of days since last rainfall heavier than 3 mm. Daily values are cumulated as long as no rainfall heavier than 3 mm happens. Values below 300 usually indicate days with minimal fire potential, while the fire potential is likely and very likely above 1000 and 10,000 respectively. NI is also used as a proxy of fuel aridity by some fire modules embedded in dynamic global vegetation models (*e.g.* SPITFIRE, Thonicke et al., 2010).

Finally, the last two indices were used to represent the Relative Water Content of the soil (RWC), *i.e.* the ratio of actual soil water content (S) over the water content at field capacity (FC). RWC was calculated by using the simplified bucket type water balance model with a limited storage capacity initially suggested by Linacre (1973). This model was applied and validated against soil water content measurements in southern France by Lavoir et al. (2011). The basic principle is to calculate the daily change in soil water content as the difference between rainfall input (minus deep drainage) and actual evapotranspiration (AET) outputs. Deep drainage occurs when soil water content exceeds FC. AET is a function of potential evapotranspiration (PET) using the following equation:

$$AET = \min\left[\beta\left(\frac{S}{FC}\right)^2, PET\right] \tag{1}$$

PET was calculated with the Priestley-Taylor formulae. β was set to 5.5 according to Lavoir et al. (2011). During summer drought, AET is therefore progressively downregulated as RWC declines, mimicking the stomatal control of transpiration.

Two different RWC indices were computed in this study, corresponding to high (180 mm; RWC_H) and low (90 mm; RWC_L) water content at field capacity. These values encompass the range of field capacities encountered in the study area (Ruffault et al., 2013).

2.2. LFMC data

We used the live fuel-moisture database of the French "*Reseau Hydrique*" (Duché et al., 2017) described in details in Martin-StPaul et al. (2018). This database consists of LFMC measurements that have been performed on shoots of various shrubs from different sites of the French Mediterranean area (Fig. 1) during the fire season (June to

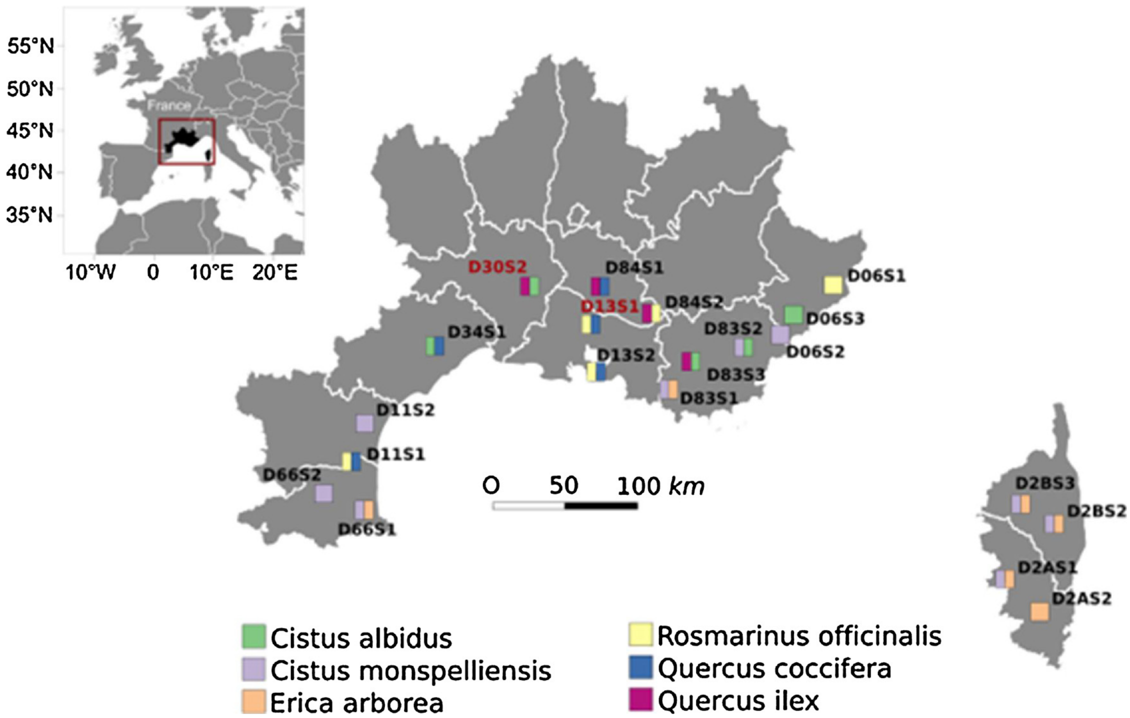

Fig. 1. Location and species chosen for the 20 studied sites in the administrative regions of Southern France. In each site, live fuel moisture content (LFMC) measurements were carried out once or twice a week during the fire season (from June to September depending on fire danger rating) over 2000-2013. Further information about sampling sites can be found in Tab. A1 and in Martin-StPaul et al. (2018). The two sites marked in red were used to illustrate the seasonal variations in LFMC (time series in Fig. 2) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

September) since 1996. LFMC is expressed in percentage of dry mass as follows:

$$LFMC = 100 \times \frac{Water \quad mass}{Dry \quad mass} \tag{2}$$

To facilitate interspecific comparisons of LFMC dynamics, the original dataset was restricted to 20 sites and 6 species, based on a selection criterion ensuring that each species was present on at least 4 different sites (Fig. 1). Each site*species combination consisted of between 219 and 279 measurements for the period from 2000 to 2013. A total of 8544 LFMC observations were compiled in the entire dataset. A summary of the principal features of selected sites can be found in Table A1. Preliminary analyses showed that the selected species had contrasted seasonal LFMC patterns in terms of seasonal variability (see Fig. A1, Table A2). According to these observations, species were classified in two groups: high responding species (*Cistus albidus*, *Cistus monspeliensis*, *Rosmarinus officinalis* and *Erica arborea*) and low responding species (*Quercus coccifera* and *Quercus ilex*), that respectively exhibit high and low seasonal variability.

