Development of a vegetation damage severity index for the Italian hyperspectral sensor PRISMA

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Abstract. The SAP4PRISMA (Development of algorithms and products for supporting the PRISMA mission) project is one of the five research projects funded by ASI (Italian Space Agency) with the objective to develop applications capable of suitably exploiting the data acquired by the satellite hyperspectral sensor PRISMA. PRISMA (PRecursore IperSpettrale della Missione Applicativa) is an earth observation system combining a hyperspectral sensor with a panchromatic medium-resolution camera. The mission, fully supported by the Italian Space Agency (ASI), is devoted to Earth Observation and Remote Sensing Research to answer to the users increasing demand of accurate quantitative information about the Earth system. SAP4PRISMA project is focusing its research activities only on those geophysical parameters/applications/products that are suitable for the characteristics of the mission and in perspective for further international hyperspectral missions (EnMAP, HyspIRI, etc.). The project is structured in interconnected research activities aimed at consolidating the methodological issues for retrieving geophysical and agro-environmental parameters to be used as inputs for the development of innovative complex products (e.g., nitrate leaching, land degradation and fuel maps, etc.). The products proposed in the frame work of the SAP4PRISMA project regard: (a) land degradation and vegetation status, (b) products development for agricultural areas, (c) management and monitoring of natural and induced hazards. Regarding the application of PRISMA for the management and monitoring of natural and anthropogenic hazards, we focus on the assessment of the damage severity and mainly on the effects of fire in vegetated areas interested by a fire. Moreover, project goal is to develop an index that, in the presence of an area where the vegetation shows a sharp decline, is able to understand the causes, that may not necessarily be linked to the occurrence of a fire (e.g., oil spills, floods, etc.). This paper aims at showing the results reached up-to-now in the process of developing such an index called DSI (Damage Severity Index).

Keywords. Damage, index, optical sensor, satellite, remote sensing.

1. Introduction

PRISMA is a small entirely Italian mission [1] of demonstrative/technological and pre-operational nature whose launch is foreseen by the end of 2014. PRISMA payload combines a hyperspectral sensor with a panchromatic high-resolution camera. The payload design is based on a pushbroom type observation concept providing hyperspectral imagery (~ 250 bands) at a spatial resolution of 30 m on a swath of 30 km. The spectral resolution is better than 12 nm in the spectral range of 400-2500 nm. In parallel, panchromatic imagery is also provided at a spatial resolution of 5 m. PRISMA represents one of the future space mission aiming at acquiring hyperspectral images of the Earth together with the German mission EnMAP (Environmental Mapping and Analysis Program) [2], the US mission HyspIRI (Hyperspectral InfraRed Imager) [3] and the Japanese mission HISUI (Hyperspectral Imager Suite) [4].

Studies on the possibility of using satellite images for estimating the damage caused on the vegetation by a disastrous events, in particular wildfires, have been carried out in the last few years by using images acquired from high spatial resolution multispectral sensors like LANDSAT/TM and ETM+. Our objective aims at developing a more general index capable of assessing vegetation

damages caused by other disastrous events in addition to fires. Basically, this involves defining indexes that allow to determine, using post-event hyperspectral images, its impact on vegetation distinguishing as accurately as possible, between different levels of damage, namely the loss of biomass products on it (Fig. 1). In particular, in the case of burned areas, a series of field-based indices have been introduced (CBI, Composite Burn Index; GeoCBI, Geometrically Structured CBI) [5], [6], [7] which were correlated to spectral indices based on multi-spectral images. In fact, the CBI index is based on a visual assessment of the quantity of fuel consumed and the degree of soil charring [8] whereas the GeoCBI represents a modified CBI where the fraction of vegetation coverage (FCOV) is introduced as a weighting factor [7] and both of them are correlated with quantitative indices like the NBR (Normalized Burn Ratio) [9], the dNBR (differential NBR) [10] or the RdNBR (Relative delta Normalized Burn Ratio) [11]. Our study aims at generalizing the approach followed for developing the fire severity index by constructing an index or a series of damage severity indices to be applied to hyperspectral images for assessing the status of vegetated areas interested by any kind of disastrous phenomenon (fires, floods, volcanic eruption, landslide, oil spills, weather events, etc.).

Figure 1. Example of vegetation damage level as consequence of a wild fire (images taken from web).

Such information can be useful to define the recovery priorities and the type of intervention on the interest areas in addition at allowing, in the case of fire, a more accurate estimate of the combustion efficiency (BE, Burning Efficiency). In any case, it should be taken into account that some authors have found that the NBR index is far from optimal - since it is insensitive to changes due to burning, as most spectral change in the near-infrared and middle-infrared reflectance occurs nearly parallel to the NBR isolines [12]. This may be a deterrent to the utility of the NBR index for certain applications. They conclude that an improved severity index should incorporate improved knowledge of how fires of different severity displace the position of pre-fire vegetation in multispectral space. This may allow not only the design of an index giving the desired degree of sensitivity to fire severity while providing insensitivity to other possible sources of spectral variation; it could also allow a rigorous choice of the wavebands used.

