# 5.6 METHODOLOGIES FOR THE PREDICTION OF FUEL MOISTURE CONTENT IN FUEL MODELS BASED IN METEOROLOGY AND REMOTE SENSING

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## 1. INTRODUCTION

The fuel moisture content, is one of the most critical inputs of Rothermel's mathematical fire spread model [1, 2], since it is the main driver of a wildfire's reaction intensity and has thus a crucial influence in the evolution of every particular combustion event. Its relevance encompasses much more than the mere computation of the numerical value of the rate of spread, and it is often considered itself as an indicator of the vegetation health state and is taken into account for the computation of almost every wildfire risk assessment systems, which is the reason why it is one of the parameters, that has been continuously monitored across the United States since the early operation days of the NFDRS (*National Fire Danger Rating System*) [3].

These motivations have led to the pursuit of models capable of its accurate determination in order to generate consistent inputs, which can contribute to both robust wildfires' spread forecasts and improvements in the wildfire risk sentineling routines. However, finding methods able to predict in an accurate way the fuel moisture content (within $\pm 1\%$ of error margin) remains as an unachieved challenge for wildfire science, and therefore it is still required to focus research efforts in this direction, in order to be able in the future to produce accurate methods for the prediction of wildfires' spread.

In this study, different models for the automatic moisture prediction of all the fuel types, based either on meteorological observations or in satellite remote sensing techniques were tested and its error quantified, so it has been possible to build a solid basis to assess the validity of such methods for forecasts and other applications. In addition, some parameters of the classical methods have been optimized, in order to minimize its prediction error.

The following lines intend to present the possibilities and limitations of the automatic prediction methods of fuel moisture content using the knowledge gathered during the last decades of wildfire science research.

### *1.1. Basic Definitions*

A real fuel complex is usually composed of two main classes (Dead and Live fuels), which in turn are sub-divided in different sizes (1-Hour, 10-Hour, 100-Hour for Dead fuels and Herb/Woody (1000-Hour) for Live fuels). Each of these sizes are the most basic units of vegetation fuels, and their individual amount in combination with their geometrical and chemical properties are enough for the description of any particular fuel model.

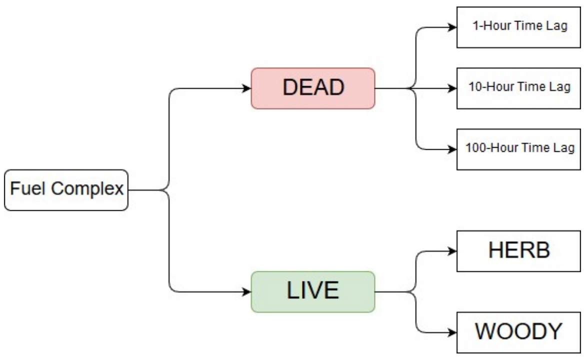



**Image 1. General Composition of a Fuel Model Complex**

For any of these basic 5 fuel types, its moisture content can be computed as a function of its wet (sampling) mass and the remaining mass once it has been dried [4]:

$$Moisture\ Content\ (\%) = \frac{mass_{wet} - mass_{dried}}{mass_{dried}} x100$$

The dried mass is the resulting mass after the sample has been dehydratated in an oven. The temperature at which such operation in executed is far from being standarized, ranging from 60ºC to 100ºC [5].

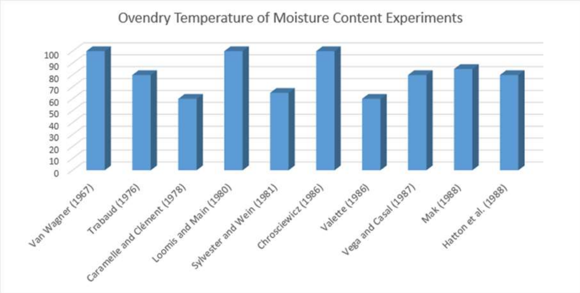



**Figure 1. Ovendry temperature for different Moisture Content Experiments (sources: [6, 7, 8, 9, 10, 11, 12, 13, 14, 15])**

Indeed, it has been reported that the ovendry temperature has been chosen with no particular reason on regular basis [4] , so it is very probable that this unconsistency in the measurement methods explains some of the existing deviations between models and reality, since it is very likely this paremeter influences the final output.

Another particularity of the moisture content is that its value can very well be over 100% since this percent is refered to the waterless mass of the collected sample instead of to the total mass. Indeed, Moisture contents over 100% are common for the case of live fuels (Herb and Woody). Conversely, for dead fuels, its moisture content is usually below 30%, which indicates that its relative fraction of water mass is very low compared to that of the live ones.

**Image 2. 1-Hour Fuels (source: [4])**

Dead fuel classes are named with time units as a reference to the time needed in order to change its moisture content. For a given size $(TL)$ at a given initial moisture content $(m_0)$ with a given environmental situation, there is an equilibrium moisture content $(m_{eq})$, which is the moisture content that the fuel would reach if such environmental conditions lasted forever. In such, conditions, the evolution of the moisture content can be expressed as:

$$m(t) = m_{eq} + \left(m(0) - m_{eq}\right)e^{(\ln(0.5)/TL)t}$$

Which implies the following change rate:

$$\frac{\partial m(t)}{\partial t} = \frac{\ln(0.5)}{TL}\left(m(0) - m_{eq}\right)e^{(\ln(0.5)/TL)t} \propto TL^{-2}$$

The time lag $(\boldsymbol{TL})$ is the amount of time required by the fuel to change from its current fuel moisture content to the average value between the equilibrium moisture content its current moisture content. This rate of change basically depends on the size of the burnable elements as it is illustrated in

Table 1.

| Dead Fuels | Timelag | Size (cm) |
|---|---|---|
| Small twigs | 1-hour | 0 - 6.35 |
| Larger twigs | 10-hour | 6.35 -25.4 |
| Small to moderate branches | 100-hour | 25.4 - 76.2 |
| Large branches, small trees | 1000-hour | 76.2 - 203.2 |

**Table 1. Timelag and size of dead fuels. (source: [4])**

### *1.2. Effect on the wildfire propagation*

In order to compute the influence of the fuel moisture in the propagation of a wildfire, it is necessary to know the fuel moisture content of each of the $n_d$ sizes of dead fuel and each of the $n_l$ sizes of live fuel. Once this has been determined, the global weight averaged fuel moisture content of each of the classes can be obtained using the following expressions [1]:

$$m_{dead} = \frac{\sum_{d=1}^{n_d} \sigma_d w_d m_{dead_d}}{\sum_{d=1}^{n_d} \sigma_d w_d}$$

$$m_{live} = \frac{\sum_{l=1}^{n_l} \sigma_l w_l m_{live_l}}{\sum_{l=1}^{n_l} \sigma_l w_l}$$

Where $\sigma$ stands for the surface to volume ratio of the burnable elements, $w$ stands for the individual mass the fuel size per unit area. These parameters are defined for each of the fuel models [16].

At this point, it is necessary to introduce the concept of the moisture of extinction. Traditionally, the moisture of extinction has been defined as the fuel moisture content at which there will be no fire propagation according to Rothermel's spread model. In practice, there might eventually exist sparse fire propagation, but no uniform flame front capable of evolving into a wildfire event will be observed [17]. Each fuel model has its own extinction moisture content, so it is a parameter given in the fuel models charts [16] . As displayed in Figure 2 , fuel models of dry climatic landscapes often shown a lower moisture of extinction in contrast to the fuel models of humid climates.