2.3. Historical predictions of drought indices

Daily climatic data (daily temperature, rainfall, relative humidity and global radiation) for each site were derived from the French reanalysis SAFRAN computed on 8 × 8 km grid by Météo France (Vidal et al., 2010). Temperatures, precipitations and relative humidity were interpolated at site level using altitude-dependent methods described and validated over the region by Ruffault et al. (2014). Daily global radiations were interpolated at site level from the processing chain described in Kumar et al. (1997) and applied in Mediterranean France by Lempereur et al. (2016). Daily climatic data were used to compute, for each site, the historical values of drought indices for days when LFMC data were available.

2.4. Statistical analyses

2.4.1. Distribution analyses

The distributions of LFMC values and the different drought indices were compared to assess the aptitude of drought indices to predict LFMC. When the drought index distribution differs from the actual LFMC distribution, it implies that the balance between the decreases and increases in index values might be different from LFMC dynamics. To facilitate the comparison between drought indices and LFMC, time series data were previously rescaled. For the indices that decreased with drought intensity (RWC_H and RWC_L) and LFMC, the rescaled index was expressed as:

$$I^* = \frac{I - Q_{0.01}(I)}{Q_{0.99}(I) - Q_{0.01}(I)} \tag{3}$$

Where I is a given index (or LFMC), I^* is the rescaled index and $Q_\alpha(I)$ is the α th percentile of I. For the indices that increased with drought intensity (DC, KBDI, DMC, NI), the rescaled index was expressed as:

$$I^* = \frac{Q_{0.99}(I) - I}{Q_{0.99}(I) - Q_{0.01}(I)} \tag{4}$$

According to these transformations, 98% of the drought index samples and LFMC data range between 0 and 1 and all rescaled indices decrease as drought increases, as does LFMC.

2.4.2. Relationships between drought indices and LFMC

We refined the analysis with linear regression models to investigate the relationships between LFMC and drought indices over data grouped by species, groups of species (high or low responding species), site*-species combinations and altogether. Note here that the pool of study sites varied with species or species group (Fig. 1) and that linear regression models were performed on raw index and LFMC values (not rescaled). The root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) were used to assess the performance linear models to predict LFMC. In order to estimate the range of RMSE, MAE and R^2 within a group (all species, low responding species, high responding species and individual species), we used the following estimator for standard deviation, which is robust for small samples (Mosteller and Tukey, 1977):

$$sd = \frac{median(|A_i - median(A)|)}{0.6745} \quad (5)$$

Where A is the studied metric (RMSE, MAE or R^2) for each group and A_i the value of metric A for each sample within a group.

2.4.3. Evaluation of drought indices to assess LFMC thresholds

Evidence is accumulating that some thresholds of LFMC are associated with the occurrence of wildfires (Chuvieco et al., 2009; Dennison and Moritz, 2009; Nolan et al., 2016). In order to assess the capacity of drought indices to assess these critical flammability conditions, we used logistic regressions to model the probability of LFMC being lower than a given threshold. As a preliminary step, we examined the capacity of drought indices to predict various LFMC thresholds (ranging between 40 and 100%) for data grouped by species, species group and altogether. To limit the impact of very unbalanced datasets on the results of logistic models, those were not fitted for LFMC threshold that resulted in prevalence ratios > 95% or < 5%. It should be noted here that, since the distribution of LFMC values differed between species and/or groups of species, it resulted in different prediction ranges between groups. Then, to go into details about the performance of logistic models, we refined the analysis on a single LFMC threshold. We chose to focus here on the 79% threshold reported by Dennison and Moritz (2009). Other thresholds might have been chosen but the preliminary analyses described here above showed that the threshold value did not have much impact on the overall performance of logistic models (see also Section 3.3). As described in subsection 2.4.2, we grouped data per site*species combinations, species, species group and altogether. For each model, the goodness of fit was evaluated with the area under the ROC curve (AUC). The AUC expresses the ability of the model to predict the right probability. For reference, an AUC of 0.5 corresponds to the random model, whereas an AUC of 1 corresponds to the model with perfect predictions. For each drought index and LFMC threshold, we determine the probability threshold that minimizes the sum of omission and commission errors. The omission error (%) quantifies the occurrence of risk underestimation (*i.e.* frequency at which the true value of LFMC is below the threshold whereas the model predicts a value of LFMC greater than the threshold). The commission error (%) quantifies the occurrence of risk overestimation (*i.e.* the frequency at which the true value of LFMC is above the threshold whereas the model predicts a value of LFMC smaller than the threshold). Standard deviations for AUC, commission errors and omission errors for each group (all species, low responding species, high responding species and individual species) were determined in the same manner as for the estimators of linear regressions (Eq. (5)).

3. Results

3.1. Seasonal variations in LFMC and drought indices

Fig. 2 shows contrasting examples of rescaled LFMC and drought indices dynamics during the fire season for two site*year combinations. 'D30S2' was characterized by very dry conditions at the beginning of the 2006 fire season whereas 'D13S1' was rather wet with high values of LFMC at the beginning of the 2010 fire season due to mid-June precipitations (Fig. 2c and d). Overall, we observed that LFMC and rescaled drought indices decreased over time as long as no precipitation happened. Conversely, the sudden increase of LFMC and drought indices matched precipitation events. We should note here that the magnitude of changes was generally more important for high responding species than for low responding species (Figs. 2a and b, A1) as previously mentioned by Martin-StPaul et al. (2018).