However, we have to take in mind that because of reflectance variability with respect to the numerous factors that may influence fire severity it may not be possible to design an index that conforms closely to index theory and that works at different sites.

For example, the Interagency Burned Area Emergency Rehabilitation (BAER) uses a semi-automatic estimate based on satellite imagery developed by the Remote Sensing Applications Center (RSAC) of the USDA Forest Service [13]. The method is derived from the CBI (Composite Burn Index) [14]. This index takes continuous values from 0 (un-combusted) to 3 (completely burned). However, in most studies dealing with the fire severity estimating from satellite imagery, levels of damage are usually grouped in four classes: un-combusted, low, moderate and severe [15], [16], [17], [8], [18].

Recent studies have proposed the use of radiative transfer models (RTM) to simulate the continuous range of measured severity levels of the damage using the CBI [6]. The radiative transfer models can simulate the spectral signatures of a set of input parameters, of both leaf and canopy. In direct mode simulation, the RTM is used to analyze the effects of the spectral reflectance characteristics of the plant, while the spectra in the reverse (from remote sensing data) are used as input to estimate some of these parameters. This approach has been adopted also in [19] for evaluating the potential synergy between visible to short-wave infrared (VSWIR, 0.4–2.5 μm) and mid to thermal infrared (MTIR, 3.5–12.5 μm) data in a post-fire environment to exploit the HyspIRI images. In that case, five endmembers have been defined: char, green vegetation, non-photosynthetic vegetation (NPV), substrate and shadow. The analysis showed that the derived char fractional cover was strongly correlated with the GeoCBI, and the percentage of black trees and shrubs measured in the field.

The use of MTR helps to get better results than those obtained by an empirical approach, especially in the case of elevated severity values of the damage. However, in the case of intermediate values, the estimate of the damage is not properly evaluated because of the contrast between the forest floor, which is strongly affected by the fire, and the foliage (tall trees) less affected. In the framework of the SAP4PRISMA project [20] we aim at developing a damage severity index (DSI) that, starting from the experience gained so far in the use of the indices CBI and GeoCBI, is capable of exploiting the potential increase of the spectral information that will be available with the advent of the PRISMA satellite hyperspectral images.

Regarding the definition of damage severity, we consider the internationally recognized one, which provides 7 classes of damage (see Table 1) [14].

Table 1. Damage severity levels

Burn Severity Scale						
No effect	Low		Moderate		high	
0	0.5	1	1.5	2.0	2.5	3.0

To get the definition of damage to vegetated area, 5 types of vegetation layers have been defined, 3 belonging to the category of the underbrush and the other 2 belonging to trees category. The 5 types are:

- substrates: inert materials to soil, waste and fuel wood cut down;
- grasses, shrubs and low trees, herbs, shrubs and trees of height less than 1 m;
- shrubs and trees: shrubs and trees with a height between 1 and 5 meters;
- intermediate trees: trees with a diameter between 10 and 25 cm and heights between 8 and 20m;
- large trees, dominant trees with crowns receiving sunlight directly and whose height extends above the average of the surrounding trees.

The estimate of the extent or severity of the damage results from the estimate of the effect produced on each of these layers and their combination.

2. Data and methods

Field data

Initially, our idea about the damage severity index (DSI) starts from the possibility, provided by hyperspectral images, to compute several indices, each one capable to assess different characteristics of the vegetation and possibly capable to evaluate the effect on it of a disastrous event whereas other authors exploit the pixel unmixing capabilities of the hyperspectral images for identifying the relative abundance of ground components (ash, soil, scorched and green vegetation) [21] following a fire event. Up to now, the assessment of the damage severity is based on the identification of a relationship between an empirical index computable by using remotely sensed data and ground based visual estimate of the damaged caused by a fire. This method has been applied to multispectral [6], [7] and hyperspectral images [5]. In some studies, based on multi/hyperspectral sensor, an evaluation of the effectiveness of several different spectral indices for assessing fire severity in a restricted type of vegetation has been carried out [22], [15], [23]. In this study we want to evaluate damage severity relying on physical measurements which can be measured in the field and at the same time which may be assessed through hyperspectral satellite images. For this purpose, spectral signatures were collected in field, in two test areas representative of typical Mediterranean vegetation. The data collected comprehend spectra at leaf level and at canopy level, in order to investigate the various effects of fire on the vegetation. The test area selected for the campaign are Sicily and Sardinia shown in figure 2.

Figure 2. Field data Area

The spectra collected during the campaign have joined to a picture, this allows to visualize the examined vegetation damage level. The most critical step in data analysis was to associate a physically measurable quantities to the damage level, that is "easily" detectable by a visual method. For this purpose, in field spectra were compared with spectra generated by a radiative transfer model in order to extract from them biophysical information associated with the damage severity degree. The MTR used in this study are PROSPECT for leaf level simulations and Prosail for canopy level simulations.

