Why is the Effect of Live Fuel Moisture Content on Fire Rate of Spread Underestimated in Field Experiments in Shrublands?

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Abstract. Live fuel moisture content (LFMC) influences fire activity at landscape scale and fire behavior in laboratory experiments. However, field evidences linking LFMC to fire behavior are very limited despite numerous field experiments. In the present study, we reanalyze a shrubland fire dataset with a special focus on LFMC to explain this counterintuitive outcome. We found that this controversy might result from three reasons. First, the range of experimental LFMC data was too moist to reveal significant effect with the widespread exponential or power functions. Indeed, LFMC exhibited a strong effect below 100%, but marginal above this threshold, contrary to these functions. Second, we found that the LFMC significance was unlikely when the size of the dataset was smaller than 40. Finally, a complementary analysis suggested that 10 to 15% of random measurement error in variables could lead to an underestimation by 30 % of the LFMC effect. The effect of LFMC in field experiments is thus stronger than previously reported in the range prevailing during the actual French fire season and in accordance with observations at different scales. This highlights the need to improve our understanding of the relationship between LFMC and fire behavior to refine fire danger predictions.

Short Abstract. Live fuel moisture content is a factor of fire rate of spread that might have been underestimated from field experiments in shrublands. Here, we show why, and evaluate the actual magnitude of its impact, which was found to be large for typical values occurring during fire seasons.

Additional keywords: Sample size, Measurement error, Generalized Additive Model, GAM, Réseau Hydrique.

Introduction

Live fuel moisture content (LFMC), which is the ratio of water mass to dry mass of vegetation, has for long been identified as a factor of fire behavior with threshold effects in Mediterranean shrub communities (Chandler *et al.* 1983). There is increasing evidence that LFMC strongly impacts fire activity at landscape scale (Dennison and Moritz 2009; Nolan *et al.* 2016; Pimont *et al.* 2018; Ruffault *et al.* 2018a). From laboratory to field experiment scale, the impact of LFMC on fire behavior remains, however, far more controversial (Alexander and Cruz 2013a; Finney *et al.* 2013). This knowledge gap is critical in a context of increasing drought conditions that might impact fuel moisture conditions and trigger some shifts in fire regimes (Flannigan *et al.* 2016).

The influence of LFMC in fire behavior (here, rate of spread, ROS) models is most often either accounted for without distinguishing live and dead fuels (e.g. Rothermel 1972), or ignored (e.g. Catchpole *et al.* 1998). The first approach suggests an overall effect of the moisture of the fuels, which results in weighting LFMC and DFMC by their respective bulk density in empirical models (Marino *et al.* 2012). Although other studies reviewed in Finney *et al.* (2013) suggested that the impact of live and dead moistures on fire behavior could differ, they generally imply a significant impact of LFMC on ROS. This significance is supported by laboratory experiments, which clearly demonstrate an important effect of LFMC (Rossa *et al.* 2016). The second approach (i.e. ignoring LFMC) is supported by the limited number of field evidences linking fire behavior to LFMC in shrublands, despite numerous field experiments. In a review, Alexander and Cruz (2013a) showed that the relationship between ROS and LFMC was not significant in none of the 14 studied datasets. According to these authors, "*It is possible that a small effect exists but the difficulty of controlling the environmental conditions in outdoor field experiments has so far precluded the quantification of this effect*". More recently, a larger dataset was gathered and statistical analysis revealed a statistically significant effect of LFMC (Anderson *et al.* 2015), but this effect was very small and it only marginally improved the model performance. The authors concluded that this low influence of LFMC might be a consequence of existing correlations between LFMC and vegetation height and bulk density. Also, the differences in impinging heat fluxes observed between laboratory and field experiments induce differences in combustion dynamics, which could explain the lower effect of LFMC observed in the field (Fernandes and Cruz 2012; Alexander and Cruz 2013a). Both arguments explain the counterintuitive discrepancy between field and laboratory and support the fact that LFMC can be neglected in an operational context.

It is possible, however, that some significant LFMC effect truly exists in the field, but that past field experiments and statistical analyses failed to detect it. A first reason could be associated with the proportion between live and dead fuel, which exhibits much larger variations in shrublands than in other fuel types such as conifer forests, and might therefore affect the statistical relationship between LFMC and ROS (Alexander and Cruz 2013a). A slightly different assumption was recently supported in Rossa and Fernandes (2017b), which showed that monthly values of DFMC and LFMC were correlated, and hence suggested that such a correlation might explain why LFMC was not significant. In addition to the above, other reasons might be suggested to explain the limited effect of LFMC in shrublands. First, there is no consensus on the functional form of response function of ROS to LFMC (beyond the question of how it combines to DFMC), nor on how it combines with other factors (Sullivan 2009a&b). This functional form has never been determined from field experiments, so that the exponential or power decays that are usually fitted to field dataset mostly arose from findings of laboratory experiments and might thus not be adapted to field experiments. Second, empirical fire science is particularly limited by measurement accuracy (Sullivan 2009b) and relatively large –random- measurement errors can result in some noise in datasets, which might in turn hide or limit the significance of some factors and induce bias in the estimation of response functions to these factors (Fuller 1987), including LFMC. Measurement errors being - in theory - smaller in laboratory than in the field, this might also contribute to the difference in LFMC significance between these two scales. Finally, the sample size in fire experiments is generally limited, as most datasets contain between 10 and 40 fires (Alexander and Cruz 2013a). It is generally acknowledged that sample size ranging between 10 and 40 is rather small to determine multifactorial effects (wind, fuel height and bulk density, DFMC, LFMC, fire width, etc.), because the selection of factors is based on tests of significance whose statistical power decreases with sample size (i.e. the ability to detect a specific effect decreases with sample size).

In this study, we aim at investigating separately whether each of these three assumptions might explain why the impact of LFMC is underestimated in previous field-based analyses. For that purpose, we carried out a series of statistical analyses on the dataset provided in Anderson *et al.* (2015), hereafter referred to as the FDS (Fire Data Set). We finally discuss the different sources of uncertainty, compare the different models that we obtained to existing relationships and provide a few recommendations regarding future research approaches. We would like to emphasize that the aim of this paper is not to propose a new model for the effect of LFMC on ROS, but rather to disentangle how different mechanisms could have led to LFMC underestimation in field studies through comprehensive statistical analyses.

2. Material and methods

Overview

We first verified if the range of LFMC in the FDS was in agreement with LFMC conditions prevailing during the fire season in a Mediterranean region (Southern France).

Second, we evaluated the influence of the range of LFMC on regression coefficients in ROS models, by fitting equations over the lower and upper sets of LFMC. For further analysis, we used Generalized Additive Models (Hastie and Tibshirani 1990) to determine the shape of the response function of ROS to LFMC thanks to relaxed assumptions regarding its shape when compared to the basic exponential or power decays.

Third, we evaluated the ability to detect the effect of LFMC as a function of sample size. For that purpose, we computed the significance of LFMC coefficients arising from model fits performed on subsets of the FDS of decreasing size.

Fourth, we used some numerical simulations to explore the sensitivity of the LFMC coefficient to random measurement errors. Measurement errors in explanatory variables are known to attenuate the observed mean response (e.g. the absolute value of the slope in linear regression) and to increase its variance (Fuller 1987). This analysis was based on the introduction of random measurement errors of specified magnitude in the dataset.