Rescaled drought indices generally showed similar temporal dynamics (Fig. 2e and h) and were therefore correlated (Table A3). However, we observed two notable differences in the dynamics and responses of these indices to climate conditions (Fig. 2e–h). First, the rates of change of DMC and NI were higher than those of DC and KBDI during dry periods, which means that DMC and NI decreased more rapidly than DC and KBDI as long as no rainfall occurs. For instance, during the drier period of summer 2006 in site D30S2 (from the 15th of July to the 15th of August, Fig. 2e), the mean rates at which DMC and NI decrease over a day were respectively of 0.015 and 0.017 while DC and KBDI decreased at a much lower rate of 0.010 and 0.007 over the same period. This is consistent with the observations that DMC and NI were highly correlated (R = 0.83, spearman rank correlation, Table A3), but relatively less correlated with DC or KBDI (0.211 < R < 0.66, Table A3). Second, while RWC were respectively highly correlated to DC and DMC (Table A3), the dynamics of RWC were different from these two indices during the driest periods (Fig. 2e and h). This pattern can be explained by the progressive regulation of transpiration that dampens the rate of decrease in RWC whereas those of KBDI, DC, DMC and NI was fairly constant (*i.e.* linear variations). This non-linear response of RWC was coherently more pronounced when the available water content was set at its lowest value (90 mm, RWC_L, Fig. 2g and h in grey) since, in that case, dry soil conditions were reached earlier.

3.2. Distributions analysis

The pattern of LFMC distribution reflected the different responses of species to drought conditions (Fig. 3). Thus, the LFMC distribution of high responding species was positively skewed (Fig. 3b), which indicates that these species were more frequently dehydrated during the summer season, whereas the distribution of low responding species was fairly symmetrical (Fig. 3c). Similarly, we observed that drought indices also exhibited different distributions that were consistent with the expected response of each index to climate. In one hand the two RWC indices, whose rates of change decrease when drought increases, showed positively skewed distributions (Fig. 3d and e), which matched the LFMC distributions. On the other hand, KBDBI, DC, DMC and NI, whose rates of change were constant, showed either a negative skewness or an almost symmetrical distribution. More specifically, KBDI distribution was not skewed, but had a longer tail and was wider than the LFMC distribution of low responding species (lower kurtosis and larger coefficient of variation) (Fig. 3h). DMC, NI and to a lesser extent DC, exhibited a negatively-skewed distribution (Fig. 3f, g and i). This difference between RWC and the other indices was also illustrated in Fig. 2, in which RWC_H and RWC_L were most often low, whereas DMC and NI often exhibited high values, and DC and KBDI were often moderate. This suggests that the increase rate of DMC and NI (and in a lesser extent DC and KBDI) in response to rain events is excessive in comparison to their decrease rate.

3.3. Linear regression models

The RMSE of the linear models for both individual species and groups of species are shown on Fig. 4. On each subplot, the colored dots indicate the multi-site values and the black range (median ± sd) expresses the range of RMSE observed among sites (within a given group). The standard deviation of LFMC samples is also reported for reference. For brevity, we did not report results concerning NI as both correlations and distribution analyses indicated a poor predictive capability of LFMC from this index (Table 1, Fig. 3). Similarly, RWC_L that generally showed lower correlations with LFMC than RWC_H (Table 1) was discarded from the following analyses.

Overall, our results showed that the RMSE, R^2 and MAE (our measures of predictive performance) were almost similar for DC, KBDI and RWC_H (Figs. 4, A2 and A3). DMC also exhibited similar performance for