For extract biophysical information, different inversion techniques have been used, based on a sample of 1,000,000 simulations at leaf level and 650 thousand simulations at canopy level (Fig.

3).

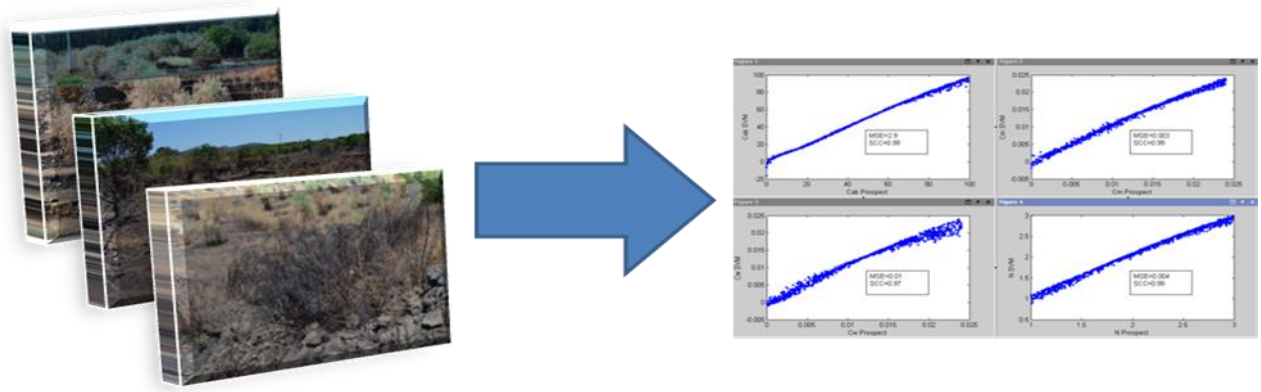

Figure 3. Correlation of damage severity to biophysical parameters

The analysis showed that the biophysical parameters better describing the grade of damage are: Cab, chlorophyll content in µg.cm-2, Car, carotenoid content µg.cm-2, Cbrown, brown pigment content, Cw, Equivalent Water Thickness (cm), Cm, Leaf Mass Area(LMA) and LAI, Leaf Area Index.

Just as a starting point we have considered the 27 indices considered by the ENVI software (ENVI, 2012) for estimating the vegetation characteristics:

- Broadband Greenness (5 indices);
- Narrowband Greenness (7 indices):
- Light Use Efficiency (3 indices);
- Canopy Nitrogen (1 index); Dry or Senescent Carbon (3 indices);
- Leaf Pigments (4 indices); Canopy Water Content (4 indices).

By applying such indices to the field data we were able to define an index capable to distinguish the different damage levels in the analyzed vegetation. The indices were combined in a way to emphasize the grade of damage providing a first version of the DSI:

$$DSI = \frac{\dfrac{CAI+1}{\max|CAI+1|} + \dfrac{MSI+1}{\max|MSI+1|} + \dfrac{PSRI}{\max|PSRI|}}{\dfrac{GI}{\max|GI|} + \dfrac{NDVI}{\max|NDVI|} + \dfrac{NDVI_{705}}{\max|NDVI_{705}|}}$$

Such relationship has been developed by assuming the availability of a sensor having the AVIRIS airborne sensor channels. The index has been applied to a series of reflectance spectra acquired during a field campaign carried out in Sardinia in October 2010 (Fig. 4). The parameters CAI (Cellulose Absorption Index), GI (Green Index), MSI (Moisture Stress Index), NDVI (Normalized Difference Vegetation Index), PSRI (Plant Senescence Reflectance Index) represent different vegetation indices [24].

