

DAILY FIRE HAZARD INDEX FOR THE PREVENTION AND MANAGEMENT OF WILDFIRES IN THE REGION OF SARDINIA

V. Pampanoni^{1*}, S. Riyaz Uddien^{1*}

¹Scuola di Ingegneria Aerospaziale, Sapienza Università di Roma, Via Salaria 851-881, Rome, Italy

[*valerio.pampanoni@uniroma1.it](mailto:valerio.pampanoni@uniroma1.it), riyaz.shaik@uniroma1.it

ABSTRACT

The purpose of this paper is to show how the process for the calculation of the Daily Fire Hazard Index described in (Laneve, Cadau, 2007)^[1] was improved upon by taking into account the effects of wind speed and direction, examining the wildfire insurgence data in the Italian region of Sardinia. The Daily Fire Hazard Index was developed in the context of the S²IGI project with the objective to provide a daily estimate of the likelihood of wildfire insurgence, in order to help coordinate the firefighting activities. Using land cover maps, fuel maps and MODIS satellite imagery, an algorithm was developed to estimate the relative amount of live and dead vegetation. Meteorological data is used to determine the temperature, the relative humidity and the wind speed. After using the FAO Penman-Monteith method (1998)^[2] for the determination of the reference evapotranspiration of the vegetation, a simple algorithm was used to correct the surface temperature accounting for the effect of the magnitude of the wind speed. After determining the wind direction using the meteorological forecast data, the correction factor takes into account the fact that in Sardinia, the majority of the wildfires occur in days of strong Mistral winds.

Keywords: wildfires, vegetation, hazard index, sardinia

Introduction

1 INTRODUCTION

It has been widely reported by a number of international organizations (such as FAO, EEA and JRC) that Mediterranean forests are gravely affected by wildfires, with overwhelmingly negative consequences on two macro-areas: the economic area, due to the destruction of crops, buildings or infrastructures, and the hydrogeological area, where the damage assessment is much more complex. The balance of the ecosystem is dramatically altered by wildfires, with further negative effects on soil erodibility, due to the partial or complete loss of the vegetation cover, and subsequent desertification. In 2014, approximately 500'000 hectares of European land burned as a cause of 65'000 wildfires^[3], and this number has gone practically unchanged through the last 30 years despite all the efforts made towards prevention and the improved technological support of firefighting activities.

The S²IGI project was funded by the Sardinia Region in the framework of the POS-FESR 2014-2020 initiative. Developed through a collaboration between the School of Aerospace Engineering of La Sapienza University, CNR-IBIMET and Nurjanatech, the project aims to contain the damage caused by wildfires by providing an integrated information system based on the usage of new techniques and satellite technology. In particular, the Daily Fire

Hazard Index covers the need for a daily fire danger assessment based on meteorological data and on an estimate of the actual state of the vegetation.

2 STATE OF THE ART

It has been widely observed that there is a strong relationship between wildfire insurgence and a number of measurable parameters, namely the characteristics and state of the fuel (in terms of vegetation type, temperature and moisture content), the topography of the area of interest (in terms of altitude, slope and illumination conditions), and the general meteorological conditions. Furthermore, given the fact that the overwhelming majority of wildfires are caused, either intentionally or accidentally, by humans, it is possible to give a reasonable estimate of the likelihood of a certain area to burn.

2.1 Methods of fire risk estimate

Following the guidelines established in (Laneve et al., 2011)^[4], we can distinguish two types of methods of fire risk estimate:

- 1) *Statistical methods* provide long term risk indices based on slowly changing parameters, such as topography, land cover and other variables that can be considered constant over short timeframes.
- 2) *Dynamical methods* provide short term risk indices, and are based on data that undergo significant variations on a daily basis, and that can be measured frequently using satellite data or forecast models.

The Daily Fire Hazard Index belongs to the second category, and makes use of the latest satellite and meteorological data to assess the actual conditions of the vegetation as accurately as possible.