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Datasets

The fire dataset (FDS)

The fire dataset (FDS) used in this study was built from the fire dataset collected by Anderson *et al.* (2015) and released in its Appendix A. Among the dataset in Anderson *et al.* (2015), 113 fires are documented with ROS (in $m.min^{-1}$), 2-m wind speed (U, in $km.h^{-1}$), vegetation height (H, in m), live and dead fuel moisture content (LFMC and DFMC, in %). Anderson *et al.* (2015) used a subsample of 79 of these fires to develop a model referred to as Equation 2 in their study, the rest of the dataset being devoted to model validation. The form of this model is Eq. (1) below and the coefficients and statistics are shown in **Table 1** (referred to as Anderson *et al.* 2015).

RH database

In order to provide an estimated range of interest for LFMC, we used the "Réseau Hydrique" database (RH) provided by the French National Forest organization (Duché *et al.* 2017) and extensively described in Martin-StPaul *et al.* (2018). In brief, this dataset reports FMC measurements on live shoot (green) samples of some of the dominant shrub species collected at different sites in the French Mediterranean area. Measurements have been performed once or twice a week during the fire season (from June to September) since 1996 (20,000 values). This dataset provides an opportunity to compare the typical distribution of LFMC during the fire season to the LFMC distribution observed in in fire experiments In the present work, we used this dataset and complementary phytovolume measurements to estimate the distribution of LFMC in shrub fuel strata during the fire season (3014 fuel strata LFMC estimates). The details of the method used to derive the fuel strata estimates is developed in Appendix A. To complete this analysis, we also extracted a subset of LFMC values corresponding to fuel strata from Bouche-Du-Rhone district (D13) where fire activity is particularly high in Southern France.

Statistical analysis

Fire ROS models

In Anderson *et al.* (2015) the following model was fitted to a subset of the FDS, with an exponential function of LFMC, referred later as "*Exp*":

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$$Exp: \qquad ROS = aU^b e^{-cDFMC} H^d e^{-eLFMC} \tag{1}$$

Here, we also fitted the following "power" model, referred later as "*Pow*", often used in empirical models:

$$Pow: \qquad ROS = aU^b e^{-cDFMC} H^d LFMC^e \tag{2}$$

These models were fitted on the whole FDS, as well as on subsets of the FDS to evaluate the sensitivity of LFMC coefficients to data range. In particular, we fitted the models to lower and upper sets of LFMC We also fitted model to partitions based on shrubland heights because Anderson *et al.* (2015) reported that existing correlations between LFMC and vegetation height might explain the little influence of LFMC in their models. These models were fitted using the *nlinfit* function of MATLAB.

To overcome the limitation induced by the prescription of *a priori* functional forms such as (1) or (2), we also carried out non-linear parametric analysis based on Generalized Additive Models (GAM, Hastie and Tibshirani 1990). The model was:

$$GAM: \qquad ROS = aU^b e^{-cDFMC} H^d s(LFMC) \tag{3}$$

where *s* is the exponential of a spline function, which enables the response function of LFMC to exhibit any smooth functional form, with relaxed assumptions on the actual relationship, contrary to Eq. (1) and (2). This model was fitted using the *gam* function of package MGCV in the R Software and a log link ($\log(ROS) \sim \log(a) + b\,log(U) - cDFMC + dlog(H) + s(LFMC)$). Note that the model formulation specifies the functional forms of *U*, *DFMC* and *H* as in Eq. 1 and 2, whereas the LFMC effect on ROS is a smooth function of which the form is to be estimated. It should be noticed that the differences between the GAM fit of Eq. 3 and the non-linear fit of Eq. 1 shown in the result section arose from the flexibility of the smoothing spline and not from differences associated with the method of fitting. Indeed, when replacing the smoothing function by a simple linear function (in this case the GAM was a simple Generalized Linear Model, GLM), we found a coefficient for LFMC (-0.00336) very similar to the one of the *Exp* model obtained with the non-linear fit of Eq. 1. With a GAM, smoothing functions can theoretically be applied to fit all variables and not only LFMC (DFMC, Height, etc.). However, the dataset was too small to do so, and the GAM behaved as a basic GLM, simply fitting

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linear responses, as data were too sparse to estimate splines beyond their first –linear- order, which suggests that the size of the dataset might be a limitation for such a multifactorial analysis.

It is important to acknowledge, that other variables, such as the fraction of live fuel and the fire length were not included in the models in order to maximize the sample size and might affect the model fits, although exploratory analyses suggest that these effects are limited.

We relied on P-values to determine the coefficient significance and used Mean Absolute Percent Error (MAPE, in %) and Root Mean Square Error (RMSE) to compare model performance.

Influence of sample size on the significance of LFMC coefficient

To evaluate sample size influence on the detection of LFMC effect, we fitted ROS models to fire subsets of various sizes (from 10 to 110), randomly selected in the FDS. The P-values were computed for each fit. Then, we evaluated, for different significance thresholds (10%, 5%, 1%), the frequency at which LFMC coefficients were significant for the different sample sizes.

Evaluation of the impact of measurement error

The aim of the following method was to explore the potential consequences of random measurements errors associated with explanatory (LFMC, wind, height and DFMC) and response (ROS) variables. As the actual measurement error was unknown, we simply estimated the impact that measurement error might have been when determining LFMC coefficient in model fits. For that purpose, we specified random errors of given magnitude in the variables of the FDS, which was used as a representative of typical field datasets.

First, we computed virtual reference values of rates of spread ROS_{ref}, for each experiment of the FDS, assuming that i) all variables of the dataset were measured without error; ii) the spread rate was a deterministic function of these variables, through Eq. 4 (a typical representative of empirical models):

$$ROS_{ref}(\alpha) = 20Ue^{-0.1DFMC}H^{0.5}e^{-\alpha_{ref}LFMC} \quad (4)$$

This approach was carried out for various values of the LFMC coefficient $\alpha_{ref} \in \{0.003; 0.005; 0.01; 0.02\}$.

Then, we introduced random additive, independent measurement errors in input variables and reference ROS (with magnitude ranging between 0 and 30 %), before fitting the model on this virtual dataset. We then compared the fitted coefficient of LFMC (α) to its actual value (α_{ref}), which provided a way to evaluate a posteriori how measurement error could have led to misestimating the regression coefficient in the initial FDS. The percentage of underestimation of the LFMC coefficient was defined as:

$$P(\%) = 100\frac{\alpha_{ref} - \alpha}{\alpha_{ref}} \tag{5}$$

In simple linear regression, random errors in the independent variable cause an attenuation bias on slope estimation (they always decrease the slope magnitude) in addition to variance inflation (Fuller 1987). This bias can be estimated under appropriate assumptions on model and measurement errors (the attenuation factor is Var(x)/(Var(x)+Var(u)), where x is the true independent variable and u the measurement error on x). In the present case, because of the non linear functional form and existing correlations between independent variables, numerical experiments can be used to estimate the attenuation factor *P*. In order to reach consistent estimates of *P* (%), 2000 altered versions of the FDS were generated for each measurement error percentage (from 0 to 30 %) and each α_{ref} to compute the mean value of estimated α. Several ways to generate measurement error (multiplicative, distinct percentage of measurement error for the different variables, etc.) and several values for (mean) coefficients of wind, DFMC and Height in (Eq. 4) in a plausible range, as well as the *Pow* function were tested, but had little influence on the results. For the sake of simplicity, we only present those obtained with the numerical values of Eq. (4), additive measurement error and constant measurement error percentage for all variables.

3. Results

Comparison of the LFMC distributions observed in fire experiments (FDS) and during the fire season in Southern France

A comparison between the distributions of LFMC in the FDS and during the fire season in Southern France (RH) is shown in Fig. 1a. Much lower values of LFMC were observed in stratum LFMC from

RH (in green) than in the FDS (in blue), confirming that fire experiments are generally conducted in moister conditions than those prevailing in a Mediterranean fire season. In particular, values of LFMC higher than 150% were infrequent in RH data, contrary to the FDS, whereas dry conditions with LFMC<60% never occurred in the FDS. These differences were even more pronounced in the subset corresponding to the most fire prone district (D13 in red). This is consistent with the fact that DFMC is also most often moist in the FDS (88% of the fires exhibit DFMC larger than 10%).