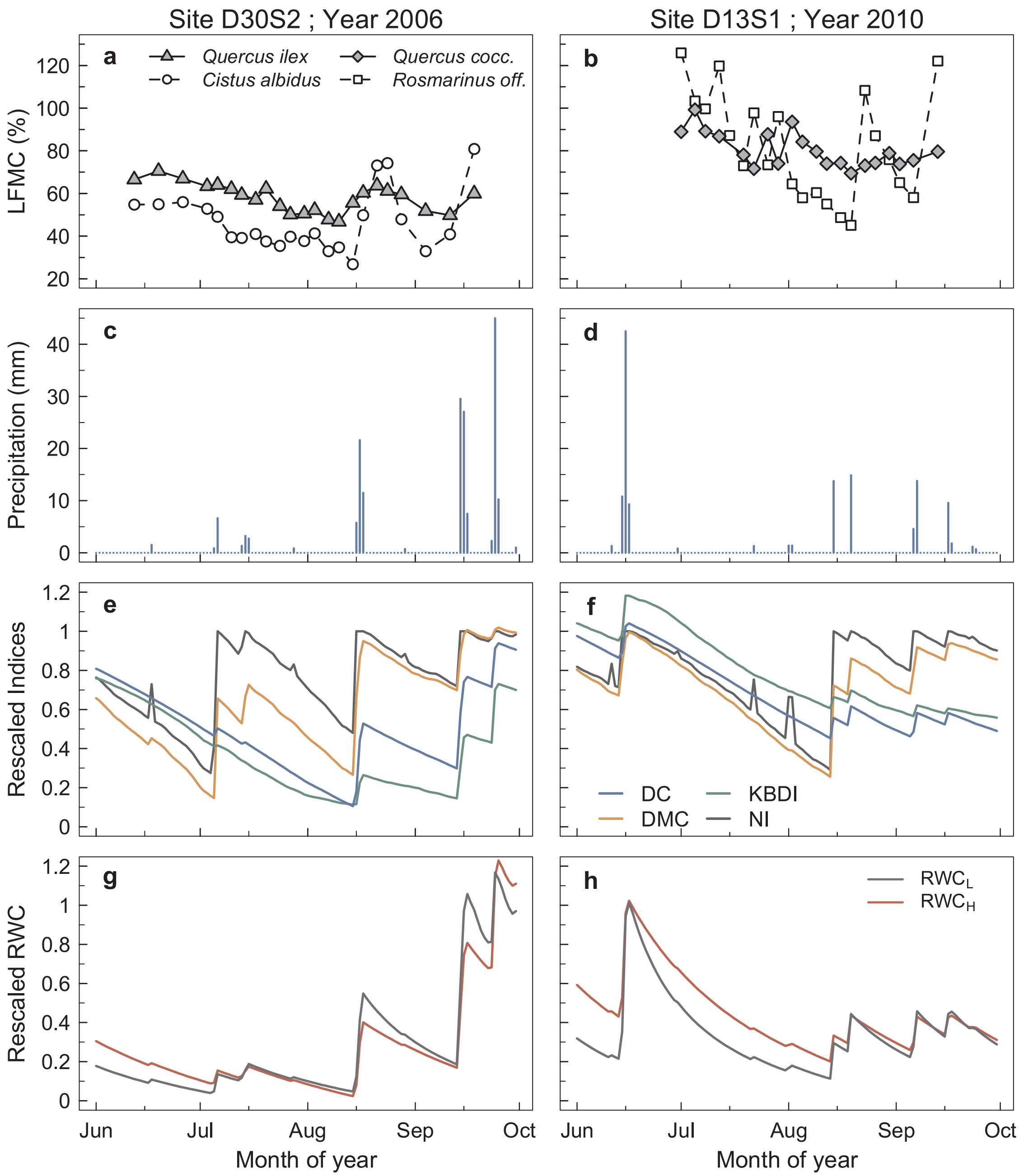

Fig. 2. Time series at two different sites for two climatically-contrasted years: a/b/ Live fuel moisture content (LFMC) measurements for two species c/d: Daily precipitations; e/f/ Four rescaled drought indices: Drought Code (DC), Keetch Byram Drought index (KBDI), Duff Moisture Code (DMC) and Nestorov Index (NI); g/h/ Soil Relative Water Content for low (RWC_L) and high (RWC_H) field capacities. For the sake of comparison, all drought indices were rescaled between 0 and 1 (see Section 2.4.1). Site location and description are indicated on the map in Fig. 1.

high responding species, but not for low responding species (R^2 from about 0.1 for DMC to 0.2 for the other indices, Fig. A2b). The predictive performance of the four indices was, however, very variable among species and within and between groups of species (high and low responding). Thus, the RMSE were about 12–13% for high responding species and 5–6% for low responding species whereas the corresponding standard deviations of LMFC samples were 23% and 8% respectively (Fig. 4b and c). This indicates that the residuals were roughly twice as large for high responding species than for low responding species although their coefficients of determination were slightly higher (see Fig. A3 for details).

When comparing the results on groups of species with each species individually, we observed a lower range of RMSE (Fig. 4d–i) and a higher Spearman rank correlation (Table 1) for individual species. This suggests a large contribution of species characteristics to the overall variance of LFMC samples (see Table A4 for all results per site*species combinations). However, the characteristics of the different sites was also significant, at least for the most variable species (*Cistus albidus*, *Cistus monspeliensis* and *Rosmarinus officinalis*), since the median of the RMSE of the models fitted on each site were systematically lower than those obtained on the multisite models (Fig. 4).

3.4. Modeling LFMC thresholds

We then evaluated the ability of drought indices to predict a given threshold of LFMC with logistic regressions. For high responding species, we observed that the LFMC threshold had only little influence on the predictive performance of drought indices, except for *Quercus ilex*

