Satellite MODIS analysis for assessing fire severity: results obtained for the case study of Pisticci (Matera, Italy) in the framework of MITRA project

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Abstract. In this paper we present the results obtained from our investigations addressed to the estimation of fire severity conducted using satellite and in situ analysis, in the framework of MITRA project. The investigations were carried on in a test area in south of Italy, municipality of Pisticci, which was affected by a severe forest fire between 26 and 28 August 2012. The total area burned amounted to 1100-1300 hectares. It was one of the largest areas burned in Basilicata in the last 15 years. Satellite data were analyzed in order to evaluate fire severity for the whole surface affected by fire using MODIS data available free of charge from the NASA web site. In situ data analysis confirmed that Satellite MODIS imagery are very useful for "near real time" fire severity estimation.

Keywords: satellite based analysis, MODIS, Fire Severity

1. Introduction

Many literature data describe the effects of fire on vegetation and soil properties and how these effects depend upon fire severity, see, for example, White et al (1996) Díaz-Delgado et al. (2003), Lugassi et al. (2010), Ruiz-Gallardo et al (2004), Lanorte et al. (2013) and reference therein quoted.

Fire severity is a qualitative indicator of the effects of fire on ecosystems, since it affects soil, forest floor, canopy, etc. Assessing and mapping fire severity is important to monitor fire effects, to model and evaluate post-fire dynamics and to estimate the ability of vegetation to recover after fire (generally indicated as fire-resilience). In an operational context, fire severity estimation is critical for short-term mitigation and rehabilitation treatments.

Remote sensing technologies can provide useful data for fire management, from risk estimation (see for example Lasaponara 2005), fuel mapping (Lanorte and Lasaponara 2005, Lasaponara et al. 2006), fire detection (Lasaponara et al 2003, Lasaponara and Lanorte 2005), to post fire monitoring (Telesca and Lasaponara 2006, Lanorte et al. 2013), including burn area mapping, severity estimation and resilience and recovery capability (Lasaponara, 2005a,b).

Traditional methods of recording fire burned areas and fire severity involve expensive and time -consuming field surveys and statistical analysis on fire regime (see for example Tuia e al 2008). The available remote sensing technologies may allow us to develop standardized burn-severity maps for evaluating fire effects and addressing post fire management activities.

The methods generally used to estimate fire severity from satellite are based on spectral indexes, obtained as a combination of bands which emphasize the changes induced by fire in the spectral behavior of vegetation. After a fire, the spectral behaviour of vegetation changes due to consumption of fuel, presence of ash, reduced transpiration of vegetation and increased surface temperature. All these effects increase reflectance in mid-infrared and reduce surface reflectance in near-infrared. This is the reason because NBR index is computed on the basis of the two burn sensitive bands, infrared (NIR) and shortwave infrared (SWIR). For this reason, it may be one of the best indexes to detect a burn area.

Several vegetation indexes were used, among them the SVI (Simple Vegetation Index), TVI (Transformed Difference Vegetation Index), SAVI (Soil Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index) and NBR (Normalized Burn Difference).

Maps of vegetation indexes obtained from the difference between pre and post-fire images provide a measure of change used to quantify biomass loss, carbon release, smoke production, etc. Such evaluations are generally performed on fire perimeter maps generally (known a priori) using fixed threshold values to classify and map the different levels of burn severity. Nevertheless, as suggested by many authors, such fixed threshold values are generally not suitable for fragmented landscapes and inadequate for vegetation types and geographic regions different from those for which they were devised. In this paper we applied geospatial analysis for mapping burned areas and fire severity.

2. Data set and Study area

2.1 Study area

The fire that covered the territory of the municipality of Pisticci between 26 and 28 August 2012 had its ignition point near the Basentana highway at a height of around 50 meters above sea level, where, aided by the strong wind and conditions of particular dryness of vegetation, spread quickly to the south direction going up the slope leading from the highway to about 350 meters of Pisticci town. The fire was later extended also on the south and east of Pisticci. The total area burned amounted to 1100-1300 hectares, one of the largest areas burned in Basilicata in the last 15 years (Fig 1).

