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A Remote Sensing and Geo-Statistical Approaches to Mapping Burn Areas in Apulia Region (Southern Italy)

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Abstract. Fires represents one of the main causes of environmental degradation and have an important negative impact on the landscape. Fires, in fact, strongly influenced ecological processes and compromise the ecosystems. Measurements of the post-fire damage levels over burned areas are important to quantify fire's impact on landscapes. Remote sensing and geo-statistical approaches are useful tools for the monitoring and analysis of burned areas on a regional scale, because provides reliable and rapid diagnosis of burned areas. Spatial autocorrelation statistics, such as Moran's I and Getis–Ord Local Gi index, were also used to measure and analyze dependency degree among spectral features of burned areas. This approach improves characterization of a burnt area and improves the estimate of the severity of the fire. This paper provides an application of fire severity studies describing post-fire spectral responses of fire affected vegetation to obtain a burned area map. The aim of this work is to implement a procedure, using ESA Sentinel 2 data and spatial autocorrelation statistics in a GIS open-source environment, a graphical model that analyzes the change detection of the potential burned area, as case of study Northern part of Apulia Region (Italy) was used. The burned area was delineated using the spectral indices calculated using Sentinel two images in the period July–August 2020 and using also the land use map of the area.

Keywords: Fire perimeter · Burn severity · ΔNBR index

1 Introduction

Every year forest fire affects wide areas in the world and cause devastating damage at global scales. Forest fires represents an environmental problem that generates negative impacts on forest ecosystems and alter the structure of vegetation [3, 19]. Fire

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is considered as a major cause of biodiversity reduction, soil fertility loss, gaseous pollutants emission, and other environmental impacts. Fire danger estimation is very important in order to quantify the impact on landscape [31] and play an important role in the framework programs for mitigation, provides information about the degree of degradation.

The fire hazard estimation provides a valid support to policy makers for the design of strategies relating to fire prevention policies and monitoring of fire areas.

Burn severity is a qualitative indicator of the effects of fire on the vegetation ad forest floor. Assessing and mapping the burn severity is important to quantify and monitoring the fire effects, to evaluate post-fire dynamics and to estimate the ability of vegetation to recover after fire (generally indicated as fire-resilience) [19]. The accurate quantitative and qualitative estimation of burn-area are crucial to analyze the impact of fire on forest [1], (Landsat-8 and Sentinel-2 based Forest fire burn area mapping using machine learning algorithms on GEE cloud platform over Uttarakhand, Western Himalaya 2020).

Remote sensing technologies can provide useful data for fire management, from risk estimation [26], fire detection to post fire monitoring [19] including burn area. Burn severity and forest fire can be identified using methods generally based on the spectral reflectance properties of healthy and burnt vegetation. Thermal differences of burning pixel and background pixel are also widely used for fire detection [11]. Several vegetation indexes were used, such as NBR (Normalized Burn Difference) SAVI (Soil Adjusted Vegetation Index), NDVI (Normalized Vegetation Index). Maps obtained by between pre and post fire indexes measure biomass loss [32]. Such assessments are generally performed on perimeter fire maps, mainly using fixed threshold values to classify and map the different levels of the severity of the burb. However, many authors suggest that these fixed threshold values are generally not suitable for all type of landscape and vegetation [17, 18]. In order to overcome these limitations, many authors have proposed a new approach based on geo-statistical analyzes applied to satellite data, both to estimate the perimeter of the burned area and to evaluate the different degree of severity of the burn.

The use of solid geo-statistical analysis for processing satellite data is relatively recent, although in recent decades, geo-statistics has been integrated with remote sensing in the processing of images [5].

To date, the availability of spatial data is increasing along with the techniques and methods adopted in geographic analysis. this allows an accurate analysis of the natural phenomena that occur in the territory with the aim of fully understanding the dynamics that act in the development of the territory and in the changes of land cover, with a quantitative and modeling approach [6, 20, 23, 25].

The aim of this work is to implement an automatic procedure (tool) capable, starting from satellite image processing, to outline quickly (i.e. as soon as possible temporally close to the event) the fires and to calculate indices of severity that allow the first order impacts to be mapped (therefore immediately after the event).