When splitting the FDS between low and tall shrublands (Fig. 1b, in cyan and purple), we observed that the discrepancy between FDS and RH distributions was more pronounced for tall shrublands (>1 m) than for low shrublands (<1 m). This also illustrates the correlations between LFMC and heights in the FDS that were pointed out by Anderson *et al.* (2015). In the next section, empirical models are fitted separately on each part of the FDS to limit the impact of confounding LFMC and heights on ROS.

Exploring the influence of the functional form and data range in the FDS

We evaluated how the estimated coefficients of LFMC varied according to the functional form of the LFMC effect and the subset of the FDS chosen for regression. The different subsets in the FDS were based on both LFMC and height thresholds suggested in Figure 1, i.e. for LFMC <150 % and height <1m. Figure 2 shows the effect of LFMC on ROS according to the different equations and subsets. For the sake of comparison, all effects were normalized to be equal to one for a LFMC of 100%. The values of corresponding regression coefficients and the respective metrics of model performance are indicated in Table 1. For reference, the black line with pluses is the equation provided by Anderson *et al.* (2015). The back line corresponds to our model fit of Eq. 1 over the FDS. The minor differences observed between these two curves might result from the subset of 79 fires used by Anderson *et al.* (2015). Although LFMC was highly significant (Table 1), both curves show a very limited effect of LFMC with an increase in ROS on the order of 10 % for the driest conditions, when compared to the 100% reference. Replacing the *Exp* by the *Pow* model led to slightly lower MAPE and RMSE (Table 1) and a steeper response in driest conditions (Fig. 2, blue line).

Fitting models on drier conditions (LFMC lower than 150 %) and lower shrub strata (lower than 1 m, which in turns decrease the range of LFMC according to Fig. 1b), tended to increase the magnitude of the response of ROS to LFMC, for both the *Exp* and *Pow* models (Table 1). Examples of such response functions (*Pow* models) are shown in Fig. 2 (blue lines with crosses and circles) and suggest that ROS can be up to 75 % higher in the driest conditions when compared to the 100% reference. We found that LFMC was not significant when exceeding 100% (not shown). This means that either LFMC has not impact in this range, or that the size of the corresponding subset is too small (53 fires) to exhibit a significant effect (Fig. 1b).

The use of the GAM (Eq. 3) showed that the shape of the response function was different from the *Exp* and *Pow* models which are usually fitted (Fig. 2, green line, with confidence interval in dotted green lines). Indeed, the response function was very steep below 100 %, whereas no significant trend was identified above 100%. This was consistent with findings obtained with usual non-linear model fits on subsets (i.e. no strong effect below 150 % and insignificant effect above 100%). The flexibility of the smooth function led to non-monotonous effect, with slight increase of ROS with LFMC in the upper range, but not significant (variations remained within the confidence intervals), so that it would be relevant to force a constant effect for predictions above 100%.

Influence of sample size on LFMC coefficient significance

Figure 3 shows the frequency at which the LFMC coefficient was significant (based on P-values) in the random subsets of the FDS. As expected, this frequency increased with sample size and with P-Value threshold. However, these frequencies were relatively low (0.27-0.5) for typical fire sample sizes (between 20 and 40) and P-value of 0.05 (in red). They were even as low as 0.12-0.24 for the 0.01 threshold (in green). It clearly suggests that the effect of LFMC on ROS cannot be detected with a typical fire dataset of 20 to 40 samples, even if such an effect is highly significant and strong on a larger dataset (Fig. 2). According to Figure 3, and for the range of conditions prevailing in the FDS, a sample size above ~100 fires would ensure the detection of a LFMC effect.

Evaluating the impact of measurement error on LFMC coefficients

Figure 4 shows the effect of measurement error on the LFMC coefficients fitted with the *Exp* model over the whole FDS. We found that the expectation of LFMC coefficients were increasingly

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underestimated as measurement error increased, reaching to underestimation percentages P expected to range between 60 and 80 % for a measurement error of 30 %, although such an error was random. Such an underestimation of the LFMC coefficient was more pronounced for low values of α_{ref}. This finding, however, should be taken with caution, since the percentage P was sensitive to the distribution of explanatory variables in the dataset sample. Indeed, we observed a stronger underestimation for high values of α_{ref} when applying the same method to a subset of the FDS (dry conditions for low shrub, Supplementary B). Overall, a 15%-measurement error led to an underestimation by roughly 30%, depending on the dataset (whole or subset) and the "true" value of the LFMC coefficient.

4. Discussion

The role of LFMC on ROS remains controversial in experimental fire sciences. This uncertainty has so far limited our understanding of the drivers of wildfire behavior and hampers our capacity to predict future fire regime changes. A major part of this debate arises from the fact that the effect of LFMC in field experiments is generally less important and significant than in laboratory experiments. In this study, we provide evidence that the discrepancy between field and laboratory experiment is only apparent and results from three limitations of the previous analyses on fire behavior at field scale (lack of flexibility of the functional forms fitted to relatively moist datasets, sample size, impact of measurement error). When including these sources of bias and error, our analyses revealed that the effect of LFMC in a large field dataset was much stronger than previously reported (especially when LFMC was smaller than 100%). In the following discussion, we examine these three factors and compare our estimations of the effect of LMFC on ROS with existing models. We then discuss the consequences of these findings in terms of operational predictions, especially in the context of the relative influence of LFMC and DFMC in these models. Finally, we propose some recommendations to improve future research in wildfire behavior.

Factors affecting the evaluation of the impact of LFMC in simple ROS models

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The lower impact of LFMC that has been observed in experimental field-based studies compared to either laboratory or landscape scales is the consequence of at least three interacting reasons. First, our analysis provided evidence that the functional forms of the equation generally used to model the effect of LFMC on ROS (Exponential or Power) in these models (which distinguish the effect of live and dead FMC) might not be suitable on the whole range of the dataset, since very different coefficients were obtained when the dataset was restricted to its driest –or moister- part. This finding is confirmed by the use of a GAM model, which shows that the LFMC effect is strong in the lower range of LFMC data, but negligible above it. This illustrates the importance of the range of variables in experiments and of the type of statistical analysis, which is reinforced by the fact that experimental fires are often carried out in conditions different from those prevailing during the fire season (here, relatively moist LFMC and DFMC conditions). Indeed, the sensitivity of the different basic models (here Power) to the range of values used is shown to be even stronger when extrapolated out of the range of data used for model development (Fig. 5, which is very similar to Fig. 2, but in a drier range, for a selection of models). This point contradicts the assumption of Cruz *et al.* (2017), who suggested that some empirical models (based on Exponential or Power functions) were likely to be valid for far drier conditions than those involved in the model development. A GAM model is more adapted than basic non linear fits or GLM to such an extrapolation (i.e. prediction out of the range of input variables), as data closest to the extrapolation range (here 67-100%) are used for the estimation of both the trend and the prediction interval (Figure 5, in green and dotted green), whereas the other approaches give the same weight to dry and moist data.

Second, our findings clearly demonstrated that most field datasets are too small to detect any LFMC effect, as they often ranged between 9 and 40 (Alexander and Cruz 2013). One should note, however, the noticeable exception of Catchpole *et al.* (1998), which was based on 133 experimental fires and nevertheless did not report any significant effect of LFMC. Other reasons such as specific vegetation (sedge grass), less reliable or incomplete data (removed in Anderson *et al.* 2015), confounding factors, unsuitable range of data or functional form might explain this finding, which to date, remains unexplained and would deserve future analysis.