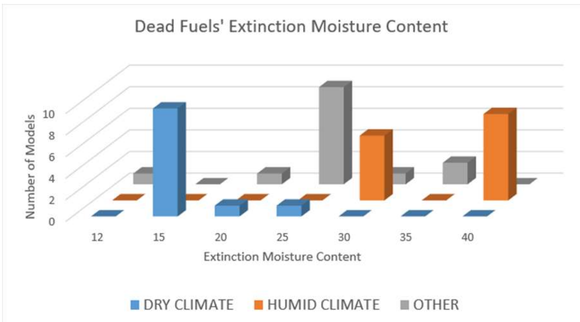



**Figure 2. Extinction Moisture Content of Scott & Burgan's Fuel Models**

Contrary to the dead fuels, the extinction fuel moisture content of the live fuels is not a constant parameter but it experiences variations driven by the dead fuels' moisture content. Following [18, 19], its value can be computed as:

$$M_{ext_{live}} = max\left\{M_{ext\,dead}, 290\left(\frac{W_{dead}}{W_{live}}\right)\left(1-\frac{m_{dead}}{m_{ext}}\right)-22.6\right\}$$

Where:

$$W_{dead} = \sum_{d=1}^{n_d} w_d e^{-138/m_{dead_d}}$$

$$W_{live} = \sum_{l=1}^{n_l} w_l e^{-500/m_{live_l}}$$

Once that the extinction moisture content is known, it is possible to compute the fuel moisture ratio as:

$$M_{r\,dead} = m_{dead}/M_{ext\,dead}$$

$$M_{r\,live} = m_{live}/M_{ext\,live}$$

Which is a decisive value in the fire spread model, since its value yields directly to the following necessary statement for the existence of a wildfire:

$$\exists\, Wildfire \leftrightarrow \left\{\, M_{r_{dead}}, M_{r_{live}}\right\} \in M_{r_{dead}} < 1 \;\cup\; M_{r_{live}} < 1$$

***Demonstration***

In order to exist a wildfire, it is necessary that there is a chemical reaction of oxidation. According to [1], the rate at which such reaction takes place is given by:

$$I_R = \eta_{m\,dead} I_{r_{\max\,dead}} + \eta_{m\,live} I_{r_{\max\,live}}$$

With $I_{r_{\max\,dead}} > 0$ and $I_{r_{\max\,live}} > 0$ the maximum possible reaction intensities for the dead and live fuels respectively, and $\eta_m$ denotes the moisture dumping coefficient which following [1, 19, 20] can be expressed as:

$$\eta_m = 1 - 2.59\,M_r + 5.11\,M_r^2 - 3.52\,M_r^3 \;\in [\,0\,,1\,]$$

Which has only a real zero for $M_r = 1$. Regarding the derivative of the moisture dumping coefficient, it holds:

$$\frac{\partial \eta_m}{\partial M_r} = -2.59 + 10.22 M_r - 10.56 M_r^2$$

In particular:

$$\frac{\partial \eta_m}{\partial M_r}(M_R = 1) = -2.93 < 0$$

All things considered, the moisture dumping coefficient will equal zero for $M_r \geq 1$ and it will never be positive again as $M_r$ increases since its only real zero is $M_r = 1$. Figure 3 Illustrates the mathematical function of the moisture dumping coefficient.

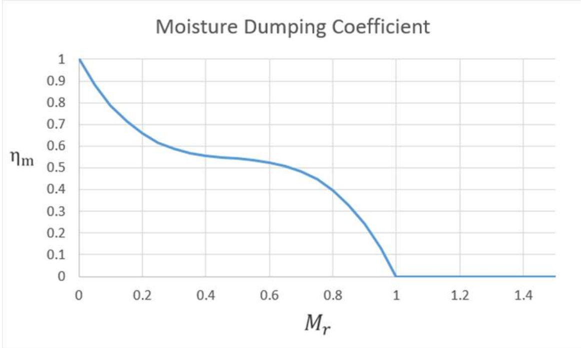



**Figure 3. Moisture damping coefficient**

Consequently, if in a given environmental context one is able to determine accurately enough that both moisture fuel ratios are bigger than the unit, this will imply the impossibility of a wildfire propagation at such circumstances. Conversely, determining that both values are close to zero would mean that on this particular circumstances the vegetation is extremely prone to propagate a wildfire and develop a violent event. The determination of fuel moisture content is thus a crucial aspect in land management and wildfire modelling.

## 2. DATA AND INPUTS

Most of the up to now developed models for the fuel moisture content prediction determine this value merely based on meteorological inputs [21, 22, 23, 24, 25, 26]. However, over the last years, new approaches and methods using satellite based remote sensing have been proposed [27, 28, 29, 30, 31, 32, 33, 34, 35]. Unlike meteorological and forest stations, satellite based remote sensing alternatives are able to develop fuel moisture content products for a whole area with regular time intervals, which improves the consistency of the outputs. Moreover, remote sensing observations measure directly variables from the studied vegetation itself, this is a remarkable difference with respect the meteorology-based methods, in which the state of the atmosphere is the origin of the inputs.

For this study, hourly meteorological records from NOAA (*National Oceanic and Atmospheric Administration*) have been used as inputs, in combination with the NDVI (*Normalized Difference Vegetation Index*) obtained from the VIIRS (*Visible Infrared Imaging Radiometer Suite*) sensor of the Suomi NPP (*National Polar Partnership*) Satellite, which is operated by the NOAA. The outputs of the different models have been compared with daily reports from the WFAS (*Wildland Fire Assessment System*) and the NFMD (*National Fuel Moisture Database*). These sources of fuel moisture data provide actual measurements of all the needed fuel types, so it has been possible to compare the predictions made by each model with actual observed values, and thus obtain objective parameters able to describe the quality of each fuel moisture prediction models.

## 3. DESCRIPTION OF THE MODELS

Modeling the fuel moisture content has always posed a great challenge for the wildfire science since its early days. For this reason, many efforts have been focused in this direction and there is a considerable number of proposed prediction models for the fuel moisture content for every single kind of fuel. This study has had its focus on methods easy to implement automatically, which do not require feedback from in situ observations, since the final goal of this project was to assess the possibilities of developing routines for automatic fuel moisture determination globally. For the dead fuels, meteorological models that had already been proposed have been used and optimized using numerical methods, whilst for the live fuels, actual observed moisture contents have been compared against satellite based remote sensing variables in order to develop models for its determination. The outputs of the models have been compared with measured values obtained through NFDRS daily reports or observations from the NFMD. Table 2 illustrates the different sources of data taken into account for each of the fuels. Contrary to the NFDRS daily reports, where all the moisture values are measured at 17:00 local time, the collecting hour of the NFMD samples remains unstated at their reports, which implies the inadvisability of using this data for the fuels, whose moisture content changes at a fastest rate i.e. 1 and 10-Hours fuels. However, since it is was the only source of measurements of the 1-Hour fuel moisture content, there has been no more alternative than finally using them.

| Fuel | NFDRS | NFMD |
|---|---|---|
| 1-Hour | No | Yes |
| 10-Hours | Yes | No |
| 100-Hours | Yes | Yes |
| 1000-Hours | Yes | Yes |
| Live | No | Yes |
| Available | | |
| Not Available | | |

**Table 2. Used measured data for the comparison of the results**

### *3.1. Meteorological models*

Models based on meteorological observations aim to predict the fuel moisture content using observed meteorological data as inputs. These models are particularly useful for the determination of the fuel moisture content of dead fuels, since the complexity of the involved biological processes is much lower than that of the live fuels, which implies that assuming the state of the atmosphere as the only driver of these fuels' water content should be a good approach.

#### *3.1.1. Small Dead Fuels*

Practically speaking, small dead fuels refer to little and large fallen twigs with timelags of 1 and 10 hours. These are the main fire drivers in most of wildfire events and thus their moisture content prediction is a matter of big concern for forest managers. The methods selected for the fuel moisture prediction were Nelson's [25, 36] and Fosberg's [21] for the 1 and 10 hours fuels respectively. In order to compute the fuel moisture content for the small dead fuels, it is necessary to possess the meteorological data of 24-48 hours prior to the time at which one wants to determine the fuel moisture content.

Regarding the fine dead fuels, its moisture content is very sensitive to the solar radiation [37], indeed this parameter must be an input for Nelson's model. The chosen clear sky solar radiation model has been EPA's [38, 39], which have been corrected afterwards, taking into account the present cloud cover by using the following correction [40]:

$$R = R_0(1 - 0.75\ CF^{3.4})$$

Where $CF$ is the cloud fraction, $R_0$ is the clear sky radiation and $R$ is the corrected solar radiation. The fact that the collecting hour of the samples remains unknown has introduced a considerable error in the method, which had led to the limitation of the optimization possibilities for these particular fuels.

For the case of the 10-hours fuel moisture content, it has been possible to use a solid database of daily reports from the NFDRS, with observed values and the time of measurement, which has allowed us to obtain the exact value of the meteorological variables at the same time, in which observations of the fuel moisture content were performed. Initially, Fosberg's model was used for the prediction of the 10-hours fuel moisture content, resulting into a fair good correlation ($R^2$ of 0.6) given its simplicity. However, in a later stage, statistical methods have been applied for the development of models with a better correlation. In this step of the study, several models were been trained and tested, in order to obtain a general view of their performance for the 10 hour moisture fuels. We implemented a hold-out approach, yielding to a 30% of the data being discarded for the training step, and used later for each model validation. All performances from different models were obtained using the same data in all models, in order to avoid differences due to different data sampling. Since variables are of different nature, an autoscaling preprocessing step was performed in order to make data comparable.