The performances obtained using satellite data were carried out for fires that occurred during the fire season in the year 2020 in the northern part of Apulia region (southern

Italy). This study area was selected, first, because it is highly representative of Mediterranean ecosystems and, second, because it is an interesting test case for wildfire occurrences within the Mediterranean basin. Apulia Region is one of the Italia Regions affected every year by incendiary phenomenon, in fact the Regional Civil Protection have been estimated in 2019 about 600 fire events, of which around 450 involved wooded area [24]. The project "MESARIP satellite methodologies for the assessment of the risk of fires in the Puglia Region", in collaboration between the CNR IMAA and the Civil Protection Puglia, aims to provide tools and methodologies useful for the prevention, forecast and management of emergencies related to risk forest fires and interface also with the use of satellite technologies. The activities included in the project include that of estimating and studying fire severity and burned areas. This paper proposes a procedure that analyze and detect the change detection of the potential burned areas using ESA Sentinel 2 data and geo-statistical approaches in a GIS opensource environment. In order to implement the detection of burned areas a graphical model has been developed. The graphical modeler has been developed using QGIS opensource software and allows you to create complex models using a simple and easy-to-use interface [24, 27].

2 Material and Methods

2.1 Remote Sensing and Fire Severity Assessment

Multi-spectral and multi-temporal satellite data with medium and high spatial resolution are very appropriate to evaluate the fire severity and burned area.

In present work, to estimate more precise and accurate burn area, images of ESA (European Space Agency) Sentinel-2A and 2B satellite have been used [4] to compute burn map to assess burned areas and fire severity using geostatistical analyses. Sentinel 2 data have been composed by 12 bandwidths (see Table 1) used in different studies of vegetation and in fire severity [8]. The higher frequency and resolution of Sentinel 2 imagery offers potential improvements in accuracy issues for application in broad-scale fire severity mapping, relative to other moderate resolution sensors such as Landsat TM (30 m resolution). The higher frequency and resolution of Sentinel 2 imagery offers improvements in accuracy issues for creation in broad-scale fire severity mapping. Fire severity was stimulated using sentinel bands 2 most sensitive to changes in the post-fire reflectance value [14, 25].

After fire events the spectral behavior of vegetation changes and this increase reflectance in mid-infrared and reduce surface reflectance in near-infrared.

The Normalized Burn Ratio (NBR) index is computed on the basis of the two burn sensitive bands, infrared (NIR) and shortwave infrared (SWIR). For this reason, it is one of the best indexes to detect a burn area. The NBR index have been estimated using Sentinel 2 A and 2 B bands most sensitive to changes in the post-fire reflectance value (Band 8a and Band 12) (see formula 1).

$$\text{NBR} = (\text{Band 8A} - \text{Band 12})/(\text{Band 8A} + \text{Band 12}) \tag{1}$$

Maps obtained by difference between NBR pre and post fire indexes (the ΔNBR index in formula 2) provide a measure of change which then can be used to estimate fire

Table 1. Sentinel 2 band set overview.

Satellite	Bands	Range wavelength (nm)	Resolution (m)
Sentinel	Band 1 –Coastal aereosol	443	60
	Band 2 – Blue	490	10
	Band 3 – Green	560	10
	Band 4 – Red	665	10
	Band 5 – Vegetation Red Edge	705	20
	Band 6 – Vegetation Red Edge	740	20
	Band 7 – Vegetation Red Edge	783	20
	Band 8 – NIR	842	10
	Band 8a –Vegetation Red Edge	865	20
	Band 9 – Water vapour	945	60
	Band 10 – SWIR – Cirrus	1375.3	60
	Band 11 – SWIR	1610.0	20
	Band 12 – SWIR	2190.0	20

severity, in fact the difference in pre and post burn NBR index could reflect the surface change and characterize burn severity degree.

$$\Delta \text{NBR} = \text{NBR pre} - \text{NBR post} \tag{2}$$

In order to assess fire severity degree, ΔNBR values was categorized. As it is known that ΔNBR ranges values are basically site-specific, fixed thresholds were not applied but [22] classification approach was adopted. In this work we selected six classes of ΔNBR: unburned; very low, low, moderate, high and very high [10, 19].

The ΔNBR index is used to produce the map of the severity of the fire on the ground. For this study, the time span analyzed was July–August 2020, where the date of July 20 was chosen as the pre fire images and the image of August 21, 2020 as the post fire image. the need to use cloud-free images.

2.2 Spatial Autocorrelation Statistics

The first law of geography "Everything is related to everything else, but near things are more related than distant things", theorized by [30], represents the cornerstone of spatial autocorrelation [6, 19].