Third, we found that the measurement error (arising from random errors affecting each individual measurement) significantly contributed to the underestimation of LFMC effect, a 15%-measurement

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error leading to an underestimation by roughly 30% of the estimated effect. The measurement error of wind has been shown to be large in canopy fires, because of the size and duration of turbulent coherent structures, reaching up to 30%, depending on vegetation height, duration and extent of the experimental burns, wind speed or the number and height of sensors (Sullivan and Knight 2001; Pimont *et al.* 2017). The wind measurement error in shrubland fires has not been studied yet, but it could be important, especially when measured close to the ground level (e.g. 2-m height). LFMC measurements are also subject to random errors related to the time, location, species sampled, definition of the fuel strata, size of vegetation element, sampling design and drying process (Sullivan 2009b; Matthews 2010). Such measurement errors are seldom quantified, despite existing methodologies (Countryman and Dean 1979), so that the magnitude and exact consequences of these errors on statistical models of ROS remain largely unknown.

Comparison with existing LFMC models

We compared the response of ROS to LFMC in shrubland fire experiments obtained when including the different sources of uncertainties and biases mentioned above with other response function derived from laboratory experiments or fire behavior models in Figure 6. Our estimations of the impact of LFMC on ROS were represented by the purple curve with circle, which combined the 30% underestimation arising from measurement error and the fit obtained on the subset corresponding to low and dry shrublands. The green curve which was obtained with GAM models fitted on the whole dataset assuming not a priori functional form of the LFMC-ROS relationship, and is therefore supposed to be as close as possible to the actual LFMC effect in the FDS. Other models are from Anderson *et al.* (2015), from the laboratory experiments of Rossa *et al.* (2016) who fitted models function of LFMC, and from the laboratory experiments of Marino *et al.* (2012) and Rossa and Fernandes (2017a), who used models of weighted LFMC (i.e. dead and live FMC), and from the Van Wagner model for LFMC effect (1989). Overall, the reanalyzes led to an impact of LFMC as strong as in Van Wagner (1989) or Marino *et al.* (2012) for the driest conditions, whereas the original analyses suggested a much smaller effect (Anderson *et al.* 2015). This comparison confirms the importance of the range of variables in experiments, since our results (model fits on dry subset) suggests that the discrepancies between field and laboratory would have been limited if field experimental fires would have been conducted in drier conditions (67-150%).

Our findings about the strong sensitivity of fire behavior to LFMC below 100% in shrublands are also consistent with empirical studies that examined the relationships between LFMC and fire activity at landscape scales (Chuvieco *et al.* 2009; Dennison and Moritz 2009; Nolan *et al.* 2016; Pimont *et al.* 2018), each of which reported a clear threshold of fuel moisture content in shrublands associated to large burnt areas. Although this threshold is currently debated (see Pimont *et al.* 2018) and varies from around 80 % to 110 % depending on analytical methodologies and vegetation types, increased burnt areas might partly result from shrubland fires spreading faster, not only because of lower DFMC but also because of lower LFMC. This suggests that the comparison of the drivers of wildfire behavior should be encouraged between different scales.

Relative role of LFMC and DFMC in models

The most straightforward approach for modelling the influence of fuel moisture in fire behavior (here, ROS) does not distinguish the influence of live and dead fuels, based on mass-weighted averages (e.g. Rothermel 1972). The combined response of ROS to both LFMC and DFMC is potentially more complex (Finney *et al.* 2013), but some laboratory experiments suggest no differential role between LFMC and DFMC (Marino *et al.* 2012; Rossa and Fernandes 2017a; Rossa and Fernandes 2018), supporting the hypothesis that the weighted FMC would be the actual explanatory factor of ROS. The objective of the present study was not to investigate this controversial question and did not include the fraction of dead mass as a variable (mostly to maximize dataset size, as this variable was not available for all fires in Anderson *et al.* 2015). However, if the above "weighted FMC" hypothesis was confirmed, it is interesting to notice that LFMC should also be detected as a significant factor even in moist conditions, which in fact was not observed with the FDS. Although this absence of significance in moist conditions might result from particular correlation with the fraction of dead mass, we suggest another mechanism. Indeed, in the moistest conditions, we can assume that fire spread is mostly driven by dead fuels. In this case, it is not surprising that ROS is little affected by the FMC of the live fuels –contrary to what would be expected from the "weighted FMC" hypothesis-, which can eventually passively burn,

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so that the role of DFMC becomes dominant. More generally, there are still open research needs on the interactions between ROS, LFMC and other factors such as height, bulk density, wind (Sullivan 2009b).

It has been suggested that predictions based on the sole use of DFMC were satisfactory for operational purposes for two reasons: i) ROS is only marginally affected by LFMC, because of the high values of heat fluxes in the field (Anderson *et al.* 2015); ii) even if such an effect exists, it is not necessary to account for it because of temporal correlation between monthly DFMC and LFMC (Rossa and Fernandes 2017b). While these assumptions are probably valid for a first approach, it should be considered with caution when applying in more specific contexts. First, our study reveals that ROS is highly sensitive to LFMC in the range of values (60-100%) corresponding to LFMC prevailing during actual fire seasons (here Southern France). This strongly suggests that monitoring LFMC during the fire season, as currently done by the French agencies is relevant and that incorporating LFMC in operational models would be useful. Second, the links between LFMC, DFMC and ROS probably require clarifications, at least when live fuel is very moist, as suggested above. Third, LFMC and DFMC are affected by different mechanisms (Jolly *et al.* 2018), i.e. DFMC physically adjusts to atmospheric conditions, responding quickly to weather changes, while LFMC should vary smoothly thanks to the plant regulation of water use; hence the daily relationship between LFMC and DFMC records could be more or less noisy, depending on weather patterns of the season, so that predictions based on solely DFMC could be sometimes spurious. Fourth, the plant regulation of water use varies among species, leading to different responses of LFMC to climate and site (Viegas *et al.* 2001; Martin StPaul *et al.* 2018; Ruffault *et al.* 2018b), while the response of DFMC to a weather series should be unique. Finally, the increased water deficit following a drought episode can trigger plant desiccation and organ mortality, leading to abrupt drop in LFMC, while DFMC exhibits marginal variations.

Towards a variety of approaches for a better understanding of drought effect on fire behavior

These different research needs can be addressed by combining a variety of methods and study scales to overcome the specific weaknesses of each individual approach. Laboratory-based experiments permit to get high quality data with full factorial experimental design and small measurement error, but suffer from conditions that differ from actual fire conditions in terms of both size and intensity. Field experiments are closer to actual fire conditions but experimental studies do not generally span across the most severe conditions of spread (including low LFMC) for economic and safety reasons (Chandler *et al.* 1983), as confirmed by our comparison between the distribution of LFMC in the FDS and in the RH. Also, they are limited in sample size, present correlations among variables and can exhibit significant measurement errors, as well as variations in factors that are poorly understood (e.g. strata cover fraction). Improved knowledge can be obtained by the integration of innovative analyses of experimental datasets, such as the ones presented in our study. We think that the use of smooth functions in GAM should be generalized, as suggested in Hastie and Tibshirani (1990), even if the small sample size limits its application to all the factors, as reported above, as it increases the accuracy of estimated response functions and their eventual extrapolations.