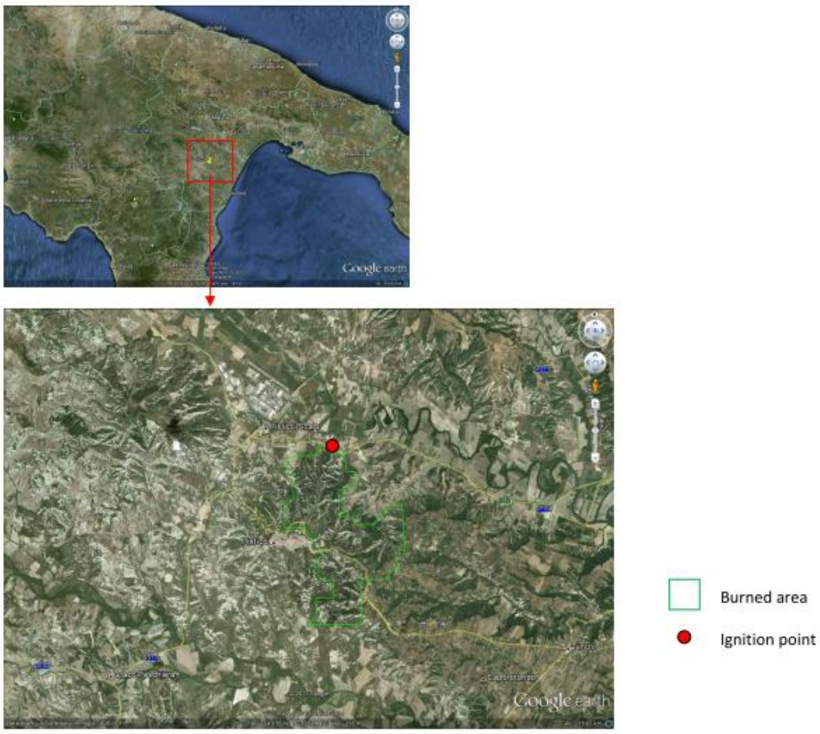


Figure 1. Study area

The fire particularly struck the areas occupied by reforestation with conifers implanted a few decades ago to counter the instability phenomena which are very pronounced in this area (Fig. 2 and Fig. 4).

The vegetative state of these stands often with the presence of dead biomass in excess, combined with their high fire potential and climatic conditions of extreme dryness, favored a very vigorous fire spread.

In addition to reforested conifer plantations, the fire also hit areas occupied by xerophytic grasslands, mediterranean maquis and cultivated areas, in particular olive groves (Fig. 3).

The fire took also the form of wildland-urban interface fire, since several isolated houses were threatened by the flames that have also lapped the town of Pisticci.

Figure 2. Burned areas in forest pine on slopes of clay

Figure 3. Fire affected Mediterranean shrubs, xerophytic grasslands and cultivated areas (here olive groves)

Figure 4. Burnt area with surface instability phenomena

2.2 MODIS data

MODIS is a key instrument aboard Terra (EOS AM) and Aqua (EOS PM) satellites.

These data will improve our understanding of global dynamics and processes occurring on land, in oceans, and in lower atmosphere. MODIS is playing a vital role in the development of validated, global, interactive Earth system models able to predict global change accurately enough, to assist policy makers in making sound decisions concerning the protection of our environment.

Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS, launched on December 18, 1999 and Aqua MODIS, launched on May 4, 2002, are viewing the entire Earth's surface, acquiring data in 36 spectral bands ranging in wavelength from 0.4 µm to 14.4 µm, with a high radiometric sensitivity (12 bit).

Two bands are imaged at a nominal resolution of 250 m at nadir, five bands at 500 m, and the remaining 29 bands at 1 km. A ±55-degree scanning pattern at the EOS orbit of 705 km achieves a 2,330-km swath and provides global coverage every one to two days.

MODIS bands used in this work are the first seven ones, corresponding to a spatial resolution of 250 and 500 m (Fig. 5). These spectral bands are suitable for the study of vegetation characteristics.

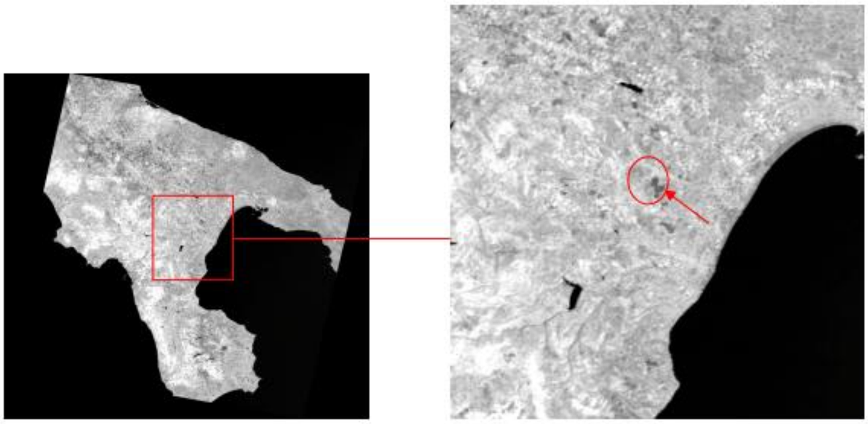


Figure. 5. MODIS image (band 2 – NIR) - August 28, 2012 (red arrow indicates burned area)

3. Data analysis

Modis based maps were processed using spatial autocorrelation analyses (see, fro example Anselin 1995, Getis 1994, Getis, A., & Ord, J. 1992) applied to the estimation of fire severity as in Lanorte et al. 2013.

Spatial autocorrelations take into account the spatial attributes of geographical objects under investigation, evaluate and describe their relationship and spatial patterns also including the possibility to infer such patterns at different times for the study area. The spatial patterns are defined by the arrangement of individual entities in space and the spatial relationships among them. Spatial autocorrelations measure the extent to which the occurrence of one object/feature is influenced by similar objects/features in the adjacent areas. As such, statistics of spatial autocorrelation provide (i) indicators of spatial patterns and (ii) key information for understanding the spatial processes underlying the distribution of object/feature and/or a given phenomenon under observation.