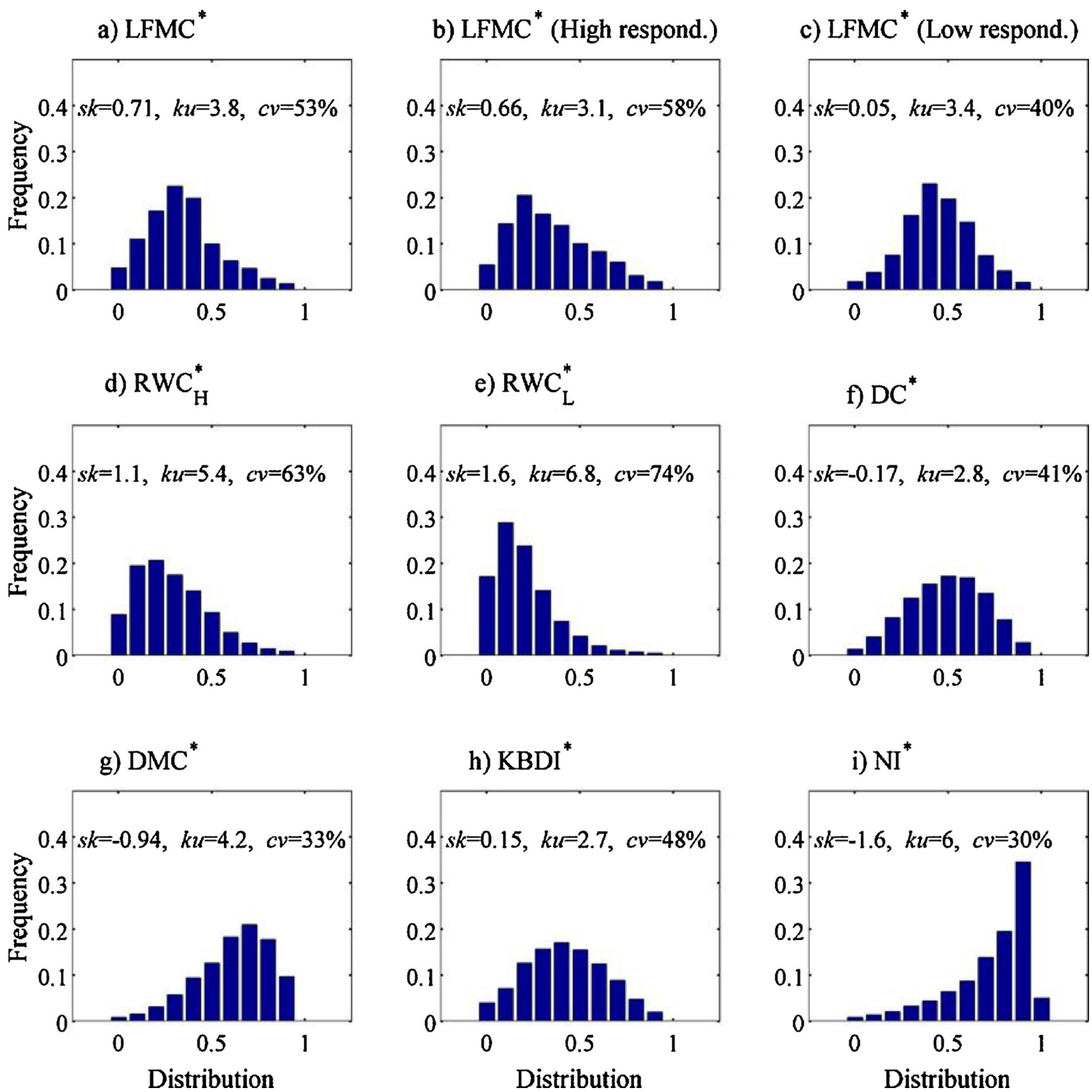

Fig. 3. Comparison of rescaled distributions between live Fuel moisture content (LFMC) (a/ All species; b/ High responding species; c/ Low responding species) and drought indices (d/ $RWC_{H;}$ e/ RWC_L; f/DC; g/DMC; h/ KBDI; i/ NI). The Skewness (*sk*), kurtosis (*ku*) and coefficient of variation (*cv*) are indicated for each distribution.

(Fig. A4). In the following, we focused on the results obtained for the 79% LFMC (Fig. 5). Except for DMC, we did not observe significant differences between the performance of the other three drought indices (KBDI, DC and RWC_H; Fig. 5). However, the variability among sites and species was very high, with some high AUC (over 0.95) for some site*species combinations and much lower values (below 0.7) on other combinations (see Table A5 for all results per site*species combination). More details regarding the performance of drought indices can be found in Figs. A5 and A6, that respectively shows omission and commission rates. The commissions (risk overestimation) occurred in 30–40 % of cases, whereas the omissions (risk underestimation) were less frequent, especially for high-responding specie (on the order of 25–30%). Both errors were strongly reduced when data were considered per site*species with omission errors between 9% and 30% (Table A5).

4. Discussion

There is considerable interest in providing reliable LFMC predictions for both the development of operational tools to assist fire risk protection and in numerous wildfire research fields, including our basic understanding of wildfire behavior or the issues of future fire activity under climate changes. Despite the fact that meteorological drought indices are widely used as a surrogate for fuel aridity, the evaluation of their predictive capacity of LFMC have, so far, received only limited attention. In this study, we found that the use of drought indices to predict LFMC can induce large errors when models were fitted on several sites and/or species. Some of these errors are due the limitations of drought indices but also from the variations in species functioning and environmental site conditions. We elaborate on these points in the following discussion. We also discuss the results of our study for operational and research applications and suggest directions for future research, based on the development of mechanistic indices.

4.1. LFMC dynamics are species-dependent

Our study provides further evidence that the dynamics of LFMC can be different from one species to another in Mediterranean ecosystems (Viegas et al., 2001; Pellizzaro et al., 2007), which can be explained by the physiological mechanisms involved in plant responses to drought. First, deep rooted species are known to rely on their underground water uptake (Rambal, 1984; Barbeta et al., 2015), leading to a "homeostatic" functioning (*i.e.* low seasonal variations). Accordingly, the two *Quercus* are deep rooted (> 4 m) and were reported to rely on underground