After computing each model and predict the moisture, $R^2$ and RMSE coefficients were calculated in order to compare between them. At this point, outliers and some influence study should be performed. However, there were two main reasons for not doing this step. The first one, is that since more than 15 models were fitted, analyzing the existence of outliers was too time consuming, and there was no possibility of implementing this in an automatic Matlab routine. Moreover, some robust strategies which weight observations according to their "normality", were implemented as well, but they did not show any relevant difference from other models. However, this is clearly a future step in order to go deeper into the data analysis step.

Among all the models, Bagged Trees reached the best result in terms of $R^2$ value, with a 0.70 of information being explained by this model. This strategy builds a Regression Tree along with bagging, which in general terms means the average of different trees built by considering some random samples of variables. This is a technique for overfitting prevention. However, a further step in the exploitation of this statistical tool would be the prune of the model, leading to more visual interpretations of the decision making process performed by the tree.

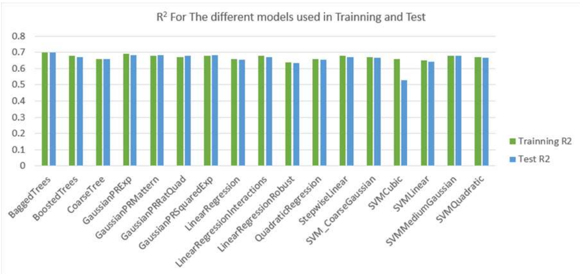



**Figure 4. Performance of the different models used for prediction of the 10-Hours Fuel Moisture content**

### *3.1.2. Large dead fuels*

The fuel moisture content for the 100 and 1000 hours timelag dead fuels have been calculated after [19, 35]. Unlike in the case of the small dead fuels, which variate along the diurnal cycle, the moisture content of the large dead fuels changes at a slower rate and thus is often considered enough to have a unique value for a given day. These methods require as inputs the daily values of the maximum and minimum temperature and relative humidity as well as the accumulated precipitation (for both snow and rain) and the light hours. This is an iterative method, in which the value of the sought variable on a given day is dependent on what its value was the day before. For this reason, it is necessary to establish an initial "guess" for the value of the variable at a given day, and then follow the iteration steps. If the initial day of an arbitrary guess is far enough from the day in which one desires to obtain the fuel moisture content, the final result will be the same regardless of the initial guessed value. One of the consequences of this, is that it becomes necessary to be in possession of a consistent and comprehensive source of meteorological observations, if these methods are wanted to be applied in the most possible accurate way.

Regarding the 100 hours fuel moisture content, the value at the $n_{th}$ day can be computed as:

$$m_{100_n} = m_{100_{n-1}} + (m_{100_{b_n}} - m_{100_{n-1}})(1 - 0.82e^{-\frac{168}{1000}})$$

Where:

$$m_{100_{b_n}} = \frac{(24 - P_n)\,\overline{m}_{eq_n} + P_n(0.5P_n + 41)}{24}$$

With $P$ meaning the precipitation durations (hours) and $\overline{m}_{eq}$ the daily averaged moisture of equilibrium, whose instantaneous value can be determined as a function of temperature $(Fahrenheit)$ and relative humidity $(\%)$ using the following formula [41] :

$$m_{eq}(T,h)\begin{cases} 0.03229 + 0.281073h - 0.00578hT, & if\ h \leq 10 \\ 2.22749 + 0.16017h - 0.014784T, & if\ 10 < h \leq 50 \\ 21.0606 + 0.0055h^2 - 0.00035hT - 0.483199h & if\ h > 50 \end{cases}$$

The value of the 1000 hours timelag fuel moisture content at day $n_{th}$ is determined through:

$$m_{1000_n} = m_{1000_{n-1}} + (m_{1000_{b_n}} - m_{1000_{n-1}})(1 - 0.82e^{-\frac{168}{1000}})$$

Where $m_{1000_{b_n}}$ denotes the last 7-day averaged boundary equilibrium moisture content. which is computed as:

$$m_{1000_{b_n}} = \frac{1}{7}\sum_{i=n-6}^{n} m_{1000_{b_i}}$$

With:

$$m_{1000_{bi}} = \frac{\left(\frac{(24 - P_i)}{2}(\overline{m}_{eq})\right) + 30P_{S_i} + P_{R_i}(2.7P_{R_i} + 76)}{24}$$

Where $\overline{m}_{eq}$ denotes the daily average moisture of equilibrium, which is calculated with the above stated equation and $P_S, P_R$ are the hours of precipitation in form of snow or rain.

Once the algorithm for computation of the fuel moisture content of large fuels have been described, there are some aspects that should be taken into account for the optimization of this method.

*Initial Value*

The initial guessed value has been taken using the recommendations of the NFDRS [19, 42] according to which, the following expressions should be considered:

$$m_{100_0} = 5 + 5\,CC$$

$$m_{1000_0} = 10 + 5\,CC$$

Where $CC$ is the climate class, which is a value ranging from 1 to 4 dependent on the mean annual precipitation. There is an available map for USA's climate classes [26, 42]. If one wants to calculate the equivalent climate class $CC$ for any spot in the world out of the USA, the following equation gives a very good fitting:

$$CC = 1.4427\ln(anual\ precipitation\ [mm]) - 6.6429$$

If we consider more recent precipitation data [43], we can see the result of applying this equation to the whole world in Image 3.

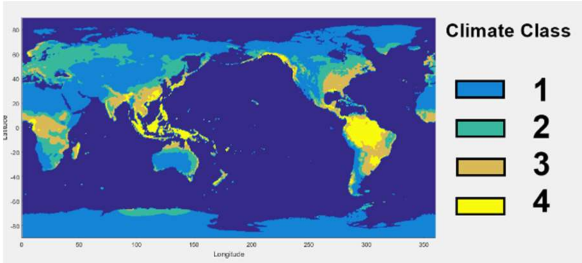



**Image 3. NFDRS Climate Classes extrapolated to the whole world**

This approximation should work fine for areas, whose climates do exist in the USA. However, as a general rule it should be used with caution, in particular in tropical and areas and wherever the seasonal trends significantly differ from the ones in the United States.

*Previous days required*

Another relevant point for the application of the fuel moisture content algorithms is to know how many days before are necessary to be taken into account with the aim of making the convergence error acceptable. In order to determine this in an objective way, it becomes necessary to study the convergence of the above stated algorithm.

*Demonstration of Convergence*

If one considers the equation for obtaining the 100-Hours fuel moisture content:

$$m_{100_n} = a\, m_{100_{b_n}} + b\, m_{100_{n-1}} = \\ = b^n m_{100_0} + \sum_{i=1}^{n} a\, b^{n-i} m_{100_{b\,i}}$$

Where the term that introduces the error i.e. $b^n m_{100_0}$ tends to zero as $n$ tends to infinite as long as the absolute value of $b$ is smaller than the unit :

$$\lim_{n\to+\infty}\left(b^n m_{100_0} + \sum_{i=1}^{n} a\, b^{n-i} m_{100_{b\,i}}\right) = \sum_{i=1}^{n} a\, b^{n-i} m_{100_{b\,i}} \leftrightarrow |b| < 1$$

Since $b = 0.684366$ ,it is demonstrated that the solution will converge, i.e. the same result will be obtained regardless of the initial guess if we consider the climatic conditions for the last infinite days, which is obviously not a practical solution. However, we can determine the magnitude of the error as a function of the number of previous days for both fuels using the following equations:

$$\begin{cases} |Error_{convergence}|_{m_{100}} = m_{1000_0}\, b^n \\ |Error_{convergence}|_{m_{1000}} = m_{1000_0} \sqrt[7]{b^n} \end{cases}$$

Finally, if we obtain the initial guessed value as a function of the climate class, we can calculate the number of days necessary to be taken into account for the achievement of convergence errors with a magnitude smaller than a given objective, for example 0.5 % or 0.1%. The results of calculating the number of iterations required are displayed in Table 3.

| CC | $CE_{m100} <$ 0.5% | $CE_{m100}$ < 0.1% | $CE_{m1000}$ < 0.5% | $CE_{m1000}$ < 0.1% |
|---|---|---|---|---|
| 1 | 8 | 13 | 63 | 93 |
| 2 | 9 | 14 | 69 | 98 |
| 3 | 10 | 14 | 73 | 102 |
| 4 | 11 | 15 | 76 | 106 |