2.2 Brief history of dynamical methods for fire risk estimate

Since 1998, the Joint Research Centre of the European Commission coordinated efforts to create a standard method for the evaluation of forest fire hazard on a continental scale. Until then, most of the indices used to assess the risk of forest fire insurgence were developed on a national scale, and the vast majority of them did not make use of satellite data. In particular, an effort was made by the JRC to adapt the Fire Potential Index (FPI), which was originally developed for North-American territories, to our European and Mediterranean forests (Sebastian-López et al., 2002)^[5].

The School of Aerospace Engineering, in the framework of the SIGRI project funded by ASI, decided to follow the same path and developed the Modified Fire Probability Index (MFPI), which made use not only of fuel maps and meteorological data, but also of satellite imagery to calculate the so-called “fire potential”, and was able to assess the actual conditions of the vegetation by distinguishing live and dead vegetation, on the basis of the work done by (Burgan et al., 1993)^[6]. Furthermore, the MFPI improved upon the FPI developed by (Burgan et al., 1998)⁽⁷⁾ by taking into account the effect of the topography on the actual illumination conditions of the area of interest, and this was achieved by computing the reference evapotranspiration ET_0 as prescribed by the FAO Penman-Monteith method^[2].

Finally, the latest version of the index, called Daily Fire Hazard Index (DFHI), corrects the temperature of the vegetation by accounting for the effect of the wind speed, and adjusts the fire hazard risk with respect to the wind direction, which allows us to model the experimental fact that in Sardinia, the majority of the fires occur in days of strong Mistral wind.

3 DAILY FIRE HAZARD INDEX CALCULATION PROCEDURE

3.1 Data Sources and Relevant Quantities

The algorithm for the calculation of the DFHI is schematically represented in figure 1, and relies on the following data sources:

- NASA MODIS MOD09GA and MOD09GQ L2 images (daily)
- Meteorological data provided by the Aeronautica Militare (daily)
- Fuel Map of the area of interest
- NDVI historical records of the area of interest
- Digital Elevation Model of the area of interest

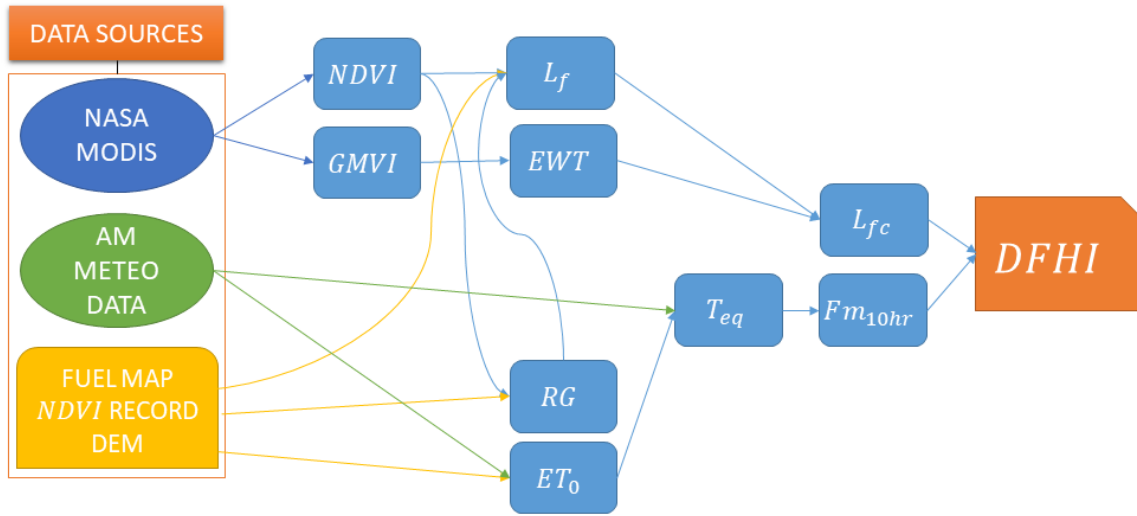


Figure 1: Flowchart representing the procedure used to compute the Daily Fire Hazard Index