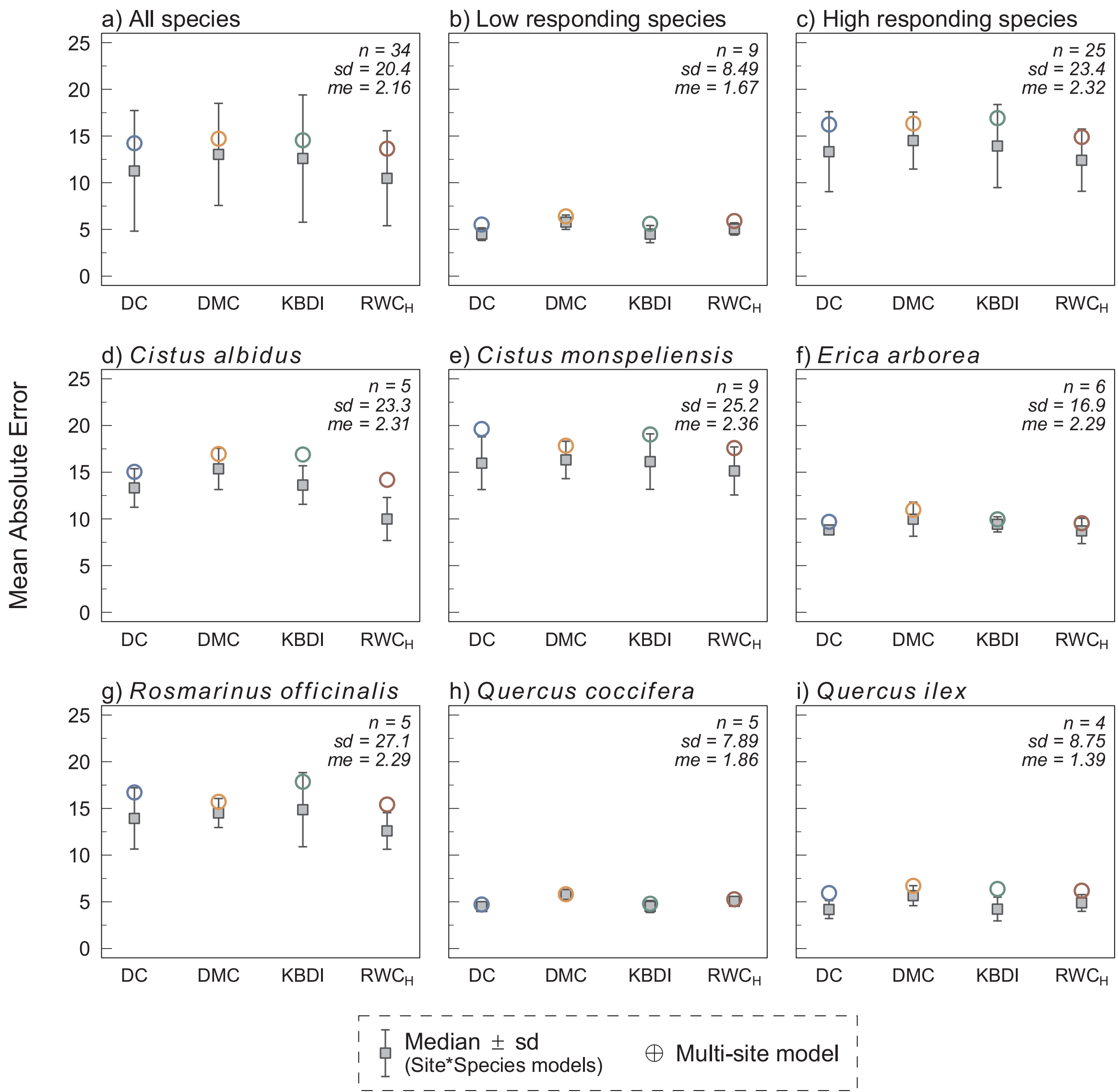

Fig. 4. Root mean square error (RMSE) of the linear models predicting live fuel moisture content (LFMC) from four drought indices (DC, DMC, KBDI and RWC_H). RMSE were computed for different group of species and individual studied species. In each case the coefficient computed on a *per-site* and *multi-site* basis are indicated. The number of sites is indicated at the top-right of each subpanel (*n*), as well as the standard deviation (*sd*) and measurement error (*me*) of the concerned LFMC sample for reference. The root mean square error (RMSE) and coefficient of determination (R^2) for the same linear models are available in Fig. A2 and A3, respectively.

water, whereas *Cistus* and *Rosmarinus* have a shallow root system (< 1.5 m) (Table A2). The case of *Erica arborea* is intermediate, with a root system reaching 2 m. Additionally, this species is often reported to behave as a shallow-rooted species (Ramírez et al., 2012). Second, high tissue elasticity in leaf (*i.e.* low leaf modulus of elasticity) corresponds to high magnitude of dehydration of living foliage during drought (Bartlett et al., 2012; Vilagrosa et al., 2014; Martin-StPaul et al., 2017), and thus to strong variations in LFMC with soil water content. Accordingly, *Cistus*, *Rosmarinus* and *Erica* have lower modula of elasticity than *Quercus* species (Table A2). Finally, other physiological processes, such as leaf shedding (Borghetti et al., 2004) and aging (Jolly et al., 2014), are likely to affect the relationship between soil water content and LFMC by respectively increasing the wood to leaf ratio or the dry matter content (Jolly et al., 2014). However, it is hard to conclude on this point unless measurements of leaf phenology are performed, which was beyond the scope of the present study.

It has been suggested that distinct, water-related, physiological traits could be associated to different types of post-fire regeneration (Vilagrosa et al., 2014). Seeders would be more prone to dehydration during drought than resprouters, causing in turn a distinct flammability (Keeley et al., 2011). Accordingly, we found that the three seeders species exhibit a pronounced LFMC dynamics whereas two resprouters (the two *Quercus*) had a low variability. *Erica arborea,* however, is a resprouter that exhibits high seasonal variations, which contradicts the hypothetical association between dehydration behaviors and post-fire regeneration types.

4.2. *Responses of meteorological drought indices to precipitation and drought*

All meteorological drought indices that were computed in this study model the water within a given layer of duff or soil. Despite this common conceptual approach, some discrepancies were observed when comparing the dynamics on these indices and their performance for LFMC predictions. These differences can be explained by the two following phenomena. First, our results showed that the indices designed to simulate long-term drought dynamics generally performed better than the others, which suggests that the reservoir size and the response

Table 1
Statistical Spearman rank correlations between live fuel moisture content (LFMC) and drought indices across sites and sites*species combinations. Correlations were computed per group of species and individual species. For each case, the number of LFMC observations (n) is indicated. All correlations are significant at the 0.01 level. Values above the 0.6 correlation threshold are indicated in bold.