**Table 3. nº of Iterations required to make the convergence error acceptable for the FMC of large dead fuels**

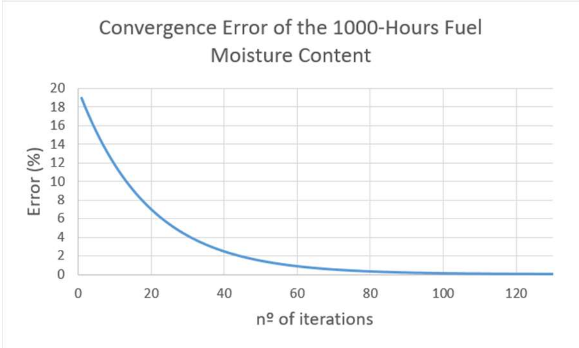



**Figure 5. Convergence Error for Climate Class 2 for the 1000-Hours timelag fuel moisture content as a function of the number of iterations.**

***Precipitation hours***

The precipitation hours is not usually a recorded parameter at the meteorological stations, so it is necessary to define an accumulated rain threshold which can be used in order to determine wether an hour should be counted as a rain hour or not. The usual minimum rain threshold is about $0.1\ mm/hour$ [44] but it is not defined in an explicit way which value should be considered when applying Fosberg's method for the prediction of the large dead fuels moisture content. In order to clarify which minimum amount of precipitation should be considered as rain, the algorithm was applied using different values as the minimum rain threshold and it was determined an optimum value of $0.1\ mm/hour$ for the 100 hours fuels and $0.8\ mm/hour$ for the size of 1000 hours. The results of the optimization test are displayed in Figure 6.

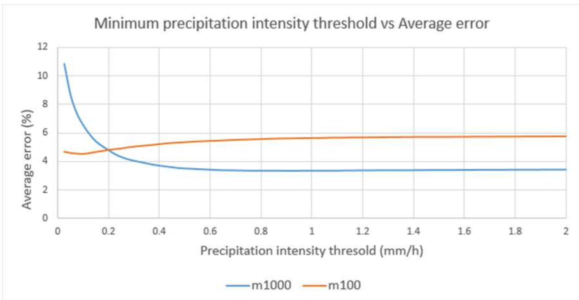



**Figure 6. Minimum precipitation intensity thresold vs Average error of the large dead fuels prediction**

***Average Moisture equilibrium content***

Another relevant point, which should be clarified is the determination of the daily average moisture equilibrium content. Initially, Fosberg [35], suggested to compute it as the average value between the maximum and the minimum equilibrium moisture content:

$$\bar{m}_{eq} = \frac{m_{eq_{max}} + m_{eq_{min}}}{2} = \frac{m_e(T_{max}, h_{min}) + m_e(T_{min}, h_{max})}{2}$$

Which relies on the assumption that the maximum temperature and the minimum relative humidity on a given day happened simultaneously and vice versa, which is probably a too simple approach. In addition, the above stated equation implies that the daily accumulated probability function of the meteorological variables is linear, which albeit being acceptable for a first approach is by no means true. A more refined possibility was the one implemented at the NFDRS [19] which includes a weighting taking into account the light hours:

$$\bar{m}_{eq} = \frac{lh\, m_e(T_{max}, h_{min}) + (24 - lh) m_e(T_{min}, h_{max})}{24}$$

However, practically speaking a more accurate way of determining the daily average equilibrium moisture content would be to integrate its value over the whole day:

$$\bar{m}_{eq} = \frac{1}{24}\int_{00:00\ AM}^{12:00\ PM} m_{eq}(T(h), H(h))dt \approx \frac{1}{24}\sum_{00:30\ AM}^{11:30\ PM} m_{eq}(T(h), H(h))$$

In order to determine, which is the best way of computing the daily average fuel moisture content, the algorithm was applied with the NFDRS method and the integral one and error of the output was compared. The results, which are displayed in Figure 7, show that the error is hardly influenced by changing the way of calculation of the daily average equilibrium moisture content. Indeed, the error is larger for the 1000-Hours timelag, although there is a slight improvement when applying this method for the 100-Hours timelag. This results show that the NFDRS system is simpler and more accurate than computing the average of the daily equilibrium moisture content.

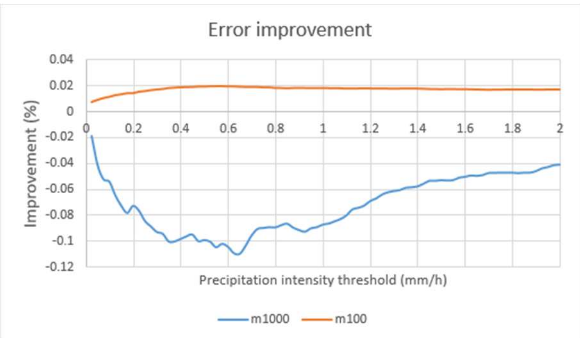



**Figure 7. Improvement of the error after applying the integral method**

### *3.2. Satellite based remote sensing models*

The use of remote sensing based models for the evaluation of the fuel moisture content is far from being as extended as the one of meteorological models. Most of the research done up to know has been performed considering the $NDVI$ [45] and the land surface temperature. For this study, the remotely sensed variable, was the $NDVI$ derived from the measurements performed by the Suomi NPP satellite. This variable is considered as a good indicator of the chlorophyll content and the health state of the vegetation , and it is computed using the following formula [46]:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

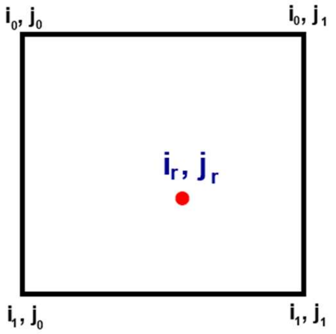
Where $\rho_{NIR}$ and $\rho_{RED}$ refer to the reflectance in the near infrared wavelength zone and in the red wavelength zone. The error of the $NDVI$ values from the dataset used is estimated to be between 0.5 and 5% [47].

When using satellite based remote sensing, it is necessary to keep in mind that the data obtained by these means, unlike in the case of in-situ measurements has a given resolution, and thus, as a general rule, it is not possible to obtain directly the value of the study variable at the particular study point. This derives in the necessity of performing an interpolation using the closest 4 points. For this study, the source resolution was 4 km at the equator, which equals roughly 3km in the latitudes, where observed fuel moisture data measurements from the NFMD was available. Regarding the temporal resolution, the NDVI dataset derived from the VIIRS sensor of the Suomi NPP has a weekly frequency. This circumstance implies the impossibility of using this techniques for prediction methods of the smallest fuels (1 and 10 hours), which experience changes within the diurnal cycle. In addition, the optical properties of the dead fuels are not sensitive enough to the change in water content, which just leaves the live fuels as the only remotely sensible fuels.

The values of the NDVI are delivered with a regular grid In practice, we require to know the value of the NDVI in a particular position at a particular date. However, as it was introduced, it is necessary to perform an interpolation . For the general case, one requires to obtain the in the position $i_r\ j_r$ of the grid, which are real numbers:

$$i_r, j_r \geq 1 \in \mathbb{R}$$

Taking into account those numbers, the closest points of the grid, which contain information are the four possible combinations of applying the floor and ceil function to the decimal values obtained for the exact position as it is displayed in Image 4.




$$\begin{cases} i_0 = \lfloor i_r \rfloor \\ i_1 = \lceil i_r \rceil \\ j_0 = \lfloor j_r \rfloor \\ j_1 = \lceil j_r \rceil \end{cases}$$

**Image 4. Closest 4 points in a data grid**

If one knows the value of the NDVI at all the four corners, then the NDVI value in $(i_r, j_r)$ can be estimated as:

$$NDVI = NDVI_{irj0} + (j_r - j_0)(NDVI_{irj1} - NDVI_{irj})$$

$Where$:

$$NDVI_{irj0} = NDVI_{i0j0} + (i_r - i0)(NDVI_{i1j0} - NDVI_{i0j0})$$

$$NDVI_{irj1} = NDVI_{i0j1} + (i_r - i0)(NDVI_{i1j1} - NDVI_{i0j1})$$

In addition, the $NDVI$ data is provided with a weekly frequency, which leads to the necessity of an additional temporal interpolation. The week of the year can be computed as a function of the day of the year as follows:

$$week_r = \frac{doy}{7}$$

Then, it is necessary to follow the procedure described before in order to compute the NDVI during the next week ($NDVI_1$) and do the same for the NDVI during the previous week ($NDVI_0$), this finally leads to the value of the NDVI in the desired position at the desired date:

$$NDVI = NDVI_0 + (week_r - \lfloor week_r \rfloor)(NDVI_1 - NDVI_0)$$

Thanks to these interpolations, it is possible to obtain the value of the NDVI in the same positions and at the same days where the moisture evaluation of samples by the NFMD took place. In this study, NDVI data from a period of 5 years (2013-2017) was considered and was compared with all the available measured fuel moisture content of different species performed by the NFMD. For all the samples, where there was enough data to extract statistical conclusions, the $R^2$ value of the following model was evaluated:

$$LFMC = n + m\ NDVI$$

Where $n$ is the intercept and $m$ the value of the slope, which is expected to be positive since high values of the NDVI are associated with healthy vegetation. Table 4 shows the fitting coefficients and the associated $R^2$ for all the species which showed an interannual correlation degree larger than 0.3. Only 14 out of the 120 species from which moisture measurements were available did, so, which indicates that the numerical value of the NDVI alone is not enough for the determination of the live fuel moisture content.