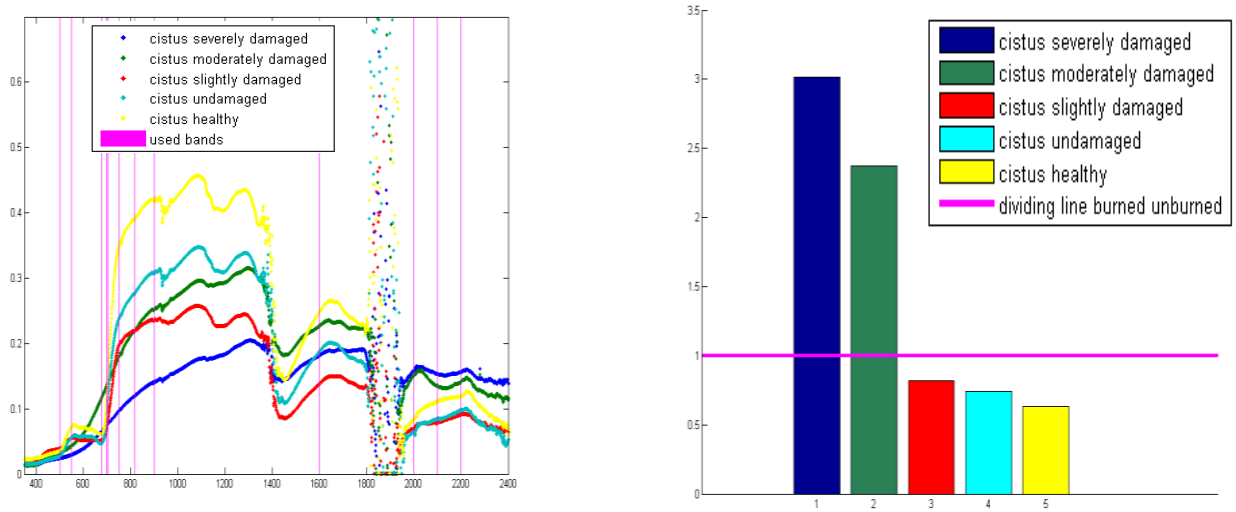

Figure 4. Example of application of the vegetation damage severity index. A) Field spectra with the indication of the position of the Hyperion channels. B) Values of the DSI index as function of the entity of the vegetation damage**.**

Fig. 4, shows that the index defined according to eq. 1 allows to distinguish the vegetation damaged by a fire from that where the degradation is due to a drying up process, caused by a different phenomenon.

When we tried to apply the DSI index to an image of a burned area located in Spain acquired by the presently available satellite hyperspectral sensor Hyperion it was necessary, due to the noise characterizing the sensor channels comprised between 2000 nm and 2400 nm, to redefine of the severity index:

$$DSI = \frac{NDII + MPSRI - NDVI}{NDVI_{0.705} + NBR + NDWI}$$

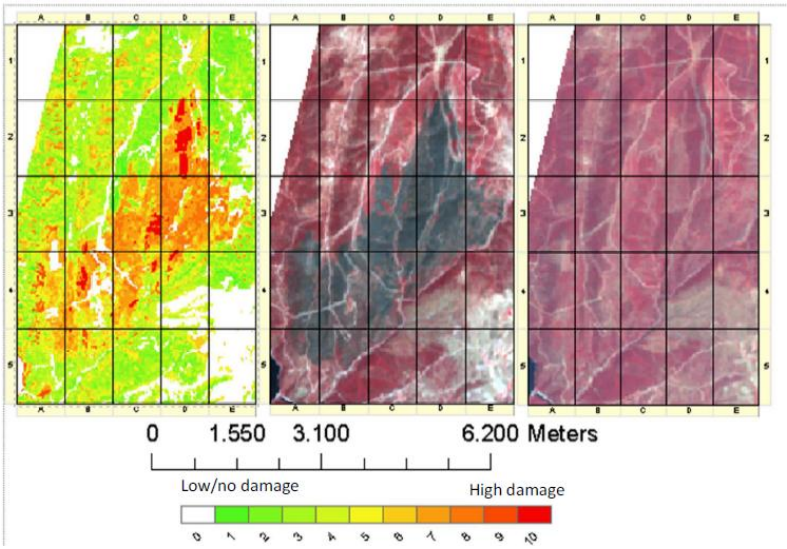

Figure 5. DSI HYPERION map (left), post-event image (center), pre-event image (right).

Demonstrated the efficacy of such index structure (Fig. 5), we proceed with the development of a suitable method for defining a similar index to be applied to the data that will be provided by the future PRISMA sensor. For this purpose, new computer based simulation were carried out by using radiative transfer model (Prospect and Sail) [25], [26]. Before proceeding with the simulations,

based on the spectra acquired during the field campaigns recalled above, we proceed with a selection of the PRISMA channels on the base of their SNR ratio and magnitude of the atmospheric effect. Introducing a suitable threshold for both SNR and atmospheric transmittance (Fig. 6) the number of useful channels of this sensor has been reduced from 238 to 140. Fig. 6 shows the region (in pink) of the electromagnetic spectrum masked on the base of the atmospheric transmittance and SNR values of the PRISMA channels.