	RWC_H	RWC_L	DC	DMC	KBDI	NI
All species (n = 8544)	*0.579*	0.562	0.518	0.512	0.481	0.387
High responding species (n = 2218)	***0.632***	***0.630***	*0.550*	0.591	0.495	0.451
Low responding species (n = 6326)	0.479	0.357	0.535	0.272	0.538	0.148
Cistus Albidus (n = 1260)	***0.694***	***0.660***	***0.654***	0.558	0.476	0.411
Cistus monspelliensis (n = 2273)	*0.560*	0.596	0.428	**0.602**	0.475	0.472
Erica arborea (n = 1516)	***0.663***	0.584	***0.641***	0.506	**0.609**	0.385
Rosmarinus officinalis (n = 1277)	***0.715***	***0.742***	***0.650***	***0.729***	0.594	0.543
Quercus coccifera (n = 1225)	0.536	0.407	***0.616***	0.323	**0.621**	0.168
Quercus ilex (n = 993)	0.502	0.365	0.542	0.243	0.414	0.144

to precipitation of the indices is of importance for LFMC predictions. For instance, DC and RWC_H generally provided better estimations of LFMC than DMC and RWC_L, respectively. Besides, the significantly lower predictive capacity of NI can be explained by the very low amount of precipitation (3 mm) required to reset the index to 0 (and leading to positively skewed distributions, Fig. 3i). These findings confirm that the dynamics of plant water status during drought is a medium term (seasonal) process in the Mediterranean area that depends on soil water content integrated over an important depth (Rambal et al., 2003). Second, the response of indices during drought periods might be improved in order to better simulate LMFC dynamics. Indeed, DC, DMC, NI and KBDI whose increase is determined by daily temperature, have a close-to-constant increase rate during summer, unbounded positive values and slight negatively skewed distributions that are not consistent with LFMC distributions (Fig. 3). Yet, it is acknowledged that plants limit transpiration through stomatal closure during drought to dampen the decay of soil water content and avoid dehydration (Jarvis and McNaughton, 1986; Martin-StPaul et al., 2017). This limitation may explain why earlier studies sometimes reported exponential relationships between these indices and LFMC

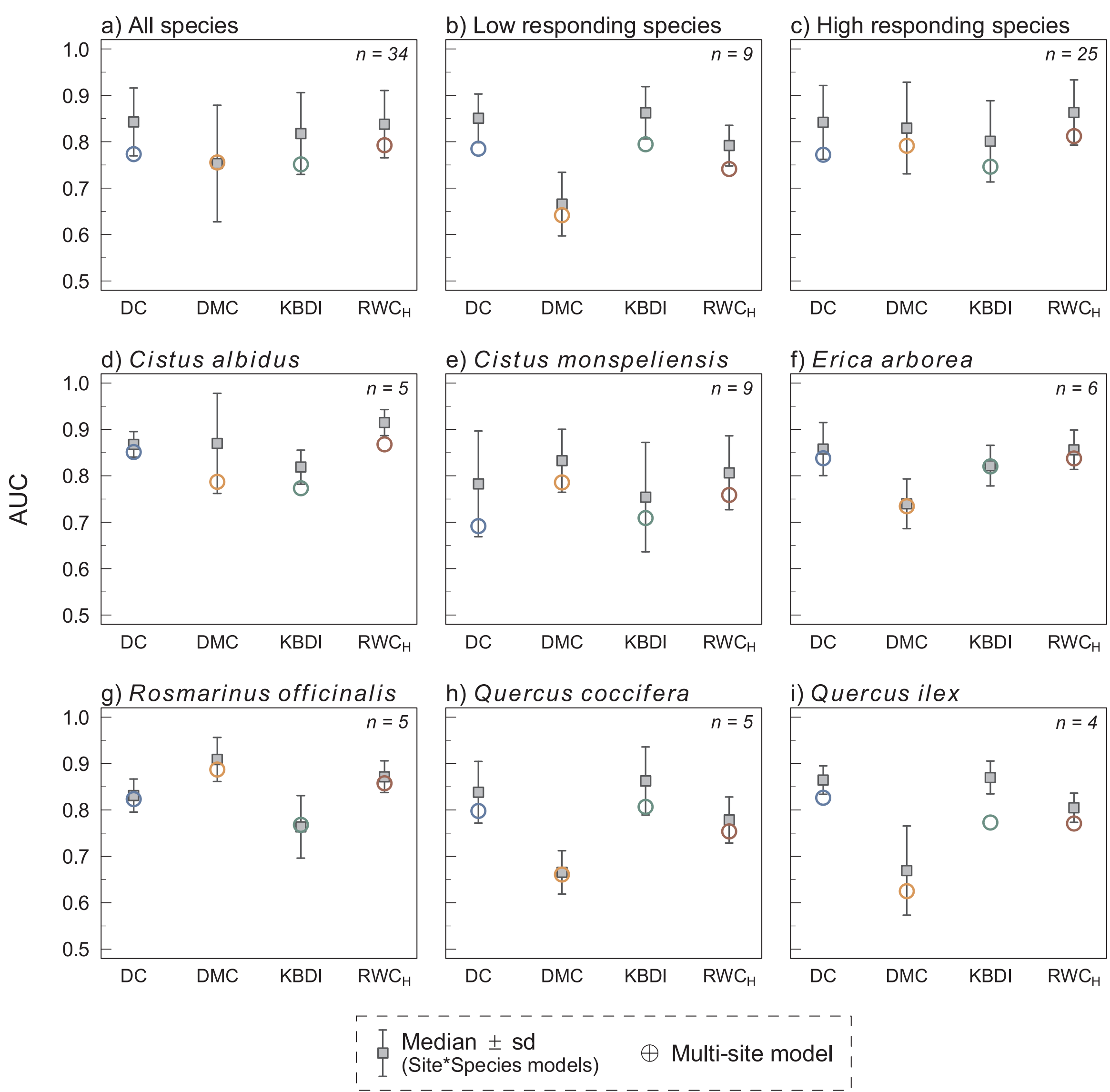

Fig. 5. Area under the ROC Curve (AUC) of logistic models predicting the 79% threshold of live fuel moisture content (LFMC) from four drought indices (DC, DMC, KBDI and RWC). AUC are computed for different groups of species and individual studied species. In each case the coefficient computed on a per-site and multi-site basis are indicated. The number of sites is indicated at the top-right of each subpanel (*n*).