| Name | $R^2$ | $n$ | $m$ |
|---|---|---|---|
| Coyotebrush | 0.634 | -45.777 | 342.823 |
| Ceanothus, Bigpod | 0.631 | -115.353 | 48.662 |
| Ceanothus, Hoaryleaf | 0.526 | -58.271 | 325.535 |
| Serviceberry, Utah | 0.478 | -37.312 | 28.418 |
| Bluestem, Little | 0.427 | 553.495 | 553.495 |
| Sumac, Skunkbush | 0.412 | -31.742 | 496.828 |
| Kinnikinnick | 0.382 | 29.492 | 181.581 |
| Red Shank | 0.371 | 16.038 | 217.957 |
| Sage, Purple | 0.371 | -43.707 | 490.360 |
| Ceanothus, Deerbrush | 0.369 | 10.025 | 176.551 |
| Mahogany, Alderleaf Mountain | 0.364 | -23.497 | 300.260 |
| Huckleberry, Blue | 0.352 | -8.679 | 224.386 |
| Yellow Rabbitbrush | 0.324 | -24.046 | 473.671 |
| Pine, Interior Ponderosa | 0.320 | 37.602 | 138.271 |

**Table 4. Linear model goodness for species studied at the NFMD**

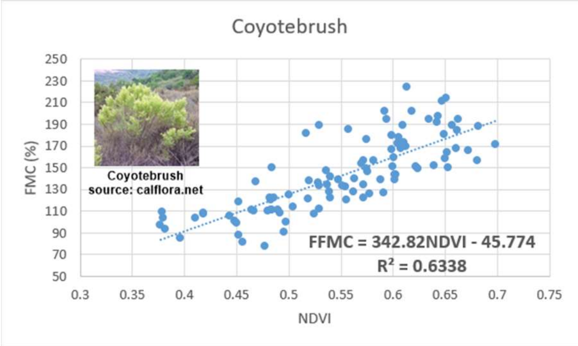



**Figure 8. NDVI vs Fuel Moisture Content for Coyotebrush**

The main reason explaining the general low correlation is that the species cannot be treated as live fuels during the whole year, but only in the green season [26]. This means, that fuel moisture content of samples collected during winter and fall is not sensitive to the change in water content, which implies the introduction of uncorrelated data in the whole conjunct that worsens the global correlation. In order to take into account this fact, only data from the green season have treated individually. For every specie, the following model was the one able to produce outputs with a higher correlation:

$$LFMC = a + b\ NDVI + c\ NDVI^2$$

With the correlation parameters displayed in Table 5.

| Name | R2 | a | b | c |
|---|---|---|---|---|
| Arrowweed | 0.3652 | 0.0806 | -0.0857 | 0.0844 |
| Bitterbrush, Antelope | 0.3697 | -1.1694 | 5.8524 | -6.5869 |
| Brome, Smooth | 0.4022 | 0.9498 | -3.1220 | 3.1188 |
| Ceanothus, Bigpod | 0.7739 | 0.1884 | -0.9764 | 1.7294 |
| Ceanothus, Deerbrush | 0.5020 | -0.0380 | 0.3873 | -0.2117 |
| Chinquapin, Bush | 0.7728 | -0.9509 | 3.4073 | -2.7185 |
| Coyotebrush | 0.7624 | 0.0053 | 0.1435 | 0.1893 |
| Kinnikinnick | 0.5597 | 0.1131 | -0.1721 | 0.3648 |
| Mahogany, Alderleaf Mountain | 0.5009 | 0.0907 | -0.3945 | 1.0309 |
| Pine, Bristlecone | 0.6281 | 0.1708 | -0.4692 | 0.6618 |
| Pine, Interior Ponderosa | 0.3917 | 0.0808 | -0.0778 | 0.2661 |
| Pine, Limber | 0.4258 | 0.1173 | -0.2837 | 0.5201 |
| Red Shank | 0.7549 | -0.2710 | 2.0826 | -2.9815 |
| Serviceberry, Utah | 0.5873 | 0.1229 | -0.3225 | 0.5616 |
| Snowberry, Mountain | 0.3899 | 0.4376 | -0.9394 | 0.7794 |
| Sumac, Skunkbush | 0.6067 | -0.3294 | 3.0537 | -5.3672 |
| Yellow Rabbitbrush | 0.4188 | -0.2707 | 2.1616 | -2.7239 |

**Table 5. Coefficients for Remote Sensing methods for Live Fuel Moisture content after the green up**

### 3.3. Mixed models

Mixed models intend to predict the fuel moisture content using both observed meteorological data and remote sensing variables as inputs. Since they imply the use of remote sensing, its use is limited to the live fuels for the reasons mentioned in the previous section.

$$LFMC = \delta + \alpha\,\bar{T} + \gamma\,\overline{FFMC_{12}} + \sum_{i=0}^{2}\sum_{j=0}^{2} \beta_{ij} NDVI^{i} m_{1000}^{j}$$

Where $\bar{T}$ is the average temperature on the day and $FFMC_{12}$ is the output of the fine fuel moisture content prediction method at 12:00. For each one of the species, the best fitting coefficients have been calculated during the green season (approximately between March to September) resulting in models with very high correlation ($R^2$ over 0.7).

## 4. ERROR ANALYSIS

For the evaluation of the goodness that each fuel moisture content prediction model exhibited, all of them have been tested individually comparing the outputs of the model with observed measurements from the NFMD. The main parameter defining the error of a fuel moisture prediction error is the average absolute error:

$$AAE = \overline{|observed\ FMC - predicted\ FMC|}$$

Its value is not divided by the observed since the fuel moisture content may have values ranging from 1% to 40% for dead fuels and from 30% to 400% for the live fuels, which would imply that the error of good predictions in low moisture situations could be oversized whilst wrong predictions in humid scenarios would have their error undersized. The parameter, which gives an idea of the error related to the study variable is the average relative error:

$$ARE = \overline{\frac{|observed\ FMC - predicted\ FMC|}{observed\ FMC}}$$

The other outputs of the error analysis are the $R^2$ correlation between predictions and observations, the average error (non-absolute) and the standard deviation of the error. These last 2 parameters are particularly relevant since as it can be seen in Figure 9, the distribution of the error is close to be Gaussian, which has implications regarding the sensitivity analysis, that will be discussed in the next section.

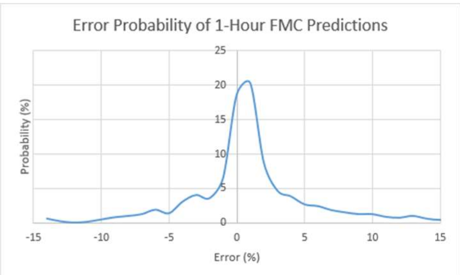



**Figure 9. Error probability for the 1-Hour fuel moisture content prediction models**

### 4.1. Model's error

#### 4.1.1. 1-Hour Fuel Moisture Content

In coherence with other studies [48], the 1-Hour fuel moisture content presents a very high deviation between expected and observed values. There are many reasons that might explain this. Firstly, since this kind of fuels change their moisture at the fastest rate, the measurement errors might be more relevant than for the other classes. In addition, the data available at the NFMD only provides the date of the measurements and not the hour of the day. For this study, it was assumed that all measurements took place at $12{:}00$, and thus much of the existing error might be explained by this reason.