Geographical observations can be arranged in spatial and temporal order, by latitude and longitude, and over given time periods. In this context time series data, such as aerial and 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.

In the analysis of satellite image, spatial autocorrelation statistics are considered very useful tools since they not only consider the value of the pixel (reflectance, temperature, spectral index) under investigation, but also the relationship between that pixel and its surrounding pixels in a given window size.

As for any type of dataset also in the case of digital image analysis there are many indicators of spatial autocorrelation that can be distinguished into the following:

- Global indicators of spatial association, join count statistics; Moran's I and Geary's c (see, for example, 1[9-20]); the null and the alternative hypothesis; general cross-product statistics; normal, randomisation and permutation approach; and spatial Correlogram.
- Local indicators of spatial association -- LISA Gi and Gi* statistics (see, for example, [19-20]); LISA statistics; local Moran; inference for LISA; spatial outliers.
- The variogram and semi-variogram; correlogram; fitting a variogram model; robust estimates of a variogram.

In absence of spatial autocorrelation the complete spatial randomness hypothesis is valid: the probability to have an event in one point with defined (x, y) coordinates is independent of the probability to have another event belonging to the same variable. The presence of spatial autocorrelation modifies that probability; fixed a neighbourhood for each events, it is possible to understand how much it is modified from the presence of other elements inside that neighbourhood.

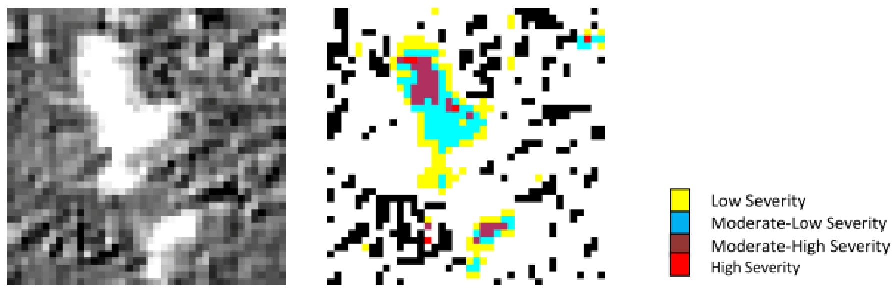
4. Results and discussion

In order to well characterize and identify burned area, we computed and used delta NBR (dNBR) expected to perform better than other methods in capturing the spatial complexity of severity within fire perimeters. Positive dNBR values represent a decrease in vegetation while negative values represent increased vegetation cover.

Maps obtained by the difference between pre- and post-fire indexes provide a measure of change which then can be used to estimate biomass loss, carbon release, aerosols production, etc.. Moreover, the difference in pre/post-burn NBR index could reflect surface change and characterize burn severity degree.

$$dNBR = NBRprefire - NBRpostfire \quad \textbf{(2)}$$

In this study, to compute dNBR we used two MODIS images (Fig.8a): the first image is of August 15, 2012 (pre-fire) and the second image is of August 31, 2012 (post-fire).



a) *b)*

Figure 6 .a) dNBR (August 15-August 31, 2012); b) Fire Severity Map

Fire severity was classified into four levels as low, moderate-low, moderate-high, and high. The severity class of high indicates fire-damaged stands in which all the vegetation are totally burned and killed and even the ground is heavily modified. The moderate severity class means the area was damaged by fire but part of vegetation was still alive after fire and the effects on the soil are more limited . The low severity class is the area burned with little damage to vegetation and soil.

The fire severity map (Fig.6b) yields a gradient of detected change in relation to the characteristics of fire propagation: greater severity (red/marron) near and around the ignition point, moderate severity (cyan) in the central part of the fire, low severity (yellow) at the end.

As already obtained in Lanorte et al (2013), also in the current case under investigation, the application of geospatial analysis enabled us to improve the results leaving out commission errors.

Our results pointed out that MODIS data allow us (i) to map fire burned areas and (ii) to discriminate fire severity and, therefore also to improve the monitoring of fire effects over time. Such information are effective data source for evaluating erosion/runoff, biomass and carbon issues, and other issues using mapped burn severity.

The approach we adopted is independent of sensors used for the evaluation as well as on vegetation cover types affected by fire. The model could be incorporated directly into the mapping process from local up to global scale.

Assessing and mapping burn severity is important for monitoring fire effects, for model and evaluate post-fire dynamic and estimating vegetation resilience, which is the ability of vegetation to recover after fire. The availability of timely MODIS satellite imagery (downloaded free of charge from NASA web site) provides the opportunity to obtain useful information for fire management from the risk evaluation to post fire damage estimation.

5. Final remarks

Moderate Resolution Imaging Spectroradiometer (MODIS), time series and in situ data analysis have been conducted to assess fire severity after the large forest fire event which affected the Pisticci Municipality (Basilicata, Southern Italy) in August 2012. Field measurements and satellite based analyses well fit each others.

The results presented here show that MODIS data offer a reliable and low cost tool for estimating fire severity in “a near real time “ approach.

Acknowledgments

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