The Daily Fire Hazard Index is able to provide an up-to-date estimate of the tendency of a certain area to develop and support wildfires by distinguishing between live and dead vegetation, and subsequently assessing their humidity content and temperature in order to determine the likelihood of wildfire insurgence as accurately as possible. Ultimately, these two fundamental characteristics of the vegetation are measured through the quantities L_f (fraction of Live vegetation) and TN_f (fraction of Ten Hour-Lag Time Fuel Moisture), that determine the $DFHI$ through the following equation:

$$DFHI = (1 - L_f)(1 - TN_f) * 100 \quad (1)$$

3.2 Estimation of the Live Vegetation Fraction

The distinction between live and dead vegetation is made by exploiting medium resolution and high frequency satellite imagery such as MODIS, which allows us to obtain daily L2 reflectances in the red and near-infrared necessary to compute the $NDVI$ (Normalized Differential Vegetation Index). The comparison between the measured $NDVI$ and the historical records for each individual pixel is what ultimately allows us to distinguish the live and dead vegetation, and this result is obtained by computing the Relative Greenness RG , which is defined as follows:

$$RG = \frac{NDVI - \min_{5y} NDVI}{\max_{5y}(NDVI) - \min_{5y}(NDVI)} * 100 \quad (2)$$

The $NDVI$ is also used in conjunction with the fuel maps to compute the L_f (fraction of green vegetation) in the following way:

$$L_f = \frac{RG_f \cdot [35 + 40 \cdot (NDVI_{mx} - 100)/80]}{100} \quad (3)$$

Where $NDVI_{mx}$ is the maximum value of the $NDVI$ found for the given pixel in the selected time period:

$$NDVI_{mx} = 100 \cdot \max_{5y}(NDVI) + 100 \quad (4)$$

MODIS reflectances in the near and shortwave infrared are used to compute another fundamental quantity that allows us to obtain a very useful estimate of the moisture content of the vegetation, which is the EWT (Equivalent Water Thickness). The seasonal decrease of this quantity that occurs every year around the beginning of summer has been directly linked to the insurgence of wildfires and the start of the wildfire season. In the form given by (Ceccato et al., 2002)^[8], the EWT is written as a function of the $GVMi$ (Global Vegetation Moisture Index):

$$GVMi = \frac{(NIR + 0.1) - (SWIR + 0.02)}{(NIR + 0.1) + (SWIR + 0.02)} \quad (3)$$

$$EWT = \frac{-(ad+c-d \cdot GVMi) + \sqrt{(ad+c-d \cdot GVMi)^2 - 4cd(a+b-GVMi)}}{2dc} \quad (4)$$

Where a, b, c, d are dimensionless coefficients, whose values are the result of an African experimental campaign which involved a wide variety of forests and vegetation types. Subsequently, EWT is used to correct the fraction of green vegetation in the following way:

$$\overline{EWT} = \frac{EWT}{\langle EWT \rangle + 2\sigma(EWT)} \quad (5)$$

$$L_{fc} = L_f [1 + 0.2(\overline{EWT} - 1)] \quad (6)$$

Where $\langle EWT \rangle$ and $\sigma(EWT)$ are the mean and standard deviation of the latest EWT map. In other words, the fact that an increase in EWT results in a decrease of the fire hazard is modelled through an increase of the fraction of live vegetation.

3.3 The Reference Evapotranspiration and the Wind Factor

The moisture content of the dead vegetation is estimated using meteorological data of humidity and temperature by means of the quantity Fm_{10hr} (Ten Hours-Time Lag Fuel Moisture):

$$Fm_{10hr} = 1.28 * emc \quad (7)$$

Where the emc (equivalent moisture content) is a function of the air moisture and temperature at 2 meters of height. While the predecessor of the DFHI, the FPI (Fire Probability Index) simply used meteorological data to compute this quantity, the DFHI improves this procedure by accounting for the effect of the wind speed in a very straightforward way. After computing the ET_0 (Reference EvapoTranspiration) following the FAO Penman-Monteith guidelines^[2],

this quantity is used to locate the pixels that show conditions far enough from an array of reference ET_0 values, computed without taking into account the topography of the area of interest, using a constant wind speed of 2 m/s and changing the temperature between 0° and 64°C with a step of 2°. These conditions, together with the net radiation R_n computed for the day of interest, are used to create a look-up table of evapotranspiration values and their corresponding temperatures in order to compare them with the reference evapotranspiration that takes into account the actual wind speed and the effects of the local topography.

