NEW COMMUNICATION METHOD FOR WILDLAND FIRE RISK ASSESMENT USING PYROWARN

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1. Introduction

The issue of wildfires pose serious threats to the conservation of the biodiversity and our tree cover, which is one of our key weapons against the negative effects of the climate change. However, the complexity of this phenomena and the multiple meteorological and orographic variables involved in it, has led to the lack of tools that provide real time accurate information at microscale levels [1]. It is often said, that the prediction accuracy of wildfires is 20 years behind hurricane and cyclone modelling. However, this environmental issue implies great economic and human losses every year [2,3], which reminds us the urge of developing robust tools that can aid the prediction and prevention of this events.

In this context, the *Pyrosat* project was bornt with the aim of providing a reliable system of information regarding the wildland fire risk and the forecast of ongoing fires around the whole globe. *Pyrowarn* is an extension of the software package *Pyrosat* and it integrates a communication system able to evaluate the most relevant risk factors and parameters involving the problematic of wildland fires and to elaborate real time risk maps and forecasts of any area of the earth taking into account the short and mid-term changes of the meteorological and environmental variables related to the process.

2. Problem Inputs

Although *Pyrosat* is able to compute aerial fires, since *Pyrowarn* is only oriented to surface wildfires, this text will only refer to the latter.

2.1. Meteorological variables

The Meteorological variables most relevant to the calculation of a wildfire´s evolution are air temperature, wind speed, relative humidity, precipitation amount and cloud cover [4]. Their effect on the process of wildfire´s spread is not only limited to their current values, but their maximum, average and minimum values of the last days and weeks, since these values are necessary In order to determine some of the intermediate variables involved in the process [4,5]. In addition, the scalar values of these magnitudes do not suffice, it is often necessary to determine the complete field of it in the study region. Figure 1 shows the spatial variation of the air temperature in the Yosemite National park. As shown in the Figure, there can be a very important variation in the same study area, which leads to the conclusion that considering it constant implies an important level of error. This reasoning is valid for all of the meteorological and environmental variables involved in the wildfire modelling.

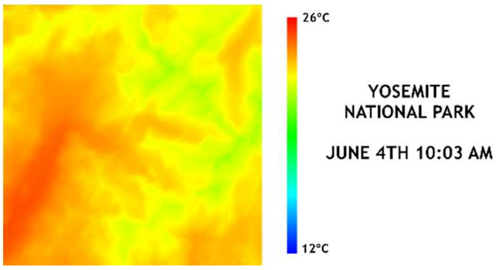

Figure 1. Field of air temperature in Yosemite at 06/04/17 10:03

2.2. Environmental variables

The environmental variables are the artificial and natural elements present in the study area, its geometry, physical characteristics and spatial distribution. The quantification of these factors is usually less obvious than the atmospheric ones, so it often implies the use and comparison of a larger amount of information. In the context of wildfire science, the environmental variables are usually determined by defining the surface fuel parameters which define the potential surface fire carriers, the geometry of the trees standing and its canopy bulk density and with the spatial variation of this parameters.

In some cases, experimental measures may undergo in order to determine a particular fuel model for a given area [6- 10]. However, in most of the cases, forest managers may choose as the present fuel model the one that better fits the present vegetation from a given list. There were originally 13 Fuel models which have been largely used in the wildland fire science [11]. However, Scott & Burgan developed in 2005 a list of 40 fuel models which may presents a greater flexibility [12]. *Pyrosat* uses mainly the models from the Scott & Burgan´s list, however its database includes a total amount of 200 different fuel models.

2.2.1 Vegetation´s structure

In order to determine the most appropriate fuel model it is necessary to know the fire carrier, which, in the case of the surface fire, it depends on the study area´s floor. There are mainly 5 different kinds of fire carriers:

- Grass
- Shrubs
- Broadleaf litter, usually in deciduous stands
- Needleleaf litter, usually in evergreen stands
- Coarse woody debris

Using the 40 Fuel Models classification system [12] , it is, in addition, necessary to know the kind of climate and the quantity of the fuel carrier in a given study area in order to determine the most appropriate fuel model. This can usually be inferred by the use of landcover maps and the analysis of the Normalized Differential Vegetation Index (NDVI) series of a particular point. The NDVI is a parameter, which assesses the quantity of vegetation contained in the point being observed, and thus, the annual evolution of this parameter provides relevant information about the typology of the information on a given point [13]. This parameter is strongly linked to the vegetation's characteristics [14] Figure 2 and 3 Illustrate the difference of the NDVI series between different forest stands in Spain.