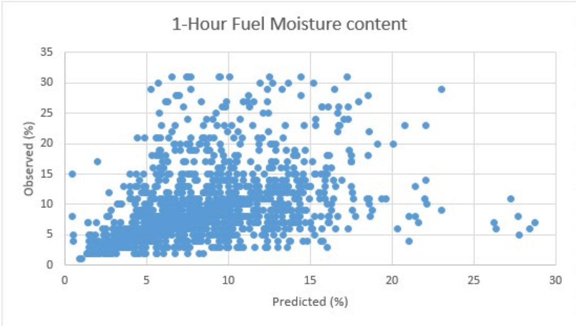



**Figure 10. Predicted vs Observed 1 Hour FMC**

| | |
|---|---|
| $AAE$ (%) | 3.469 |
| $ARE$ (%) | 37.84 |
| $R^2$ | 0.1848 |
| $\sigma$ (%) | 5.4782 |
| $n$ | 1547 |

#### 4.1.2. 10-Hours Fuel Moisture Content

Using statistical methods for the prediction of the 10-hours fuel moisture content, has proved to be able to improve Fosberg's tradicional model from an $R^2$ correlation of 0.6 to 0.7, resulting into the most accurate predictions for the dead fuels.

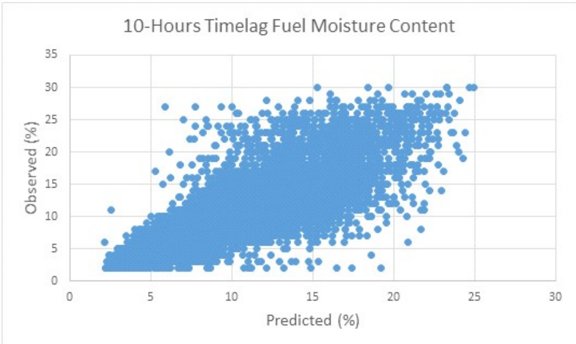



**Figure 11Predicted vs Observed 10 Hours FMC**

| | |
|---|---|
| $AAE$ (%) | 1.702% |
| $ARE$ (%) | 18.27% |
| $R^2$ | 0.7 |
| $\sigma$ (%) | 2.5954 |
| $n$ | 14088 |

**Table 6. Performance of the prediction of 10-Hours FMC**

#### *4.1.3. 100-Hours Fuel Moisture Content*

Since it is necessary to use much more meteorological data for the computation of the fuelmoisture content of the large dead fuels, the amount of predictions compared with observed data is much more smaller. The 100-Hours fuel moisture showed a fair correlation, although very far from being considered as accurate.

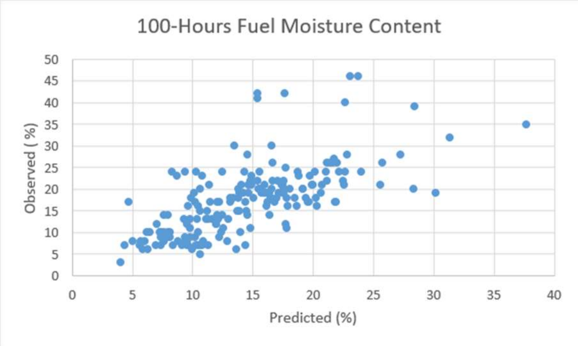



**Figure 12.Predicted vs Observed 100 Hours FMC**

| | |
|---|---|
| $AAE$ (%) | 4.1634 |
| $ARE$(%) | 25.99 |
| $R^2$ | 0.4565 |
| $\sigma$ (%) | 4.2576 |
| $n$ | 187 |

**Table 7. Performance of the prediction of 100-Hours FMC**

#### *4.1.4. 1000-Hours Fuel Moisture Content*

The prediction of the 1000-hours fuel moisture content presented almost the same correlation as the one of the 100-Hours fuels, although being slightly better. The reason of this small improvement may lay in the fact that they are more insensitive to external factors involved with the measurement process.

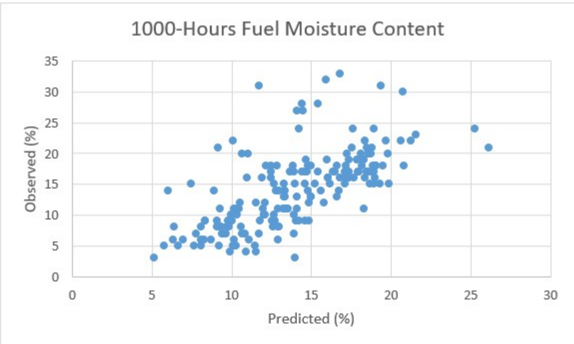



**Figure 13.Predicted vs Observed 1000 Hours FMC**

| | |
|---|---|
| $AAE$ (%) | 3.2450 |
| $ARE$ (%) | 23.62 |
| $R^2$ | 0.5403 |
| $\sigma$ (%) | 4.4722 |
| $n$ | 282 |

**Table 8. Performance of the prediction of 1000-Hours FMC**

#### *4.1.5. Live Fuels' Moisture Content*

*Remote Sensing Models*

The remote sensing models based on the NDVI demonstrated a very good correlation. Considering the 50% of most sensitive species, the $R^2$ was 0.66.

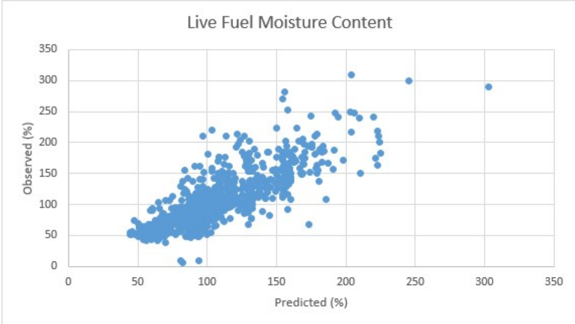



**Figure 14.Predicted vs Observed Live FMC for RS Models**

| | |
|---|---|
| $AAE$ (%) | 16.209 |
| $ARE$ (%) | 15.43 |
| $R^2$ | 0.6623 |
| $\sigma$ (%) | 23.921 |
| $n$ | 1035 |

**Table 9. Performance of the prediction of LFMC for RS Methods**

*Mixed Models*

Mixed models demonstrated by far the highest correlation values among all the prediction, which has been translated into the smallest average relative error, which demonstrates the capabilities of mixing both optical and meteorological inputs for the fuel moisture content determination.

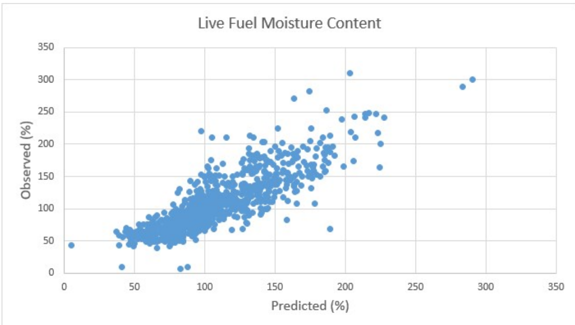



**Figure 15.Predicted vs Observed Live FMC for Mixed Models**

| | |
|---|---|
| $AAE$ (%) | 13.7 |
| $ARE$ (%) | 13.05 |
| $R^2$ | 0.7677 |
| $\sigma$ (%) | 20.35 |
| $n$ | 1035 |

**Table 10. Performance of the prediction of LFMC for mixed models**

### *4.2. Spatial variation*

Unless satellite based remote sensing methods are used for the fuel moisture content determination, the daily available information is not equally distributed in the space and thus, the construction of maps intending to represent the spatial distribution of the variables is based on a non comprehensive data set, i.e. a list of individual measurements, which leads to the necessity of applying interpolation techniques.For the determination of the fuel moisture content in any point based on a dataset of individual measurements can be written as:

$$m(\varphi,\lambda) = \frac{\sum_{i=1}^{n} c_i m_i}{\sum_{i=1}^{n} c_i}$$

Where $c_i$ is the weighting coefficient (usually distance-based) of each of the individual measurements $m_i$ that were made at a given coordinates $(\varphi_i, \lambda_i)$, and it is a function of the position where the value of the moisture content is sought and the position of the $i_{th}$ measurement . In the case of the NFDRS it is computed as follows:

$$c_i(\varphi,\lambda) = f_{dist}(\varphi_i,\lambda_i,\varphi,\lambda)^{-2}$$

$With$:

$$f_{dist}(\varphi_i,\lambda_i,\varphi,\lambda) = $$
$$= \frac{\int_{\min(\varphi,\varphi_i)}^{\max(\varphi,\varphi_i)} 2N(\varphi) asin\left(\sqrt{\sin\left(\frac{\varphi_i-\varphi}{2}\right)^2 + \cos(\lambda_i)\cos(\lambda)\sin\left(\frac{\lambda_i-\lambda}{2}\right)}\right) d\varphi}{|\varphi-\varphi_i|}$$

$$N(\varphi) = \frac{a}{\sqrt{1-e^2\sin^2(\varphi)}}$$

Where $a$ is the radius of the Earth at the equator and $e$ the eccentricity as defined by IERS (*International Earth Rotation and Reference*) conventions [49]. However, this interpolation method seems rather arbitrary and its use has not been yet justified. In addition, its error has not been properly assessed, and thus the uncertainty associated with the interpolation method surrounding theses maps remains unveiled. For these reasons, the error of the method has been measured and compared with an exponential model, which may correspond better with the spatial distribution of the fuel moisture content over large areas. In the exponential case, the coefficients are calculated as:

$$c_i(\varphi,\lambda) = e^{-k\, f_{dist}(\varphi_i,\lambda_i,\varphi,\lambda)}$$