Considering the occurrences of a space variable (etc. fire events), spatial autocorrelation measures the degree of dependence between events, while considering their similarity and their long-distance relationships. Time series data, like satellite images, can provide useful data sets to examine changes in homogeneity over time, as well as to measure the strength of the relationship between values of the same variables over a given time window [25].

The integration between satellite images and geostatistical analyzes with satellite data is a lot innovative for map and image processing. In the study of spatial variables, that is, with values that represent the variable in territorial areas, the topic of spatial autocorrelation is essential to verify whether the presence of a particular intensity of a phenomenon in a given area implies the presence of the same phenomenon in the contiguous areas.

Local indicators of spatial autocorrelation have achieved us in locating clustered pixels, by measuring the amount of elements within the "fixed neighborhood" file they are homogeneous. Among the first statistics for local spatial autocorrelation was suggested by Getis and Ord in 1992 [9], and subsequently elaborated in Ord and Getis in 1995 [9]. The index is derived from a point pattern analysis logic. In its first formulation, the statistic consisted of a ratio of the number of observations within a given one-point interval to the total count points. Statistical analysis is applied to values at nearby locations (as defined by space weights) [19]. In this paper Getis-Ord Local Gi [9, 15] have been used according with the subsequent formula (3):

$$\mathrm{G_i(d)} = \frac{\sum_{i=1}^{n} w_i(d)x_i x_i \sum_{i=1}^{n} w_i(d)}{S(i)\sqrt{\frac{\left[(N-1)\sum_{i=1}^{n} w_i(d)-\left(\sum_{i=1}^{n} w_i(d)\right)^2\right]}{N-2}}} \tag{3}$$

The interpretation of the Getis - Ord statistics is very simple: a value greater than the average suggests a High-High cluster or hotspot, while a less than average value indicates a Low-Low cluster or a cold spot.

Geostatistical analysis tools are available in different software, such as GIS and those of image processing. In this work, tools from packages were used QGIS software.

In the application of autocorrelation method, it is important to define the nature of the events that we investigate and the geometric relationships that exist. In the context of processing images, the spatial event is associated with a pixel and spatial autocorrelation statistics they are usually calculated considering the geographic coordinates of its centroid. The intensity, on the other hand, should be chosen by rigorously considering the empirical nature of the case study. The conceptualization of geometric relationships in the case of elaboration of images is very simple because the distance between the events is always the same or a multiple of the pixel size. The application of spatial autocorrelation statistics to remotely sensed images allow us to obtain a new raster that contains in each pixel a number that expresses how much it is autocorrelated to another pixel [24, 27].

3 Discussion and Results

The study area (see Fig. 1) was carried out in the northern part of Apulia Region (South of Italy) in Foggia Prefecture, which present an increasing of number of fire events, generally occurred in the period June–September 2020. The area is characterized by grasslands, coniferous and oak woods, and agricultural land. Climate is a typically Mediterranean climate with mild and slightly rainy winters alternating with hot and dry summers [27].

Specifically, Sentinel 2 remote sensing data used in this paper were downloaded from the THEIA website [29]. The sets of spectral bands available on the THEIA website are atmospheric corrected TOA (top of atmosphere) by means of the MAJA (Multi-sensor Atmospheric Correction and Cloud Screening) algorithm [12, 13]. The spatial coverage