The actual ET_0 is therefore compared with the evapotranspiration values in the look-up table in order to find the position that corresponds to the minimum difference, and subsequently, the temperature that generated this value is selected as an “equivalent temperature” T_{eq} that will be assigned to the vegetation:

$$T_{eq} := T^*: |ET_0(T^*) - ET_0(T)| = \min_{T^* \in [0;64^\circ C]} |ET_0(T^*) - ET_0(T)| \quad (8)$$

This allows us to compute the Ten Hours-Time Lag Fuel Moisture using a temperature that is more representative of the actual status of the vegetation, rather than simply using the air temperature at 2 meters, while also taking into account the effect of the wind speed. Finally, the Fm_{10hr} is computed using the equivalent temperature and converted to the corresponding fractional quantity, which is ultimately used to compute the DFHI as shown in equation (1).

3.4 The Effect of Wind Direction: The Case of Sardinia

Given all the historical records of wildfires in Sardinia, the majority of the fires occur in days of strong Mistral winds. This effect can be very easily included in the fire hazard assessment using a multiplicative factor:

$$DFHI_{SAR} = wf \cdot DFHI \quad (9)$$

Where the *wind factor* wf is larger than unity only in case of Mistral and Sirocco wind. Otherwise, its value is always one, as shown in table 1:

Wind Direction	Wind Name	wf
N	Tramontane	1.0
NW	Mistral	1.25
E	Ponente	1.0
SW	Libeccio	1.0
S	Ostro	1.0
SE	Sirocco	1.10
E	Levant	1.0
NE	Gregale	1.0

Table 1: wf values assigned to each Mediterranean wind.

4 PERFORMANCE OF THE DFHI

Firstly, the typical products of the algorithms will be showcased to demonstrate how the Daily Fire Hazard Index reacts to quick changes in the meteorological conditions, and therefore in the state of the vegetation. Secondly, the latest available wildfire records for the region of Sardinia will be used to assess the performance of the new version of the index.

4.1 Typical Products

The DFHI is computed daily using a Matlab algorithm that runs on a server. After downloading the latest MODIS images and the meteorological data of the reference day, DFHI maps are generated for the midday of the reference day and the two following days. Figure 2 provides an informative look at the behaviour of the index during the beginning of the fire season.