Physically-based modelling can also provide some insights, especially for models which explicitly account for the mixing of live and dead fuel (such as WFDS, Mell *et al.* 2007) and could be used to investigate in depth the relationship between ROS, DFMC and LFMC. More generally, these models might help to disentangle the complex interaction between variables (e.g. FMC and Height), thanks to full factorial numerical experiments containing no measurement error. To date, the sensitivity to LFMC has not been much addressed by these models (with the exception of Marino *et al.* 2012). The question of their evaluation/validation, however, is not straightforward, as pointed out in Alexander and Cruz (2013b).

Conclusion

By reanalyzing an existing dataset, our study shows that the fire rate of spread might be more sensitive than expected to live fuel moisture content, especially in dry conditions (<100%). From innovative statistical methods, we demonstrated that the previous underestimation of its effects from experiments in shrublands could arise from some limitations in the statistical approaches applied to experiments conduced in relatively moist conditions, small size of datasets and random errors in measurements.

These findings reaffirm the critical need for a better understanding of both LFMC dynamics and LFMC impact on fire spread, in order to improve our capacity to rate fire danger more accurately and to anticipate the impact of climate change on fire activity.

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Conflicts of Interest

We declare no conflict of interest.

References

Anderson WR, Cruz MG, Fernandes PM, McCaw L, Vega JA, Bradstock RA, Fogarty L, Gould J, McCarthy G, Marsden-Smedley JB, Matthews S, Mattingley G, Pearce HG, van Wilgen BW (2015) A generic, empirical-based model for predicting rate of fire spread in shrublands. *International Journal of Wildland Fire* **24**, 443.

Alexander ME, Cruz MG (2013a) Assessing the effect of foliar moisture content on the spread rate of crown fires. *International Journal of Wildland Fire* **22**, 415–427.

Alexander ME, Cruz MG (2013b). Are the applications of wildland fire behaviour models getting ahead of their evaluation again? *Environmental Modelling & Software* **41,** 65–71.

Catchpole WR, Bradstock RA, Choate J, Fogarty LG, Gellie N, McCarthy G, McCaw WL, Marsden-Smedley JB, Pearce G (1998) Cooperative development of equations for heathland fire behaviour. In 'Proceedings of 3rd International Conference on Forest Fire Research and 14th Conference on Fire and Forest Meteorology, Volume II', 16–20 November 1998, Luso–Coimbra, Portugal. (Ed. DX Viegas) pp. 631– 645. (University of Coimbra: Coimbra, Portugal)

Peer-reviewed version available at *International Journal of Wildland Fire* **2019**; doi:10.1071/WF18056

Chandler C, Cheney P, Thomas P, Trabaud, L, Williams, D (1983). Fire in forestry. Volume 1. Forest fire behavior and effects. (John Wiley & Sons, Ed.). New York

Chuvieco E, González I, Verdú F, Aguado I, Yebra M (2009) Prediction of fire occurrence from live fuel moisture content measurements in a Mediterranean ecosystem. *International Journal of Wildland Fire* **18**, 430–441.

Countryman CM, William AD (1979) Measuring moisture content in living chaparral: a field user's manual. USDA Forest Service, Pacific Southwest Research Station General Technical Report PSW-36. (Berkeley, CA)

Cruz MG, Alexander ME, Sullivan AL (2017) Mantras of wildland fire behaviour modelling: facts or fallacies? *International Journal of Wildland Fire* **26**, 973.

Dennison PE, Moritz MA (2009) Critical live fuel moisture in chaparral ecosystems: A threshold for fire activity and its relationship to antecedent precipitation. *International Journal of Wildland Fire*, **18(8)**, 1021–1027.

Duché Y, Savazzi R, Toutchkov M, Cabanne E (2017). Multisite and multispecies live fuel moisture content (LFMC) series in the French Mediterranean since 1996. Zenodo. http://doi.org/10.5281/zenodo.162978

Finney MA, Cohen JD, McAllister SS, Jolly MW (2013) On the need for a theory of wildland fire spread. *International Journal of Wildland Fire* **22**, 25–36.

Fares S, Bajocco S, Salvati L, Camaretta N, Dupuy J-L, Xanthopoulos G, Guijarro M, Madrigal J, Hernando C, Corona P (2017) Characterizing potential widland fire fuel in live vegetation in the Mediterranean region. *Annals of Forest Science* **74**, 1-14

Fernandes PM, Cruz MG (2012) Plant flammability experiments offer limited insight into vegetation-fire dynamics interactions: *Letter*. *New Phytologist* **194**, 606–609.

Flannigan MD, Wotton BM, Marshall GA, De Groot WJ, Johnston J, Jurko N, Cantin AS (2016) Fuel moisture sensitivity to temperature and precipitation: climate change implications. *Climatic change* **134(1-2)**, 59-71

Fuller WA (1987) Measurement Error Models, Wiley, New York.

Jolly WM, Johnson DM (2018) Pyro-Ecophysiology: Shifting the Paradigm of Live Wildland Fuel Research. *Fire* **1**, 8.

Hastie T, Tibshirani R (1990). Generalized Additive Models. Chapman and Hall/CRC. 352 pp.

Marino E, Dupuy JL, Pimont F, Guijarro M, Hernando C, Linn R (2012*)* Fuel bulk density and fuel moisture content effect on fire rate of spread: a comparison between FIRETEC model predictions and experimental results in shrub fuels. *Journal of Fire Sciences* **30(4),** 277-299.

Martin-StPaul N, Delzon S, Cochard H (2017). Plant resistance to drought depends on timely stomatal closure. *Ecology Letters* **1–23**.

Martin-StPaul N, Pimont F, Dupuy JL, Rigolot E, Ruffault J, Fargeon H, Cabane E, Duché Y, Savazzi R, Toutchkov M (2018) Live fuel moisture content (LFMC) time series for multiple sites and species in the French Mediterranean area since 1996. *Annals of Forest Science* **75**, 57.

Matthews S (2010) Effect of drying temperature on fuel moisture content measurements. International *Journal of Wildland Fire* **19**, 800-802.

Mell W, Jenkins MA, Gould J, Cheney P (2007) A physics-based approach to modelling grassland fires. *International Journal of Wildland Fire* **16**, 1-22.

Nolan RH, Boer MM, Resco de Dios V, Caccamo G, Bradstock RA (2016). Large-scale, dynamic transformations in fuel moisture drive wildfire activity across southeastern Australia. *Geophysical Research Letters* **43(9)**, 4229–4238.

Pimont F, Dupuy J-L, Linn RR, Parsons R, Martin-StPaul N (2017) Representativeness of wind measurements in fire experiments: Lessons learned from large-eddy simulations in a homogeneous forest. *Agricultural and Forest Meteorology* **232**, 479–488.

Pimont F, Ruffault J, Martin-StPaul N, Dupuy J-L (2018). A cautionary note regarding the use of cumulative burnt areas for the determination of fire danger index breakpoints. Under revision in *International Journal of Wildland Fire*.

Rossa CG, Veloso R, Fernandes PM (2016) A laboratory-based quantification of the effect of live fuel moisture content on fire spread rate. *International Journal of Wildland Fire* **25**, 569-573.

Rossa CG (2017) The effect of fuel moisture content on the spread rate of forest fires in the absence of wind or slope. *International Journal of Wildland Fire* **26(1)**, 24–31.

Rossa CG, Fernandes PM (2017a) Fuel-related fire-behaviour relationships for mixed live and dead fuels burned in laboratory. *Canadian Journal of Forest Research* **47**, 883-889.

Rossa CG, Fernandes PM (2017b) Short communication: On the effect of live fuel moisture content on fire-spread rate. *Forest Systems* **26**, eSC08.

Rossa CG, Fernandes PM (2018) Empirical Modeling of Fire Spread Rate in No-Wind and No-Slope Conditions. *Forest Science* **64**, 358–370.