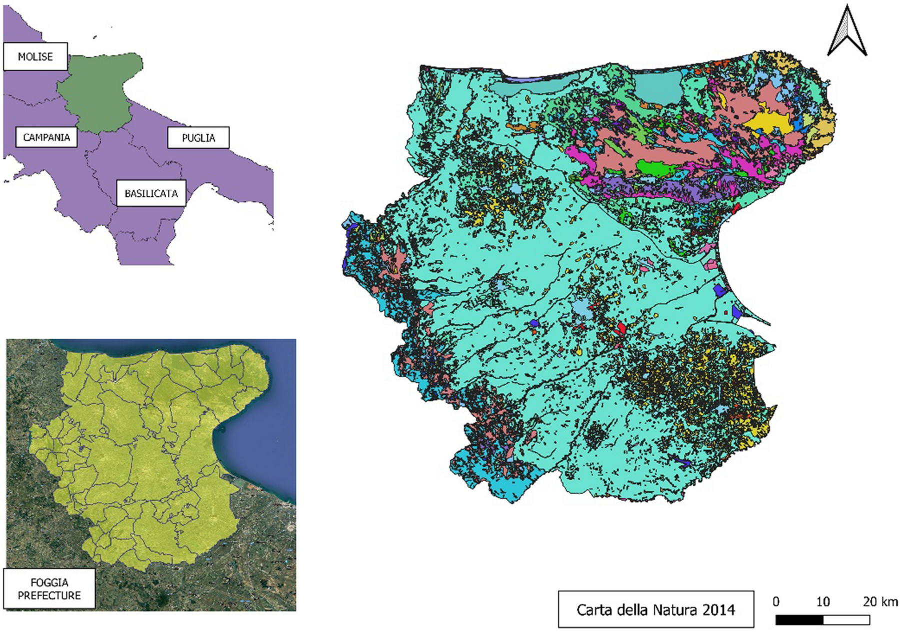

Fig. 1. Study area.

of the study area (see Fig. 1) provided by the swath of the satellite determined the extension of the study area. The ΔNBR index is used to produce the map of the severity of the fire on the ground. For this study, the time span analyzed was July - August 2020, where the date of July 20 was chosen as the pre fire images and the image of August 21, 2020 as the post fire image. The choice of these two dates is linked to the need to use images that are as clean as possible from the presence of the cloud. After calculating the ΔNBR index, we proceeded to mask it from clouds, water and shadows, in order to correct all the pixels that could have created false positives.

This kind of correction aims to eliminate the distortion of the pixels related to the presence of clouds and shadows. For the pixels with cloud cover, the clouds and shadows have been masked by operating respectively on the blue band (band 2) and on NIR (band 8), using the threshold value that best corrected the pixels affected by the presence of clouds and of shadows.

Subsequently we proceeded with the masking of all the pixels affected by the presence of water and all wetlands (sea, lakes, rivers, etc.). The index was used for this purpose NDWI (Normalized Difference Water Index) (Eq. 4):

$$\text{NDWI} = (\text{Band } 3 - \text{Band } 8)/(\text{Band } 3 + \text{Band } 8) \tag{4}$$

The main difficulty is to reliably discriminate events identifiable as fires from fakes positive. These can often be traced back to spectral response of dry vegetation or even rapids land cover changes in agricultural areas (typically from soil with vegetation to plowed land). Since the applied methodology aims to identify burnt areas outside agricultural areas, after masking water, clouds and shadows, we proceeded to masking agricultural areas, using the Nature Charter of the Puglia Region [16] whose latest update dates back to 2013.

The ΔNBR index has been classified finding empirically its minimum and maximum value in the burned area [21]. Range between such values have been split in equal classes (see Table 2, see Fig. 2).

Table 2. ΔNBR RANGE.

Severity level	ΔNBR range
Unburned	0.05–0.1
Very low severity	0.1–0.3
Low severity	0.4
Moderate severity	0.5
High severity	0.8
Very high	>0.8

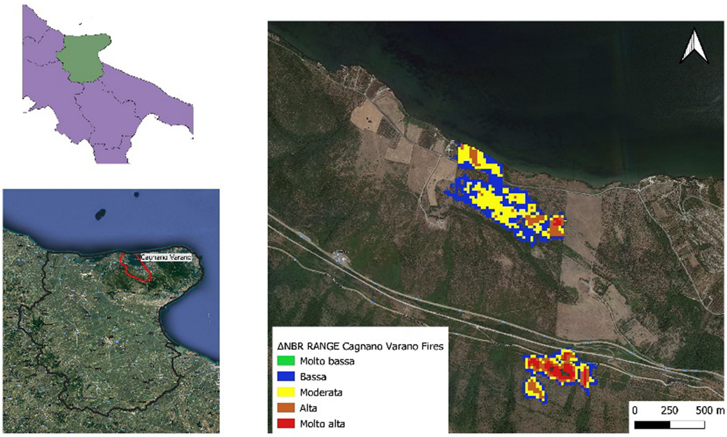

Fig. 2. Example of ΔNBR range map in Cagnano Varano municipalities.

In order to exclude false positives not otherwise identifiable, to the map of the ΔNBR obtained and corrected as described above, an analysis was subsequently applied local spatial statistics (Getis and Ord's interpretation) aimed at identifying clusters of similar or dissimilar values. The application of spatial autocorrelation statistics to remotely sensed images allow us to obtain a new raster that contains in each pixel a number that expresses how much it is autocorrelated to another pixel.