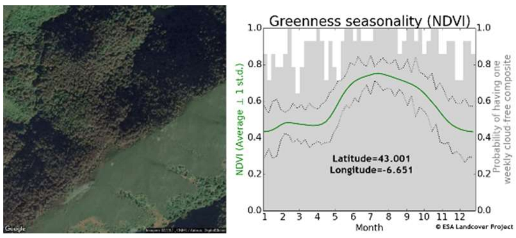

Figure 2. NDVI in a deciduous forest stand, Asturias (Spain)

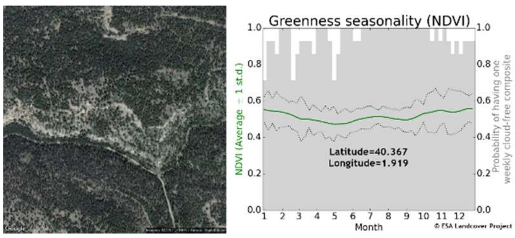

Figure 3.NDVI in an evergreen forest stand, Cuenca (Spain)

By comparing both Figures, one can see, that although the stand in Asturias reaches a higher level of vegetation (around 0.8), with the start of the winter season it decreases greatly, reaching values much lower than the lowest point of the evergreen stand in Cuenca, which presents a more regular distribution during the year. Evergreen stands are in the most cases associated to conifers, and therefore producing the needleleaf litter that is shown on the Figure 4, whilst the deciduous forests are usually composed of broadleaf species and generate the kind of forest litter illustrated on the Figure 5. However, since the relationship between the caducity of the foliage and litter kind is not unequivocal, it is necessary to compare the NDVI series data with other sources of geospatial information in order to determine accurately the kind of litter present on a particular forest floor. In this direction, the Figure 6 illustrates one Chinese Swamp Cypress, which is one of the only 20 remaining species in the planet of deciduous conifers and the sole living species in the genus *Glyptostrobus*, and is regrettably nearly to complete extinction [15,16]. This particular cases justify the performance of deeper analysis techniques in order to determine forest´s floor leaf litter composition which is necessary to select the most appropriate fuel model.

Figure 4. Needleleaf litter

Source: soil-net.com

Figure 5. Broadleaf litter

Source: stockphoto.com

Figure 6.Example of a deciduous conifer: Glyptostrobus pensilis

Source: Patrick Breen landscapeplants.oregonstate.edu

It can be easily deduced that the most appropriate fuel model in the same stand is susceptible to the particular instant of time considered. For example, In the Stand of the Figure 2, although there will usually be broadleaf litter in the forest floor, its quantity, and therefore the most appropriate fuel model may vary during the year.

To sum up, *Pyrosat* uses geospatial information from different sources in order to determine the existent vegetation in every point of the desired study surface on a given moment, which is one of the most important inputs in the wildfire modelling. The Figure 7 shows the results of *Pyrosat's* system applied in the Ashley National Forest.

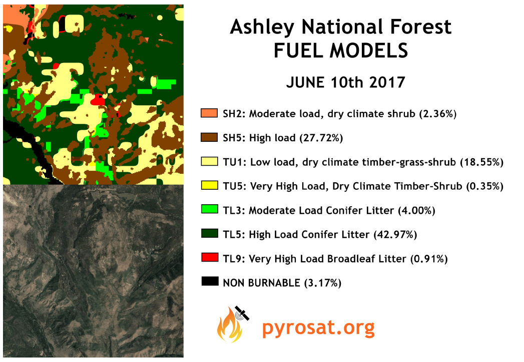

Figure 7. Fuel models map, Ashley National Forest,Utah/Wyoming (USA)

2.2.2. Orography

Another relevant non-meteorological parameter is the orography. The importance of this factor becomes clear if we take a look at the Rothermel´s firespread equation [17]:

$$R\ [feet/minute] = R_0(1 + \varphi_s + \varphi_w) \qquad [1]$$

Where R is the rate of spread; R_0 the rate of spread in absence of wind and slope and φ_s, φ_w the slope and wind parameters, which can be much greater than one. The value of the wind parameter is limited by the reaction intensity [17, 18] but the value of the slope parameter will tend to infinite in the case of perpendicular slopes [17]. For this reason, there is no possibility of developing any optimal wildfire model that does not take into account the terrain´s orography. The Figure 8 shows the tridimensional view of the Yosemite National Park generated by *Pyrosat.*