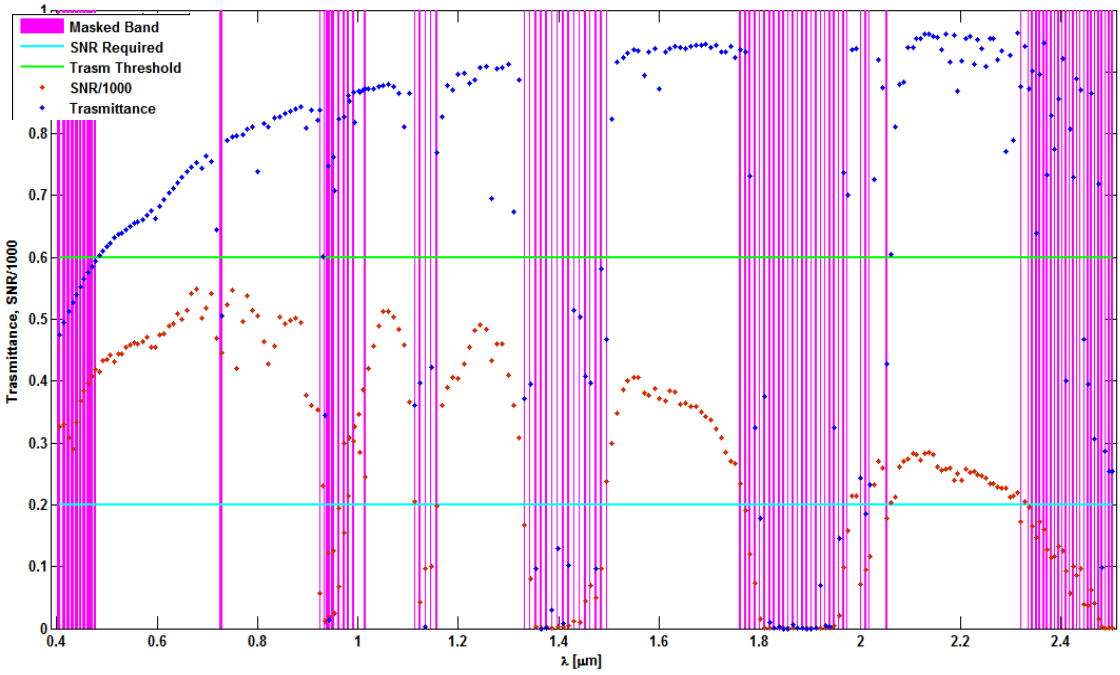

Figure 6. Electromagnetic regions analysis in PRISMA.

Our objective now is the construction of one or more indices, specifically adapted to PRISMA, capable to represent the variation of the vegetation geophysical parameters, for a large range of target/species, by exploiting in an optimal way the large amount of information that the selected 140 channels are able to provide.

Therefore a new analysis, based on the definition of normalized difference spectral indices NDI, has been carried out:

$$NDI = \frac{B1 - B2}{B1 + B2}$$

where B1 e B2 are the reflectances at two different wavelengths (140) of the “Simil-Prisma” simulated spectra. All possible combinations of two spectral bands were used to compute normalized indices. The correlation matrix between such indices and the six biophysical parameters that we considered essential in damage assessment, defined in the previous paragraphs, has been computed. In Fig. 7 the results are shown, it is worthwhile to note that NDI indices well correlated with everyone of the six biophysical parameters exist.

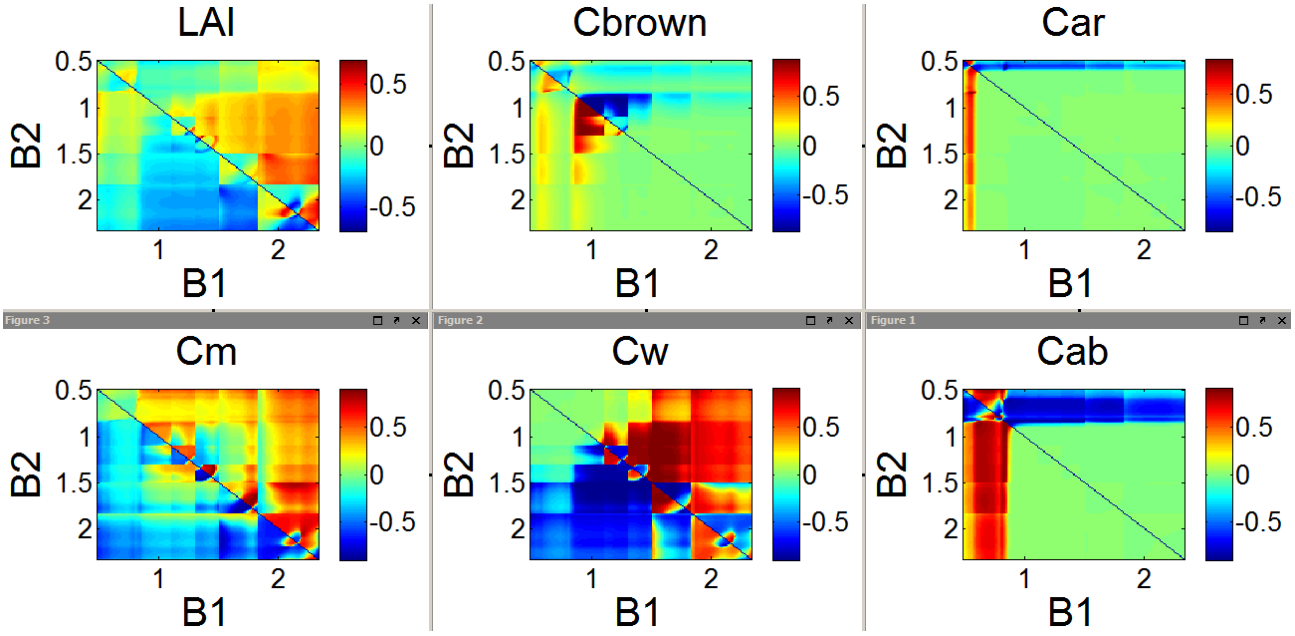

Figure 7. Correlation coefficients between biophysical parameters and all combinations of NDI for the "Simil-Prisma" spectra. Row and columns indicate the wavelengths used to create the NDI.