A model, called Fire Area Detection Model, (see Fig. 3) for the determination of fire severity was subsequently implemented in QGIS, which involves identifying the areas covered by the fire starting from the use of the binary map obtained from the application of spatial autocorrelation methods to the ΔNBR map and from the ΔNBR map obtained from the masking procedure.

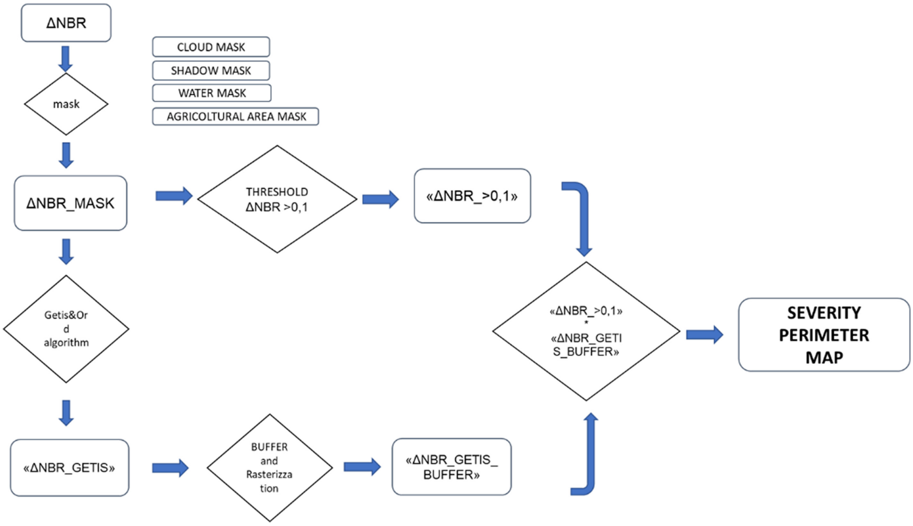

Fig. 3. Simplified representation of the applied methodology.

By applying the methodology described, it was possible to identify that, in the analyzed area, the burnt areas occupy a total one of surface of about 5 km^2 (Fig. 4).

The application of this model allows a quick and easy identification and perimeter of the burned areas.

A comparison with the true and false color images and also with the pre and post fire NBR images clearly suggests that the identified areas are correctly classified as a burnt area connected to a fire (see Fig. 5 and Fig. 6).

The output products they consist of the maps relating to the pre and post event NBR indices, in the ΔNBR for the estimation of the severity of the focus and of images in RGB composition and False Colors which are also useful for discriminating the burned areas.

The definition of the Fire Area Detection model for estimating the fire severity and perimeter of the areas traveled by fire predicts as input data the satellite data of the images relating to the days immediately before and after the fire and vector data that will be used by mask to clip the satellite image in the area of interest. The use of Sentinel 2 images with high spatial resolution and the masking of agricultural areas limited the overestimation of burnt areas. In addition, the joint use of NBR and ΔNBR spectral indices and statistical analyzes made it possible to accurately detect the burned areas.

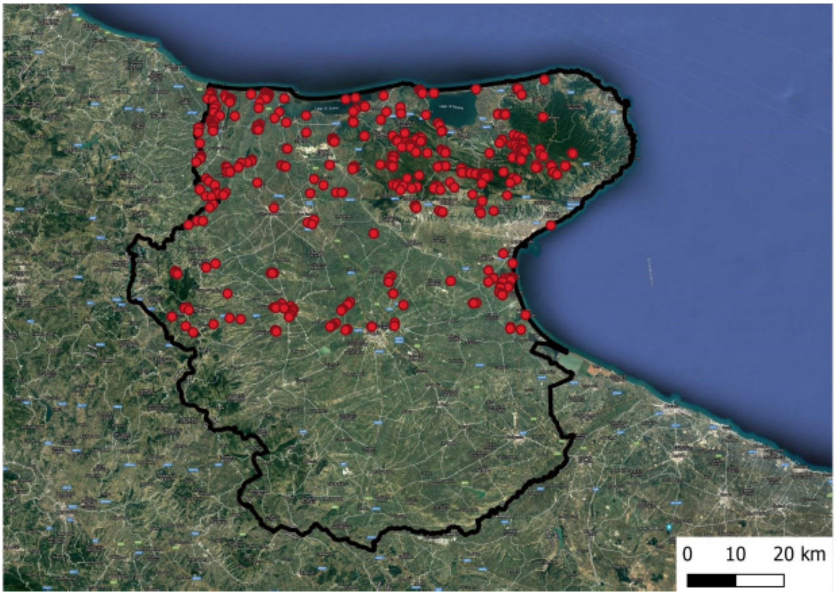

Fig. 4. Hot Spots Areas resulting from the application of the Fire Area Detection model for the period 21 July 2020/20 August 2020.