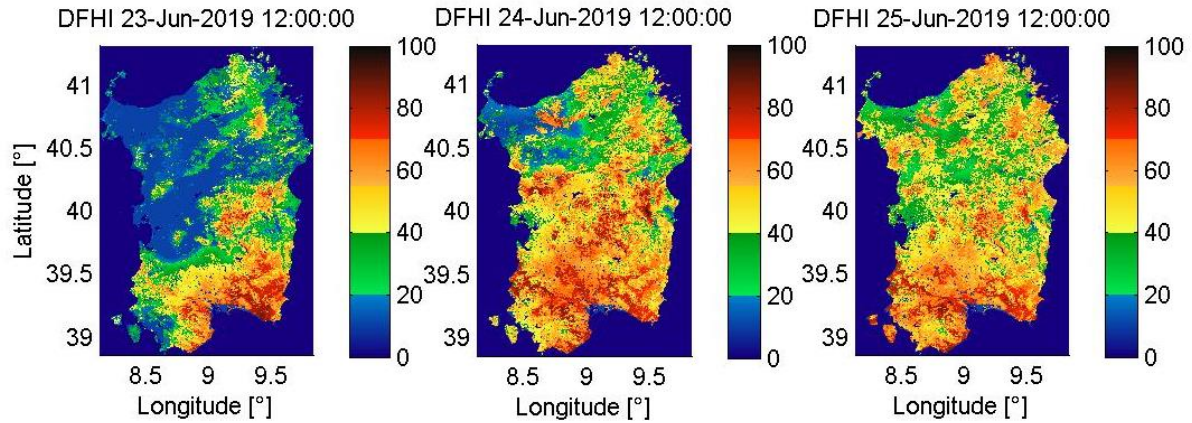


Figure 2: Daily Fire Hazard Index maps in the late June 2019

The quickly increasing temperatures and the overall decrease in relative humidity result in an evident increase of the hazard index in the entire Sardinian territory. However, the areas with the highest values of the index (namely, the red and dark red areas on the map), tend to be determined mostly by the decreasing value of quantities such as the EWT and the ET_0 , which are representative of the progressive loss of moisture of the vegetation due to the beginning of the summer season and therefore of the wildfire season. By contrast, in figure 3, during the rainy days of the late May 2019, we can see how the fire risk is practically non-existent despite the high temperatures and vegetation greenness, as one would expect.

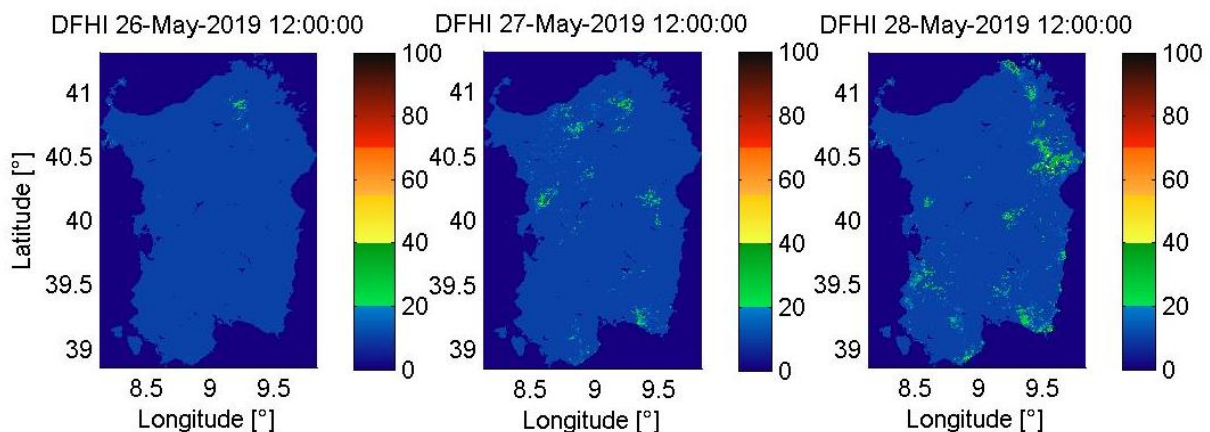


Figure 3: Daily Fire Hazard Index maps in the late May 2019

4.2 Distribution of the Fire Hazard

At the time of writing, the latest available wildfire records in the area of interest provided by the Regione Autonoma della Sardegna are related to the year 2017. Our analysis was focused on the wildfire season, and therefore the months of June, July and August were selected as the timeframe of our validation procedure. Firstly, DFHI maps for each day of the timeframe were

created, and each pixel of the area of interest was assigned a hazard class following the classification described in table 2.

DFHI Interval	Hazard Class
0 – 20	No Hazard
20 – 40	Low Hazard
40 – 55	Medium Hazard
55 – 70	High Hazard
70 – 100	Very High Hazard

Table 2: *DFHI* values and hazard classes.

Secondly, the process was repeated selecting only the burnt areas rather than the entire region, and subsequently, this new distribution of the fire hazard index was compared to the global one in order to assess its performance. The desirable outcome of this process would be to find that most of the wildfires occur in the areas that show the highest hazard levels, while normally the majority of the pixels should fall under lower fire hazard classes.

The results of this process are summarized in the bar graphs of figure 4. The left bar graph shows how, considering the *DFHI* maps of the entire region of Sardinia, 86.56% of the pixels fall under the “no hazard”, “low hazard” and “medium hazard” categories as one would expect, with the highest number of occurrences found in the “low hazard” class. On the other hand, if we focus only on the areas stricken by wildfires, the hazard distribution changes visibly, with almost three quarters of the burnt pixels falling under the “high hazard” class.