(Viegas et al., 2001; Castro et al., 2003; Pellizzaro et al., 2007). By contrast, a transpiration regulation is incorporated in RWC_L and RWC_H. This leads to a nonlinear decline of the soil water content during drought. This mechanism resulted in negatively skewed distribution of RWC, which was also a characteristic of the LFMC distributions. Yet, despite its better agreement with the actual LFMC distribution and its physical bases, RWC did not exhibit a better predictive performance than the other long-term drought indices. We can expect, however, that a better parameterization (*e.g.* water content at field capacity was assumed constant among sites) of such types of models would improve the results, but it still has to be demonstrated.

4.3. Empirical drought indices induce large spatial uncertainties

Our results pointed out that using drought indices might be relevant to predict LFMC at stand scale. Errors (RMSE) associated to LFMC predictions for the best predictors (RWC_H, DC and KBDI) were on the order of 10–15 % for high responding species at some sites (Fig. 4). These figures are consistent with previous studies (Viegas et al., 2001; Dimitrakopoulos and Bemmerzouk, 2003; Castro et al., 2003; Pellizzaro et al., 2007) although the performance of drought indices was generally lower in our study. However, the predictive capacity of these empirical relationships could be substantially improved with nonlinear forms for each site*species combination (as in Viegas et al., 2001 and Pellizzaro et al., 2007) or with the use of additive models (as in Castro et al., 2003). In this study, we chose linear predictors for all sites*species combinations not only for the sake of parsimony but also to allow fair comparisons between indices and to identify their potential weaknesses (see Section 4.2). It also important to note that, in agreement with previous findings (Viegas et al., 2001; Pellizzaro et al., 2007), the LFMC of high responding species was better predicted by the different indices comparing to low responding species.

4.4. Drought indices induce large spatial uncertainties

Our results showed that the use of drought indices for LFMC predictions should be considered with caution when it comes to spatial applications. Indeed, we showed that the performance of the models fitted on several sites and/or species was significantly below the best results obtained on a per site basis (Figs. 4 and 5). In addition, we almost systematically observed that the predictive performance of LMFC for multi-site relationships was lower than the median of site*species combinations (Figs. 4 and 5). This uncertainty might be explained by differences between species responses to drought, as suggested above (Section 4.1), but is also likely to be due to differences between sites (such as vegetation density, soil, elevation or climate) and by the weather predictability. For instance, the SAFRAN re-analysis climate database used in this study brings some uncertainties in weather variables that is known to exhibit substantial spatial variations (Vidal et al., 2010). When combining these different sources of uncertainty, our results showed, for instance, that RMSE was about 20% for high responding species (Fig. 3c). By comparison, some studies based on spectral indices generally reported a RMSE for spatial LFMC predictions on shrublands between 8% and 20% (Yebra and Chuvieco, 2009; Caccamo et al., 2012; Yebra et al., 2018). For real-time monitoring or short-term historical reconstructions, *i.e.* for periods when remote sensing products are available, the use of spectral indices is a relevant alternative for LFMC estimations. More studies using both drought indices and spectral indices should be carried out in order to directly compare the performance of these two approaches (as in Caccamo et al., 2012).

Given the large uncertainties in LFMC predictions reported above, the question then arises as to whether meteorological drought indices should be used for spatial LFMC predictions. As pointed out by Yebra et al. (2018), "an error of 20% added to or subtracted from an estimated LFMC of 90% would result in shrubland fire danger ranging from low (ignition probability = 19% associated with a LFMC = 110%), to high (Ignition probability = 60% associated with a LFMC = 70%) when ignition probability is calculated as in Chuvieco et al. (2004b)". Another approach to evaluate the impact of LFMC uncertainty on fire behavior is to rely on the empirical dependency between the rate of spread (ROS) of the fire and the LFMC, which can be expressed as: $ROS = exp(-a*LFMC)$ (with a on the order of −0.015; Marino et al., 2012; Rossa et al., 2016). Following this empirical equation, an error of 20% added to or subtracted from an estimated LFMC of 90% would result in a 1.75 factor in the final estimations of ROS. Similarly, we found 30 to 40% commission errors (risk overestimation) and around 20% omission errors (risk underestimation) when considering threshold predictions. We argue here that this approach can induce large uncertainties in research studies and management. Furthermore, as LFMC forecasts may affect safety and resource costs associated with wildfire suppression we do not recommend the use of these drought indices, as are, for operational applications.

4.5. Potential for improvement and research directions

One promising approach to improve the performance of meteorological drought indices for LMFC predictions is to shift towards more mechanistic indices that includes species traits and local parametrization of soil and vegetation. In this study, both RWC indices (RWC_H and RWC_L) were designed to propose a more mechanistic approach of LFMC dynamics. Our results show that they did not exhibited a better predictive capacity of LFMC dynamics than some other indices, as explained above. However, they meet two important criteria that are important for future improvement in LFMC prediction. First, these indices had similar distributions to LFMC which suggest that they offer a more realistic representation of dehydration mechanisms. In addition, we showed that certain traits involved in dehydration might explain the species dependence of LFMC dynamics, as well as to its predictability with soil water budget models (Section 4.1). Interestingly, species functional traits related to dehydration dynamics are increasingly available (Choat et al., 2012; Martin-StPaul et al., 2017). This is encouraging regarding potential improvements through an approach that would not aim at modelling soil water content (as it is the case for most drought indices), but plant water content. Second, RWC indices can be parametrized to account for local soil properties and vegetation cover that largely influence stand water budget and might therefore significantly improve model performance. Indeed, such parameters can be obtained through measurements on study sites and are increasingly made available at larger scales (*e.g.* Ruffault et al., 2013; Caceres et al., 2015). We advocate to shift towards more mechanistic indices based on up-to-date plant water science that would include both aspects. We recognize, however, some limitations both in terms of data and model structure, including the impact from seasonal dry matter changes, that need to be explored (Jolly et al., 2014; Jolly and Johnson, 2018).

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agrformet.2018.07.031.

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