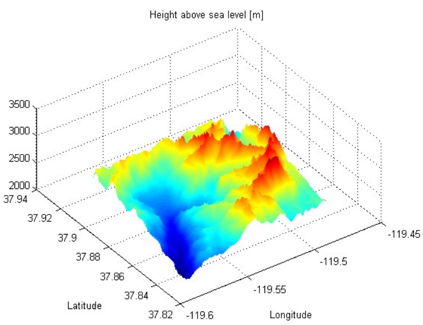

Figure 8. Tridimensional view of Yosemite National Park

3. Problem Outputs

Since *Pyrowarn* aims to report information relevant to the risk of wildfire, the software´s main outputs are the USA NFDRS (National Fire Danger Rating System) values and the Canadian FWI (Fire Weather Indexes). However, as an additional feature, some of the most relevant outputs from the Rothermel´s fire spread model are additionally computed in order to provide useful information for the forest managers. *Pyrowarn* computes the current values of the stated indexes and their prediction in 6 hours intervals in the case of the NFDRS parameters and 24 hours for the Canadian FWI. In the Figure 9 it can be seen the height of the flame in the event of a wildfire. As the software´s interface illustrates, *Pyrowarn* is able to display the other NFDRS indexes and forecasts in the chosen study area.

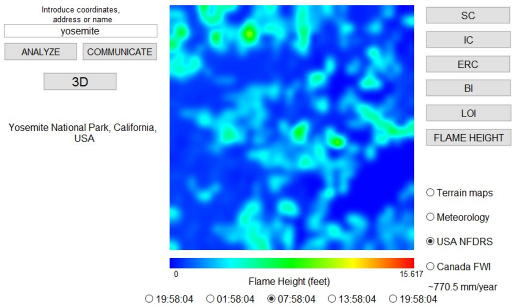

Figure 9. Output's window of the NFDRS indexes

4. Introduction to the Pyrosat Algorithm

Pyrosat´s algorithm is based on two principles:

- Analysis of large amount of information applying the current scientific knowledge.
- Use of machine learning for a continuous improvement and calibration of the algorithm.

In order to make this possible, it has been necessary to incorporate more than 20 Landcover maps produced by different institutions, in conjuction with many other sources of geospatial information and global maps containing environmental, meteorological and geological information, which in total add up for more than 500 world maps.

The process for developing new equations that correct the model error can be observed in the Figure 10. As the diagram shows, the model´s outputs are compared with the observed values, and then, the algorithm develops new equations by comparing the experimentally measured error with environmental parameters from Pyrosat's geospatial database generating new equations for the wildfire model.

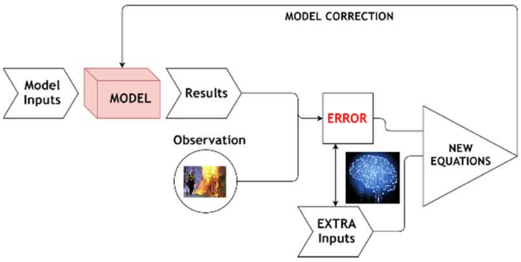

Figure 10. Pyrowarn's machine learning algortihm diagram

The extra inputs candidates that are determined too by a computational intelligence method, which selects the better candidates to influence the measured parameter according to the existent bibliography.

5. Methodology and Validation

Although the validation of the whole methodology is not yet completed, some of the most relevant parameters of the model have already been evaluated and the gained accuracy is remarkable. To serve as an example, of the methodology, in this text we will present the improvement of the remote sensing computation of the 1000 hour time lag fuel moisture content. This value corresponds to the amount of water contained in the sticks of dead vegetation of around 8 inches of diameter, such as the ones shown in Figure 11.

Figure 11. Dead Fuel of the 1000 Hour Time Lag

Source: David Stephens, Bugwood.org

This factor is very important in the wildfire modelling and is one of the parameters continuously measured for safety reasons. The Figure 12 shows one of the daily generated maps by the Wildland Fire Assessment System (WFAS).

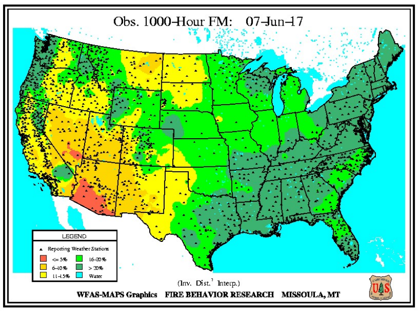

Figure 12.Observed 1000 Hour Fuel Moisture Content in USA

There are several methods developed in order to calculate this value [19, 20], *Pyrosat* uses historical data obtained from remote meteorological stations and the geographical position of the study site in other to determine the moisture content of this dead fuels. The accuracy this methodology's application can be observed in the Figure 13, whereas the Figure 14 shows the relationship between predicted and observed values after processing the data with *Pyrosat´s* algorithm and developing new equations that improve the model as it is illustrated.