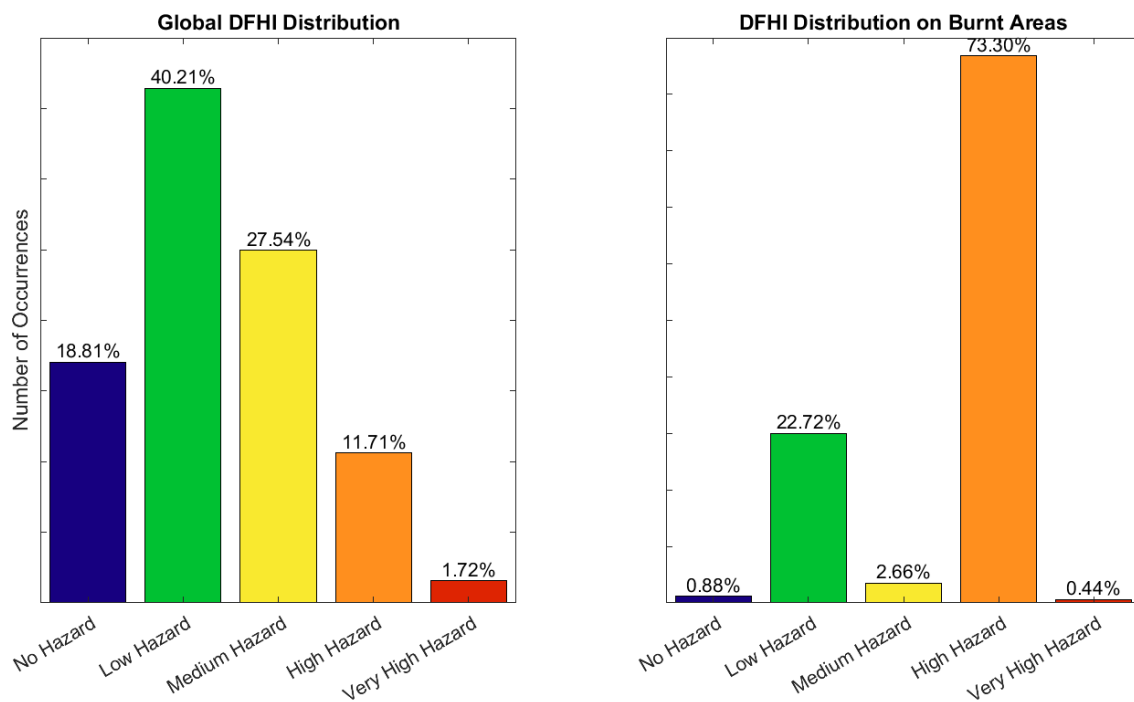


Figure 4: Comparison between the distribution of the fire hazard on the entire region and on the burnt areas

The comparison between the two distributions shows that the fact that most of the burnt pixels fall under the “high hazard” class is not due to an inherent bias of the algorithm towards high risk classes, since regularly most of the pixels fall under the low hazard classes, but rather to the accurate estimation of the state of the fuel provided by the latest version of the model.

5 CONCLUSIONS

The latest version of the DFHI improves upon its predecessors in evaluating the actual state of the vegetation both on the model side, by including the effects of the wind speed and direction, and on the algorithm side, by using daily atmospherically corrected L2 MODIS imagery to obtain the required reflectances in the visible and near-infrared. Qualitatively, the algorithm responds well to the changes in temperature, EWT and ET_0 , so that relevant day-to-day shifts in the model parameters always translate in visible changes in hazard risk values, justifying the need for a daily tool to estimate the risk of wildfire insurgence. Quantitatively, the distribution of the fire hazard over the region of Sardinia shows the absence of a bias towards high risk classes, and the analysis of the predicted risk over actual burnt areas shows that the Daily Fire Hazard Index is a valuable tool for the support of the decision makers in short term wildfire prevention.

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