In order to select the indices more suitable to estimate damage severity, we built a cost function based on: correlation coefficient value, SNR and atmospheric effect. Cost function minimization led to the selection of the following indices:

$$NDcabI = \frac{B1233 - B698}{B1233 + B698};\ NDcarI = \frac{B718 - B523}{B718 + B523};\ NDcwI = \frac{B1233 - B1612}{B1233 + B1612};$$

$$NDcbrownI = \frac{B1082 - B770}{B1082 + B770};\ NDcmI = \frac{B1528 - B2211}{B1528 + B2211}\ NDlaiI = \frac{B1506 - B2062}{B1506 + B2062};$$

where Bxxx is the spectral reflectance at xxx nm. This indices were tested on a dataset called ANGERS that was measured in 2003 at INRA in Angers (France); In Fig. 8 the results obtained by applying this indices to ANGERS dataset are shown.

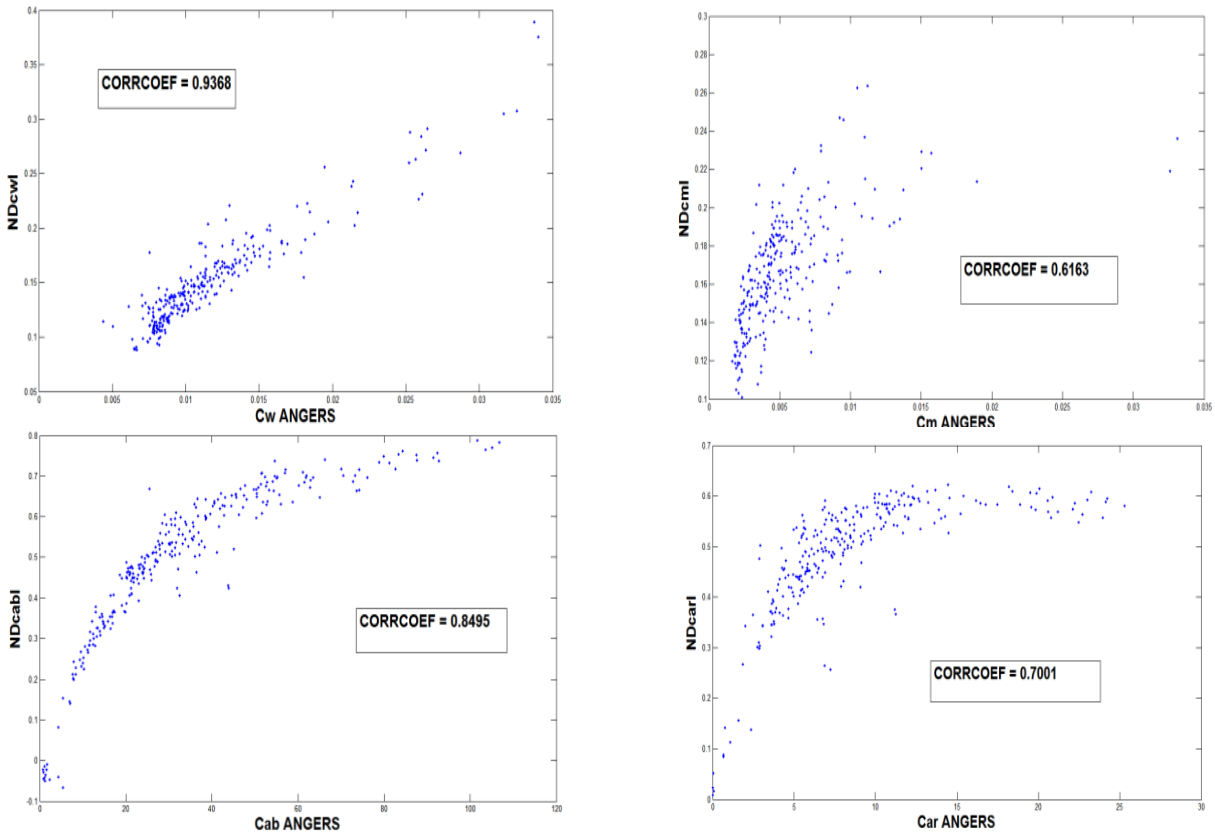

Figure 8. Indices tested on ANGERS dataset

Therefore, as shown from Fig. 8 the developed indices are highly correlated to the vegetation biophysical parameters. The combination of the values of these biophysical parameters provides and estimate of the vegetation health in the pixel but, to assess the damage severity, it is critical to know the pre-event land cover class in the pixel for assigning an appropriate damage factor. In fact, the six indices were combined with a pre-event classification image (4 classes) to assess the damage level. The information provided by the six vegetation indices and the classification map were joined by a regression tree method (Fig. 9). The damage severity is a nonlinear parameter and heavily dependent on the pre-event condition, indeed the developed vegetation indices take on a different meaning depending on the pre-event land cover class present in the pixel. The regression tree structure can represent these characteristics. The regression tree was constructed on the base of field data and a severity map developed by USGS EROS and USDA in the MTBS (Monitoring Trends on Burn Severity) project.