Rothermel RC (1972) A mathematical Model for Predicting Fire Spread in Wildland Fuels. USDA Forest Service, Intermountain Forest and Range Experiment Station Research Paper INT-115 (Ogden, UT).

Ruffault J, Curt T, Martin StPaul NK, Moron V, Trigo RM (2018a) Extreme Wildfire events are linked to global change type droughts in the northern Mediterranean. *Natural Hazards Earth System Science* **18**, 846-856.

Ruffault J, Martin-StPaul N, Pimont F, Dupuy J-L (2018b). How well do meteorological drought indices predict live fuel moisture content (LFMC)? An assessment for wildfire research and operations in Mediterranean ecosystems. *Agricultural and Forest Meteorology* **262,** 391-401.

Sullivan AL (2009a) Wildland surface fire spread modelling, 1990–2007. 1: Physical and quasi-physical models. *International Journal of Wildland Fire* **18(4)**, 349–368.

Sullivan AL (2009b) Wildland surface fire spread modelling, 1990-2007. 2: Empirical and quasi-empirical models. *International Journal of Wildland Fire* **18**, 369-386.

Sullivan AL, Knight IK (2001) Estimating error in wind speed measurements for experimental fires. *Canadian Journal of Forest Research* **31**, 401–409.

Van Wagner CE (1989) Prediction of crown fire behavior in conifer stands. In 'Proceedings of the 10th Conference on Fire and Forest Meteorology', 17–21 April 1989, Ottawa, ON (Eds DC MacIver, H Auld, R Whitewood) pp. 207–212. (Forestry Canada and Environment Canada, Ottawa, ON).

Weise DR, Koo E, Zhou X, Mahalingam S, Morandini F, Balbi, J (2016) Fire spread in chaparral — a comparison of laboratory data and model predictions in burning live fuels. *International Journal of Wildland Fire* **25**, 980–994.

Viegas DX, Piñol J, Viegas MT, Ogaya R (2001). Estimating live fine fuels moisture content using meteorologically-based indices. *International Journal of Wildland Fire* **10(2)**, 223-240.

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Figures

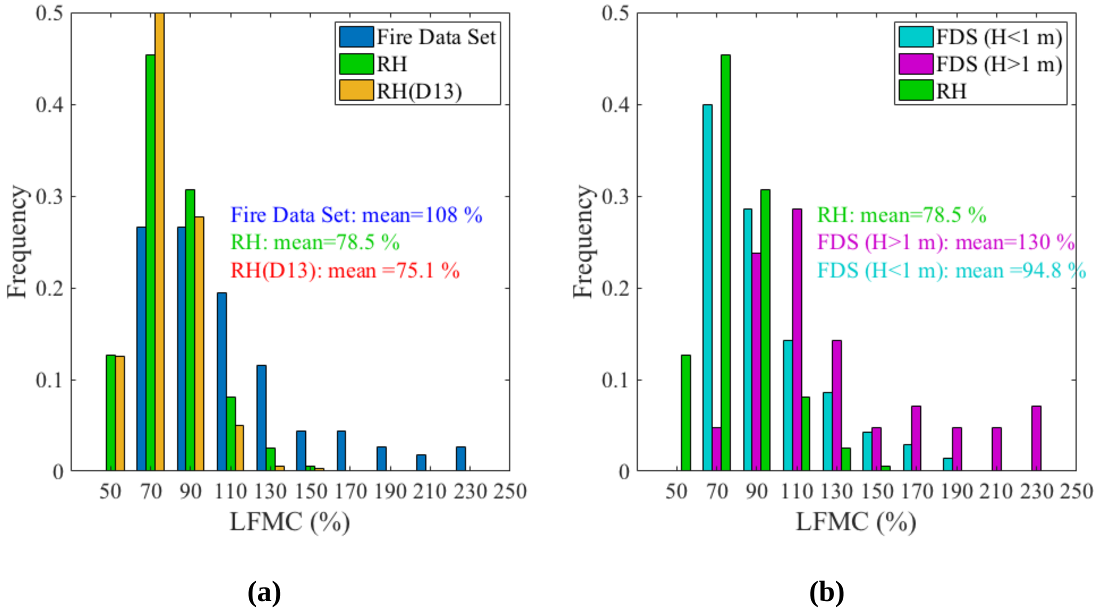

Fig. 1. Comparison between the distributions of LFMC data in the fire dataset (FDS) from Anderson *et al.* (2015) and in from LFMC of the shrub stratum estimated from LFMC of the “Réseau hydrique” dataset (RH) during the fire season in Mediterranean France: a) FDS in blue, RH for all south-east of France in green, RH for D13 (Bouche-du-Rhone, one of the most fire prone area) in red; b) Low shrublands of the FDS (H<1 m) in cyan; Tall shrubland of the FDS (H>1 m); RH for all south-east of France in green.

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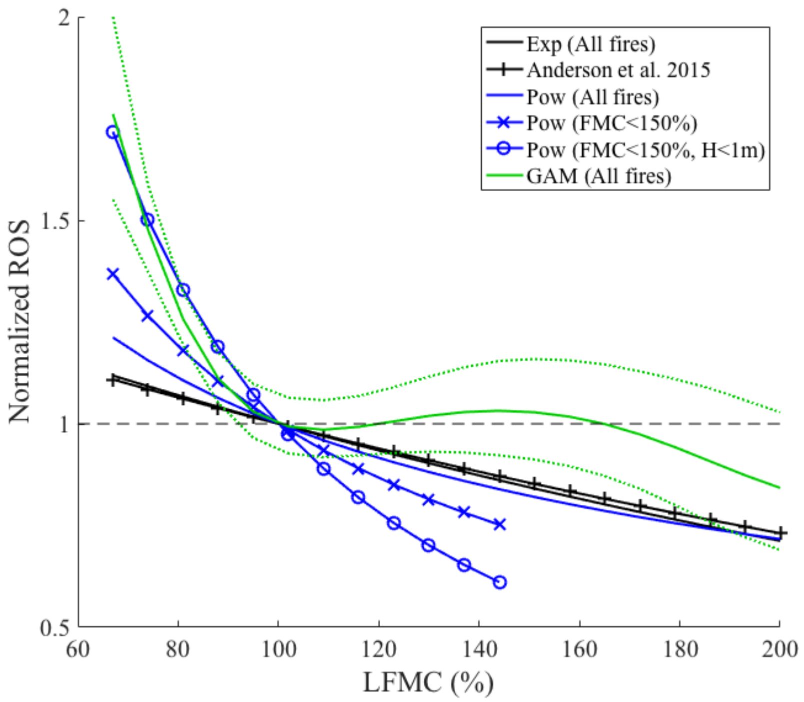

Fig. 2. Sensitivity of rate of spread (ROS) to Live Fuel Moisture Content (LFMC) according to various models fitted to the entire and different subsets of the Fire Data Set (Anderson *et al.* 2015). Note that ROS were normalized so that ROS was set to 1 at LFMC=100%. In black, the equation obtained with the Exponential model for the subset of 79 fires as in Anderson *et al.* (2015) is here for reference. In black with pluses is the same exponential model fitted on the whole dataset (Obviously almost identical to Anderson *et al.* 2015). In blue are the power models fitted to the whole dataset, dry subset (blue crosses) and dry and low subset (blue circles). In green is the GAM model fitted on the whole dataset with its confidence interval in dotted green.