The value of $k$ must be determined in order to obtain minimize the error, i.e. the difference between the observed and predicted value. For the optimization of the value of $k$, daily reports of $N$ days from the WFAS stations have been taken, each of them having at a particular day $(d)$ $n_d$ active stations reporting measurements. For each of these stations, the observed values have been predicted using the measurements from the remaining $n_d - 1$ stations, and the value of $k$ have been optimized in order to obtain the maximum performance of the interpolation method i.e. :

$$k = \arg_{min_k}\left\{\sum_{d=1}^{N}\left(\frac{1}{n_d}\sum_{j=1}^{n_d}\left|m(\varphi_j,\lambda_j) - \frac{\sum_{i=1}^{n_d} c_i m_i(1-\delta_{ij})}{\sum_{i=1}^{n_d} c_i(1-\delta_{ij})}\right|\right)\right\}$$

$With\ \delta_{ij}$ being the Kronecker delta.

In this particular study, $N = 5924$ , which correspond to days for a period from January 2000 to December 2017, in which the value of $n_d$ ranges from 150 to 2000. The results after optimizing the value of $k$ are displayed in Figure 6 and Table 11.

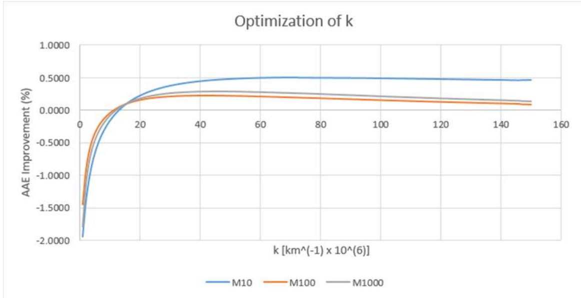



**Figure 16. Results of the optimization test**

| FUEL | k_opt (10^(-6) km^(-1)) | AAE Exp(%) | AAE NFDRS(%) | Improvement(%) |
|---|---|---|---|---|
| M10 | 72 | 2.7562 | 3.2657 | 0.5099 |
| M100 | 42 | 1.9636 | 2.1882 | 0.2246 |
| M1000 | 46 | 2.2992 | 2.5611 | 0.2907 |

**Table 11 Optimal value of k for all the fuels**

The following Figures show an example of the deviations derived from using each of the different interpolation models. As it can be seen, the exponential interpolation error's heat map shows lower values on average if compared with the map using the inverse square interpolation error.

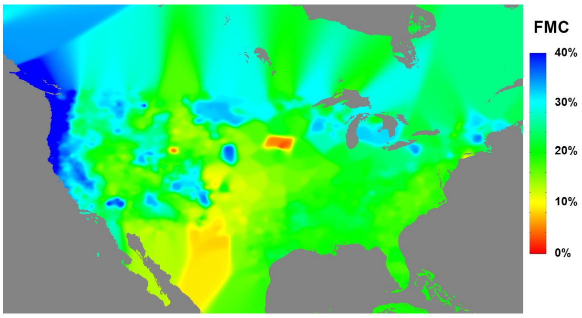



**Figure 17. Map of 1000 Hour FMC for March 4th 2017 using exponential mehod with optimized k**

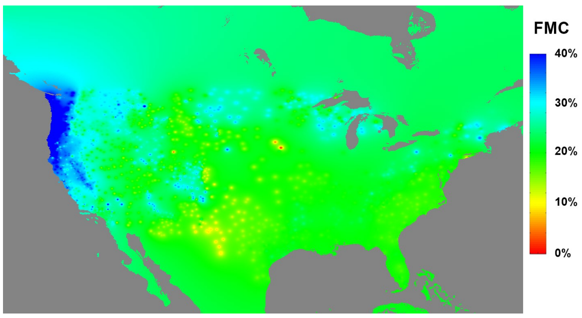



**Figure 18. Map of 1000-Hours FMC for March 4th 2017 using exponential mehod with optimized k**

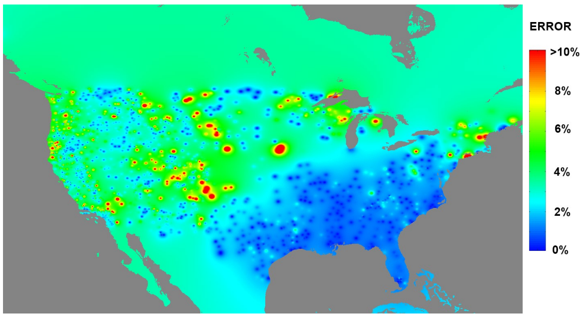



**Figure 19. Heatmap of error (AAE) for the exponential method in 1000-Hours FMC March 4th 2017**

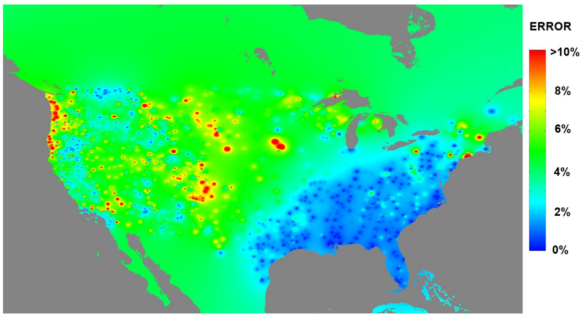



**Figure 20.Heatmap of error (AAE) for the NFDRS Interpolation in 1000-Hours FMC March 4th 2017**

## 5. SENSITIVITY ANALYSIS

Once the error of the different models have been quantified, it is possible to perform a sensitivity analysis, whose objective is the determination of the error introduced in the final fire's spread model as a consequence of the existing errors in the fuel moisture predictions. Applying the equations stated in the introduction, it is possible to calculate the error introduced in the final numerical value of the rate of spread as:

$$R_{err\quad dead} = \frac{\int_0^{m_{max}} \int_0^{+} dev_{dead}(m,e)p(m)p(e)dm\, de}{2\, m_{max}}$$

With $p(m)$ the probability function of moisture content prediction and:

$$dev_{dead}(m,e) = \left(\eta_{m_{dead}}(M_{r_{min}}) - \eta_{m_{dead}}(M_{r_{max}})\right)$$

$$\begin{cases} M_{r_{min}}(m,e) = \dfrac{m_{dead}+e}{m_{ext}} \\ M_{r_{max}}(m,e) = \dfrac{m_{dead}-e}{m_{ext}} \end{cases}$$

The error introduced in the rate of spread for a given predicted fuel and a given prediction error. Assuming a Gaussian distribution of the error and a prediction probability function computed numerically considering climatic records. Following an analogue procedure, it is possible to obtain the error introduced in the rate of spread as a consequence of the existing error of the live fuels prediction method.