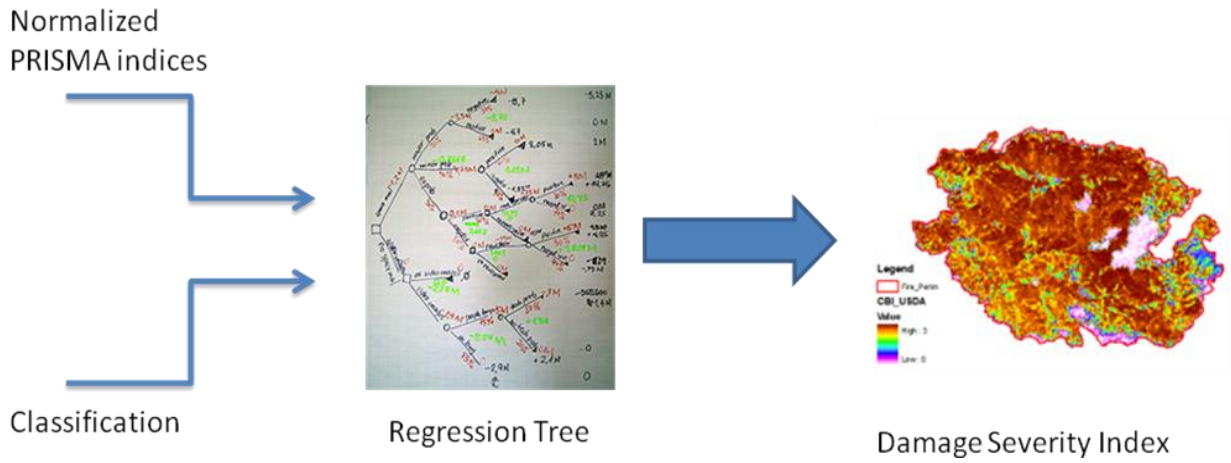

Figure 9. DSI assessment method.

3. Results

The Angeles National Forest was established by an Executive Order in December, 1892. It covers about 700,000 acres and is the backyard playground to the huge metropolitan area of Los Angeles. The Angeles manages the watersheds within its boundaries to provide valuable water to southern California and to protect surrounding communities from catastrophic floods.

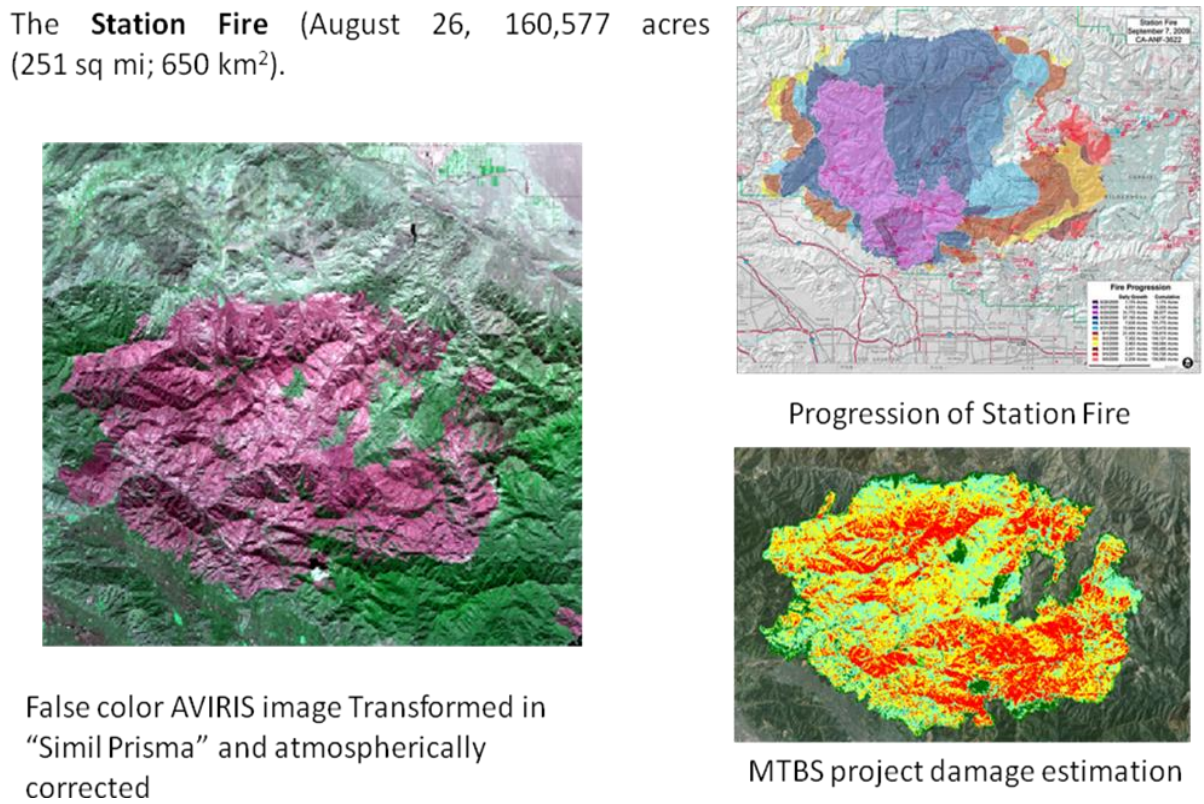

Figure 10. Study Area.