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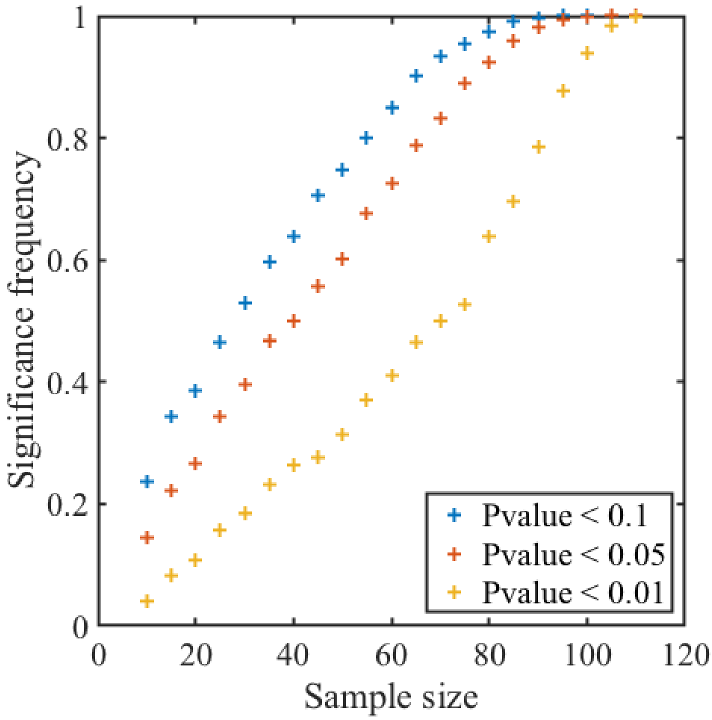

Fig. 3. Frequency at which the LFMC coefficient is significant according to three different P-value thresholds (in blue, green and red) in subsets of the FDS with size ranging between 10 and 110.

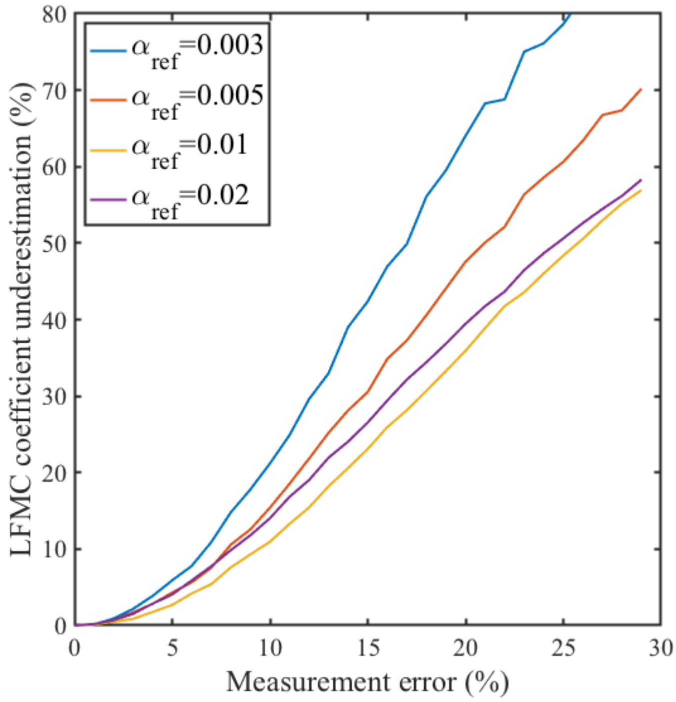

Fig. 4. Underestimation of the LFMC coefficient (in % of coefficient value) arising from measurement errors (in %), evaluated over the FDS. The four lines correspond to different coefficient in the exponential model (alpha ranging between 0.003 and 0.02).

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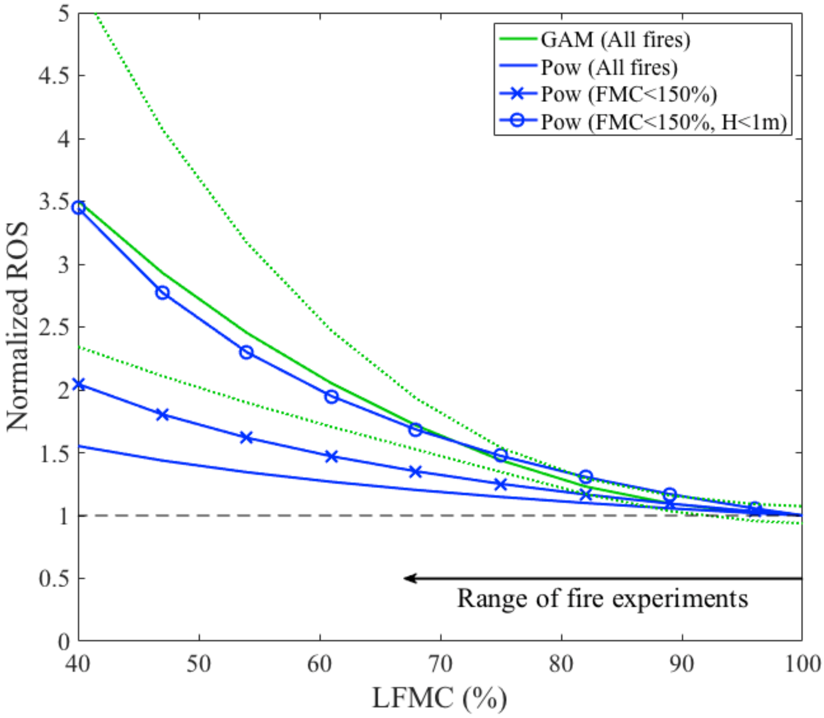

Fig. 5. Figure similar to Fig. 2, but showing the extrapolation of some statistical models in a drier range of LFMC. In blue are the power models fitted to the whole dataset, dry subset (blue crosses) and dry and low subset (blue circles). In green is the GAM model fitted on the whole dataset with its confidence interval in dotted green.

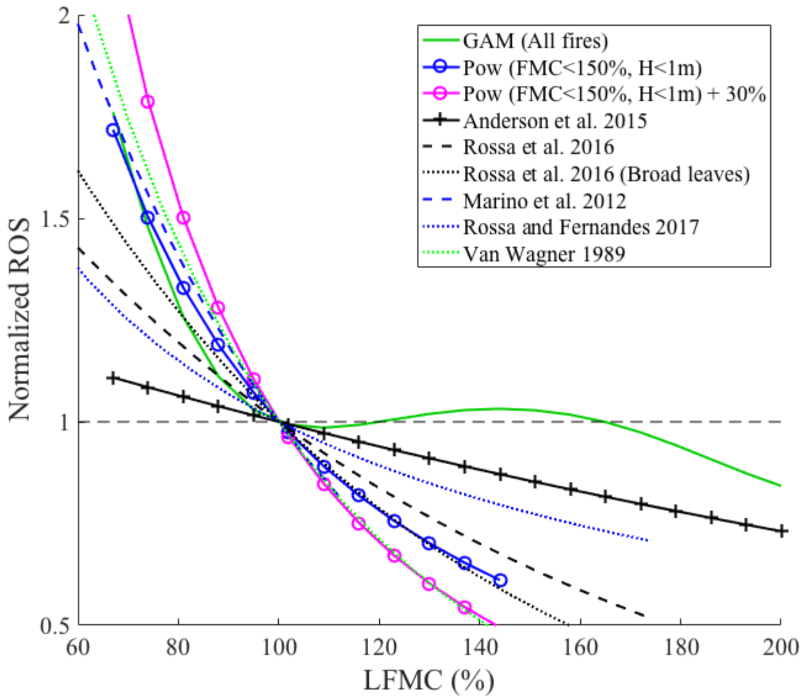

Fig. 6. Relative impact of LFMC on ROS depending on the functional form and subset (similar to Fig. 3) and when accounting for measurement error (+30% in magenta). Anderson *et al.* (2015) is here for reference. Rossa

et al. (2016) corresponds to laboratory experiments with live fuels (in black) and for broad leaf shrubs (dashed black). Marino *et al.* (2012) and Rossa and Fernandes (2017) are also derived from laboratory-based experiments but are function of weighted FMC (combination of live and dead fuel).