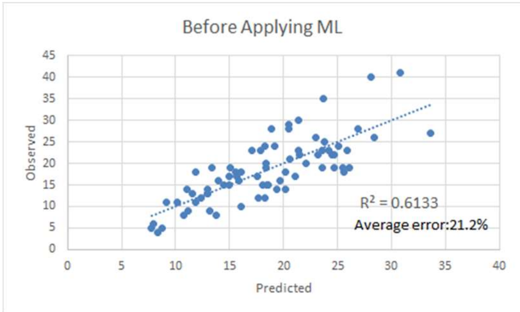

Figure 13. Observed vs Predicted 1000 Hour FMC

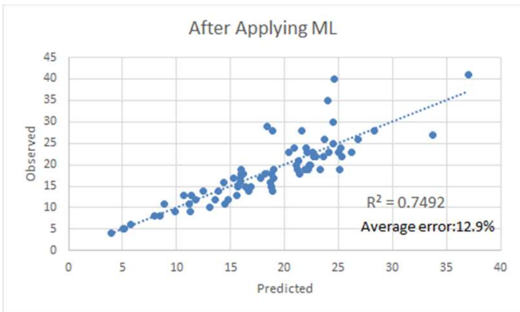

Figure 14. Observed vs predicted 1000 Hour FMC after ML Algorithm

Thanks to this methodology, it is possible to generate similar maps like the ones produced by the Wildland Fire Assesing System in other parts of the globe. This is the final aim of the Pyrosat project, to generate information derived from the the currently scientific knowledge that can assess the risk of wildland fires in any part of the globe.

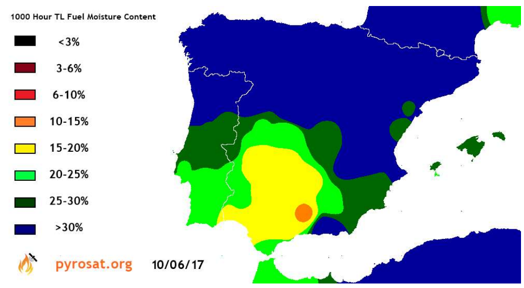

Figure 15. Computed 1000 Hour Fuel Moisture Content in southeast Europe

6. Communication

As it has been mentioned, *Pyrowarn´s* aim is to combine geospatial information with the current scientific knowledge in order to report in real time risk indexes and its prediction of any chosen study area of the globe. For this reason, the software includes a communication toolbox that can serve to automatically analyze and report values of the indexes that pose an important risk. The Figure 16 shows the window where the user can introduce the reporting frequency and set the trigger values that he/she considers subjectively as dangerous. After this information has been input, the program will automatically perform continuous analysis of the field and when the current value or its forecast crosses the trigger values an email will automatically be sent.

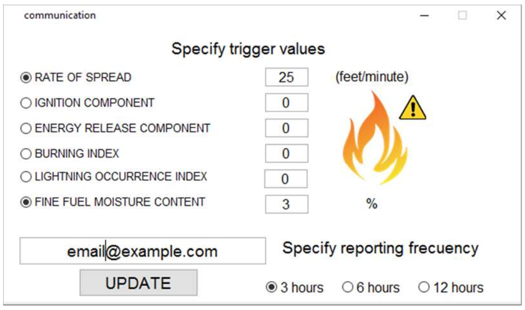

Figure 16. Pyrowarn's email communication toolbox

7. Discussion

The complexity of the wildfire modelling implies the requirement of huge amount of information and the consideration of tiny details and environmental variables, which are usually difficult to be included in a mathematical model. For this reason, the accuracy of the wildfire models is not yet a match for the precision of other natural hazards' forecast models.

The use of computational intelligence and big data is an interesting approach to the wildfire´s modelling accuracy problem. Despite the promising results stated above, the complete validation of such methodology would require a more exhaustive approach than the one presented in this text. However, the usefulness that these techniques have previously shown in other fields [21, 22] suggests that the application of these techniques could imply a significant improvement in the modelling of wildland fires.

8. References

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