The results of the sensibility analysis are presented in the following tables. The columns represent the average $\pm$ error margin in fraction of the final computed rate of spread for both live and dead fuels. These results are in quite good agreement with the general error of Rothermel's model that recent studies [50] noted, which might prove that the main source of error the prediction of wildland fires is the fuel moisture content. Following the definitions of Rothermel's fire spread model [1], the final error in the rate of spread must be between the two values that are displayed in the table.

| Fuel | Average Error Dead (±) | Average Error Live (±) |
|---|---|---|
| GR1 | 0.2002 | 0.1692 |
| GR2 | 0.2002 | 0.1683 |
| GR3 | 0.1657 | 0.1896 |
| GR4 | 0.2002 | 0.1683 |
| GR5 | 0.1235 | 0.1627 |
| GR6 | 0.1235 | 0.1681 |
| GR7 | 0.2002 | 0.1683 |
| GR8 | 0.1735 | 0.1886 |
| GR9 | 0.1198 | 0.1747 |
| Fuel | Average Error Dead (±) | Average Error Live (±) |
| GS1 | 0.2002 | 0.1683 |
| GS2 | 0.1953 | 0.1806 |
| GS3 | 0.1204 | 0.1744 |
| GS4 | 0.1229 | 0.1701 |
| Fuel | Average Error Dead (±) | Average Error Live (±) |
| SH1 | 0.1953 | 0.1797 |
| SH2 | 0.1916 | 0.1814 |
| SH3 | 0.1031 | 0.1776 |
| SH4 | 0.1778 | 0.1882 |
| SH5 | 0.1928 | 0.1815 |
| SH6 | 0.1779 | 0.1912 |
| SH7 | 0.1827 | 0.181 |
| SH8 | 0.1107 | 0.1694 |
| SH9 | 0.1187 | 0.1684 |
| Fuel | Average Error Dead (±) | Average Error Live (±) |
| TU1 | 0.1842 | 0.1898 |
| TU2 | 0.1755 | 0.2223 |
| TU3 | 0.1824 | 0.1824 |
| TU4 | 0.1939 | 0.1695 |
| TU5 | 0.1956 | 0.2003 |
| Fuel | Average Error Dead (±) | Average Error Live (±) |
| TL1 | 0.1739 | 0 |
| TL2 | 0.1941 | 0 |
| TL3 | 0.185 | 0 |
| TL4 | 0.1872 | 0 |
| TL5 | 0.1913 | 0 |
| TL6 | 0.1995 | 0 |
| TL7 | 0.1788 | 0 |
| TL8 | 0.1511 | 0 |
| TL9 | 0.1498 | 0 |
| Fuel | Average Error Dead (±) | Average Error Live (±) |
| SB1 | 0.1907 | 0 |
| SB2 | 0.1973 | 0 |
| SB3 | 0.1994 | 0 |
| SB4 | 0.1984 | 0 |

**Table 12. Average error in the Rate of Spread prediction for the different fuels**

One remarkable point from these results is that using the same methodology for the prediction of fuel moisture content leads to different levels of uncertainty from one fuel model to another. Taking into account the previously stated equations, this circumstance can be explained as a combination of two different factors:

- The relative influence of the different fuel sizes, which means that the global error is somehow a weighted average of the error of the individual models considering its own spatial density. Therefore, those fuel complexes, whose rate of spread is more dependent on unpredictable fuel sizes will be more unpredictable.

- The different moisture of extinction that every fuel model has. This value is inversely proportional to the sensitivity of the rate of spread to the fuel moisture content. In other words, the larger the moisture of extinction, the more predictable a fuel model is.

## 6. POTENTIAL APPLICATIONS

The described algorithms can be applied for the automation of the wildfire risk assessment routines at any point of the globe, as long as it is possible to obtain the required meteorological or remote sensing inputs. Since the error of each methodology is provided, it is possible to determine wether the use of the outputs is appropriate or not a given application, depending on the required accuracy. The fuel moisture content is a valuable input for both wildfire risk calculation and for the estimation of the wildfire behavior itself for both static and dynamic simulation techniques. Wildfire simulations are having a key role 3 possible operation scenarios: alarm's evaluation, support to wildfire analysts in the control station and in the direct wildfire analysis. In all of the cases, the knowledge of the fuel moisture content is a key element if realistic outputs of the simulations are wanted.

The evolution of the live fuel moisture content is highly variable depending on the species and on phenological aspects, which leads to the inaccuracy of static models traditionally used for its determination. As a contrast, the proposed methodology for the fuel moisture content prediction provides more precise values, with high temporal and spatial resolutions.

The assessment of the deviation from the reality that the individual prediction models exhibit can have implications in emergency management operations, by enhancing the possibilities of the wildfire spread prediction systems. Assuming, that the main source of error is the uncertainty surrounding the fuel moisture content determination and since the statistical behavior of the error inherent to the prediction methodologies is known, it is possible to define confidence bounds and consider them in wildfire spread models, so that the prediction routines output possible evolutions of the fire spread that correspond to boundaries with a given confidence interval. This is what is shown in Figure 21, in which a wildfire spread prediction has been computed by Pyrosat considering a best case (the fuel moisture content is the predicted one plus twice the standard deviation of the prediction models) , the most probable case (Computation with the predicted fuel moisture content) and the worst case (Computation with the fuel moisture content minus twice the standard deviation). This implies, that for the 95% of the cases, the actual fire spread will be somewhere between the upper and lower confidence bounds.

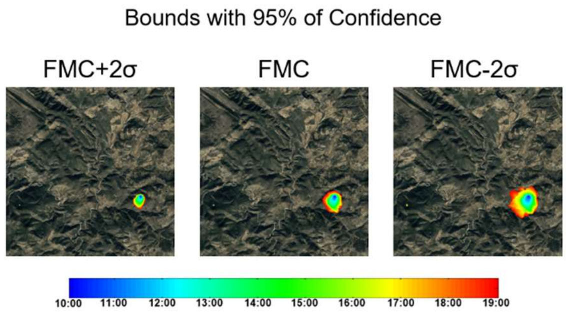



**Figure 21. Upper and Lower bounds with a 95% of Confidence of a wildfire spread prediction done by Pyrosat**

Another possible application would be its use in prescribed burns. The wildfire behavior of the controlled burns often differs with the expected one, mainly because of the uncertainty surrounding the fuel moisture content, which contrast with the accuracy, with which meteorological and topographical variables are known. In addition, the application of these methodologies at a particular area for long term, could be a determinant factor to be taken into account during the process of designing and placing the facilities for prevention and control of wildfires (firebreaks, road paths, water deposits…)

Although these are the most obvious applications of the algorithms presented in this paper, there are many other possibilities such as: real time management of prevention resources, implementation in fuel maps or estimation of burning severity levels and contaminant emissions.

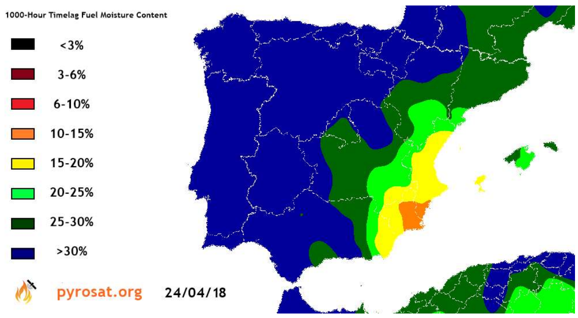



**Figure 22. 1000 Hours Timelag Fuel Moisture Content for the Iberian Peninsula , 24th April 2018**

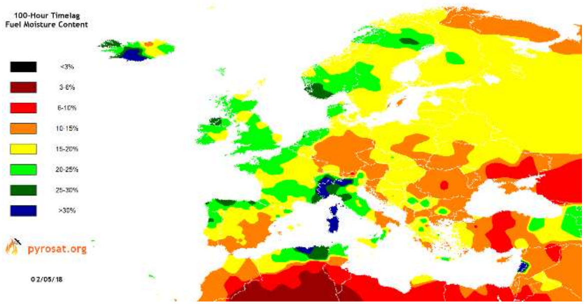



**Figure 23. 100-Hours Timelag fuel moisture content for Europe, 2nd May 2018.**

## 7. CONCLUSSIONS

Predicting the fuel moisture content in an accurate and automatic way remains as an unsolved problem in wildfire science, which limits many potential applications of developed models for fire spread or intensity. However, much progress has been done during the last decades, and new possibilities are emerging, particularly regarding the use of satellite based remote sensing techniques.

The error of automatic methods for predicting the fuel moisture content based either in meteorology or in remote sensing is close to the interpolation error in the NFDRS maps, which are based on real measurements. This implies, that the use of the presented models shall be used for the moisture content prediction around the globe in order to produce products, with an accuracy similar to that of NFDRS maps. In addition, there is a lot of room for improvement in the error of the NFDRS maps, by only changing slightly the interpolation method, using the same procedures and inputs.

Mixed models adapted to particular species demonstrated to be the most powerful tool for the automatic prediction of the moisture content. Regarding meteorological models, with the exception of the 1-Hour fuel moisture content, they demonstrated a quite good performance, especially the ones for the prediction of 10-Hours Fuel moisture content. This allows them to be considered for being used for the development of spatial products, that will be able to improve the wildfire risk assessment capabilities in areas around the globe regardless of the availability of forest stations performing in-situ measurements.

With the current automatic models for fuel moisture content prediction, the error introduced in the computation of the rate of spread is around $\pm 20\%$, which limits its applications for spread predictions. Future models intending to be highly accurate ($ARE < 10\%$) might require to consider the particularities of each species, even for the dead fuels, since many of the existing error might be associated to the generalizations done in the models.

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