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Tables

Table 1. Coefficients and statistics for the different models fitted to the Fire Data Set (Anderson *et al.* 2015) and various subsets.

Equation	FDS or FDS Subset	Intercept	Wind	DFMC	H	LFMC	n	MAPE (%)	RMSE
Exp (Eq. 1)	FDS	5.50 (***)	0.920 (***)	0.0581 (***)	0.497 (***)	**-0.00339 (***)**	113	34.3	5.76
	LFMC<150%	11.1 (**)	0.765 (***)	0.0547 (***)	0.496 (***)	**-0.00758 (**)**	98	34.6	5.47
	LMC<150% H<1m	24.0 (*)	0.799 (***)	0.0967 (***)		**-0.0144 (***)**	66	38.5	5.09
Pow (Eq. 2)	FDS	35.2 (0.13)	0.915 (***)	0.0574 (***)	0.515 (***)	**-0.481 (***)**	113	33.9	5.73
	LFMC<150%	182 (0.42)	0.766 (***)	0.0532 (***)	0.504 (***)	**-0.782 (***)**	98	34.6	5.45
	LMC<150% H<1m	2690 (0.58)	0.804 (***)	0.0948 (***)		**-1.35 (***)**	66	38.0	5.07
GAM (Eq. 3)	FDS	4.02 (***)	0.799 (***)	0.0441 (***)	0.565 (***)	**Spline (***)**	113	34.0	5.56
Anderson *et al.* 2015	79 fires	6.42	0.994	0.0761	0.372	0.00313	79	38	6.7

Pvalue (*) < 0.05, (**) < 0.01, (***) < 0.005

NB: When strata height was limited to 1m, the height parameter was not significant and was thus removed in *nlinfit*.

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Supplementary material:

Appendix A. Fuel stratum LFMC estimates

The RH dataset is an operational network to survey FMC of live shoots of a selection of species in Southern France during the fire season (Martin-St Paul *et al.* 2018). In experiments such as those reported in Anderson *et al.* (2015), LFMC does not refer to the LFMC of some species, as in the RH network, but to the moisture content of the live elements of the whole shrub stratum, which can be obtained by weighting the LFMC of the different species (as measured in the RH network) with the bulk densities (kg m^{-3}) of each species in the stratum. In 2016 and 2017, complementary measurements were performed on the RH sites, including vegetation properties. The phytovolumes of the different species were estimated from heights and cover measurements (segmented by classes of heights [0 0.5] m, [0.5-1] m and [1-2] m), as follows:

$$V(m^3ha^{-1}) = 100(h_{0-0.5}C_{0-0.5} + h_{0.5-1}C_{0.5-1} + h_{1-2}C_{1-2}) \qquad \text{(A1)}$$

where *h* and *C* are respectively the actual heights (in m) and the cover fractions (in %) of the different strata of a given species present in the fuel complex. The 100 constant arises from the fact that cover fraction is in % (factor 0.01) and than a hectare represents 10000 m^2.

For a fuel shrubland with *n* species, the LFMC of the stratum can be estimated as:

$$LFMC_{stratum} \approx \frac{\sum_{i=1,n} V_i LFMC_i}{\sum_{i=1,n} V_i} \qquad \text{(A2)}$$

where $LFMC_i$ and $LFMC_i$ are respectivey the phytovolume and LFMC of species *i*. This formulation neglects the impact of variations in bulk densities of the different species, but this is expected to be of limited impact in such a weighted average, regarding the range of variation of species bulk densities. We will be able to improve this estimation in the future, thanks to ongoing analysis on individual shrubs, which have been sampled in the field for bulk density estimation, but the estimates are yet not available. Another limitation of the the RH dataset is that it only reports two of the dominant shrub species in each site, so that not all $LFMC_i$ values are available. For the present analysis, we selected the sites in which the phytovolume of the two sample species (1 and 2) represented more than 80% of the total phytovolume of the strata (10 sites). The LFMC of the stratum for these sites were estimated by:

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$$LFMC_{strata} \approx \frac{V_1 LFMC_1 + V_2 LFMC_2}{V_1 + V_2} \tag{A3}$$

This process led to 3014 fuel-stratum-LFMC estimates sampled between 1996 and 2016 on 10 sites of the French Mediterranean basin, on of them being located in the Bouche-Du-Rhone district (D13) where the fire activity is particularly high. The accuracy of these values is limited by the above assumptions, but sufficient for a coarse evaluation of the range of LFMC data observed during actual fire season, for comparison to fire experiments.

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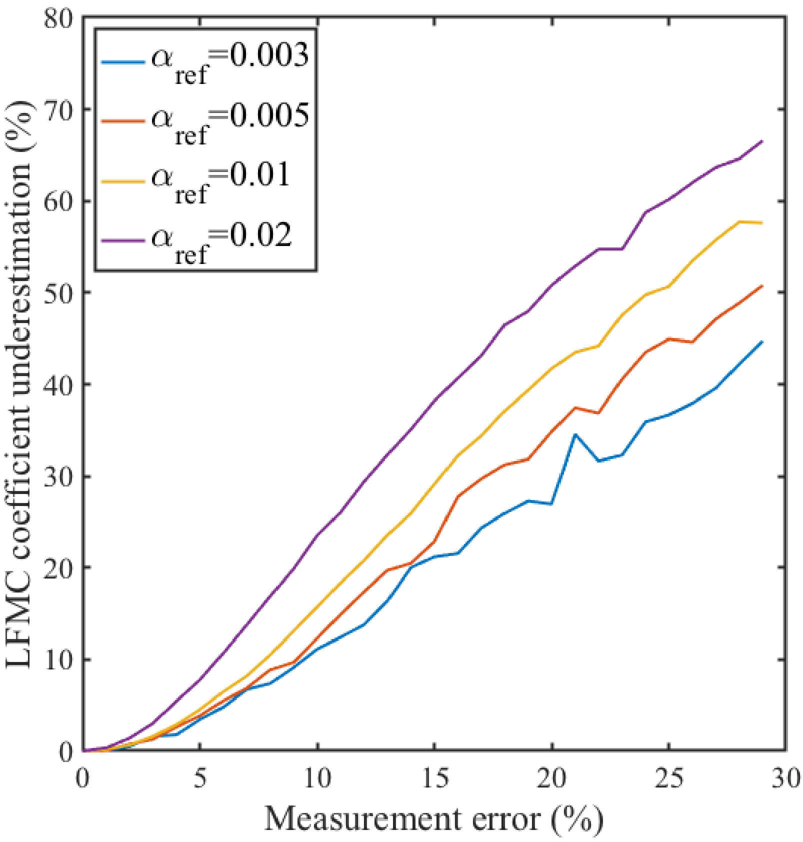

Fig. B. Figure similar to Fig. 4, but assessed on a subset. Underestimation of the LFMC coefficient (in % of coefficient value) arising from measurement errors (in %), evaluated subset corresponding to low and dry shrubs (H<1 m, LFMC <150 %). The four lines correspond to different coefficient in the exponential model (alpha ranging between 0.003 and 0.02). The introduction of measurement error in data leads to a systematic and strong underestimation of the estimated effect of LFMC on ROS, but were slightly different from Fig. 4.