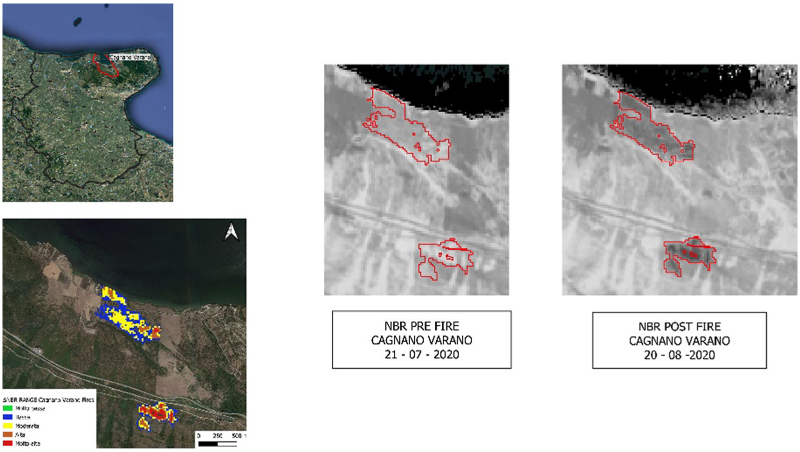

Fig. 5. Fire Severity Map and NBR PRE and POST FIRE maps, Municipality of Cagnano Varano.

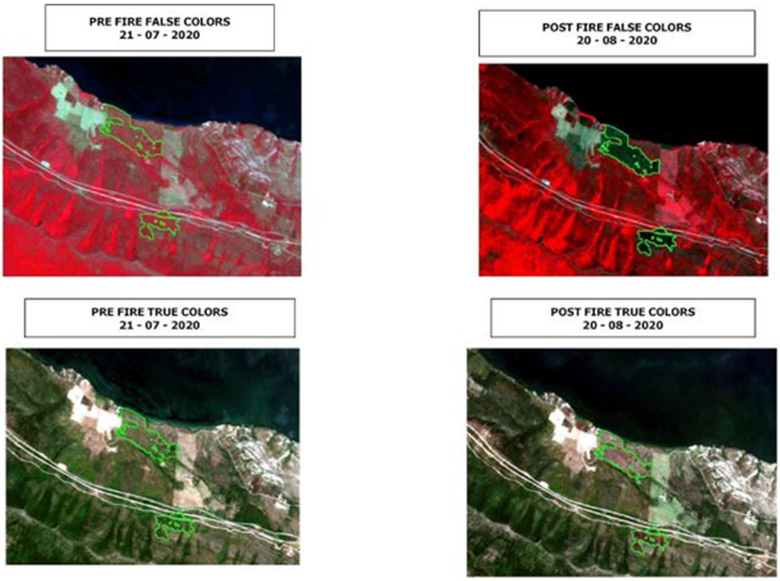

Fig. 6. Combinations in true and false colors before and after the fire, of the burned area of Cagnano Varano Municipality.

4 Conclusions

Fire severity refers to the effects of a fire on the environment, typically focusing on the loss of vegetation and including soil impacts. The accurate quantitative and qualitative estimation of burn areas are crucial to analyze the impact of fire, for monitoring fire effects, evaluating post fire dynamics as the ability of vegetation to recover after the fire event.

The availability of satellite high resolution imagery provides the opportunity to obtain useful information for fire management, from risk evaluation to post-fire damage estimation.

By combining the use of geographic information systems, remote sensing and geo-statistical analysis, the model proposed in this study provides a reliable estimate of the perimeter and mapping of burnt areas in the investigated area.

This study can be useful to spatial planning authorities as a tool for assessing and monitoring of burned areas, representing a useful tool for land management.

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