Elevations of the area range from 1,200 to 10,064 feet. Much of the Forest is covered with dense chaparral which changes to pine and fir-covered slopes as you reach the majestic peaks of the higher elevations [http://www.fs.usda.gov/angeles].

In 2009, a wildland fire in the Angeles National Forest known as the Station Fire led to the death of two firefighters, destroyed 89 homes and dozens of other structures, and burned more than 160,000 acres.

The Station Fire started on the afternoon of August 26, 2009, in steep terrain covered with highly flammable vegetation during very dry conditions.

After escaping initial containment efforts, the Station Fire underwent periods of rapid growth and extreme fire behavior over the following several days, ultimately threatening thousands of homes in nearby communities. Data available for the "Station Fire" are:

- 7 AVIRIS hyperspectral images acquired on: 06/10/2009
- 3 Landsat TM5 images acquired on: 20/09/2008, 23/09/2009 and 29/09/2011
- Severity map created by MTBS project [http://www.mtbs.gov/index.html]
- Severity map created by the USDA Forest Service fire and fuels monitoring project [http://www.fs.usda.gov/detail/r5/landmanagement/gis/?cid=fsbdev3_048275]
- The Existing Vegetation Type map (refresh 2008) created in LANDFIRE program

The 7 AVIRIS images were downloaded from JPL web site and then were calibrated, atmospherically corrected and resized to a 30 meter spatial resolution in order to make it similar to the expected PRISMA images (Simil-Prisma). From the "Simil-Prisma" image the six vegetation indices described above were extracted and then they were normalized.

The 3 TM5 images were calibrated and atmospherically corrected, from all the 3 images NDVI and NBR were calculated. The dNBR and dNDVI were calculated subtracting the two year later post-burn NDVI and NBR (29/09/2011) from the pre-burn indices (20/09/2008).

Two severity maps are available for the area of interest, the maps were developed using two different methodologies.

The severity map created by the USDA Forest Service in the framework of the Fire and Fuels Monitoring project (fig. 11A) was derived from TM data. A pre-fire scene and a post-fire scene were analyzed to create a Relative Differenced Normalized Burn Ratio (RdNBR) image. The RdNBR image portrays the variation of the burn severity within the fire.

Higher RdNBR values are correlated with more severe burns. The RdNBR image is converted to CBI units based upon a regression model. The CBI based severity classes represented on the classified map were "calibrated" by using field data collected one year after the fire on several fires from 2001 through 2004. The field data were collected on fires that occurred in similar vegetation types to calibrate or determine where the cutoff thresholds are set. The Composite Burn Index (CBI) field protocol was used to measure severity in the field.

The other severity map was created by MTBS project (fig. 11D). It was also derived from TM data by using a different approach. A pre-fire scene and a post-fire scene are analyzed to create a Differenced Normalized Burn Ratio (dNBR) image. The differenced NBR was computed by subtracting the post-fire NBR from the pre-fire NBR:

$$PreNBR - PostNBR = dNBR$$

Further processing is required to generate the 'Relativized' dNBR (RzdNBR). The RzdNBR takes into account pre fire conditions related to the amount of vegetation cover vs. bare soil. In other words, an area covered at 25% of vegetation that burns completely should be considered 'high severity' as would be an area covered at 100% that burned completely. The dNBR does not allow that distinction. To calculate the RzdNBR, the analyst should determine the 'dNBR offset value': the averaged dNBR value of a nearby area of unburned vegetation (similar to the vegetation that did burn). The RzdNBR is computed as follows:

$$(dNBR - dNBROffset)/\sqrt{(PreNBR/1000)} = RzdNBR$$

Higher dNBR and RzdNBR values are correlated with more severe burns. The dNBR image is analyzed to determine the threshold value between burned and unburned areas.

The two methods described above are similar but they mainly differ in two things:

- The MTBS method requires a human intervention to define dNBROffset, and it is more accurate;
- The MTBS method uses a post image acquired on 08/07/2010 (after a vegetation growing season) whereas the USDA Forest Service fire method made use of a post event image acquired on the 23/09/2009 immediately after the event. This allows the MTBS method to assess the vegetation really damaged.

The regression tree described above, was applied to the "Simil-Prisma" image, the results are shown in Fig. 11 in comparison with the other severity maps.

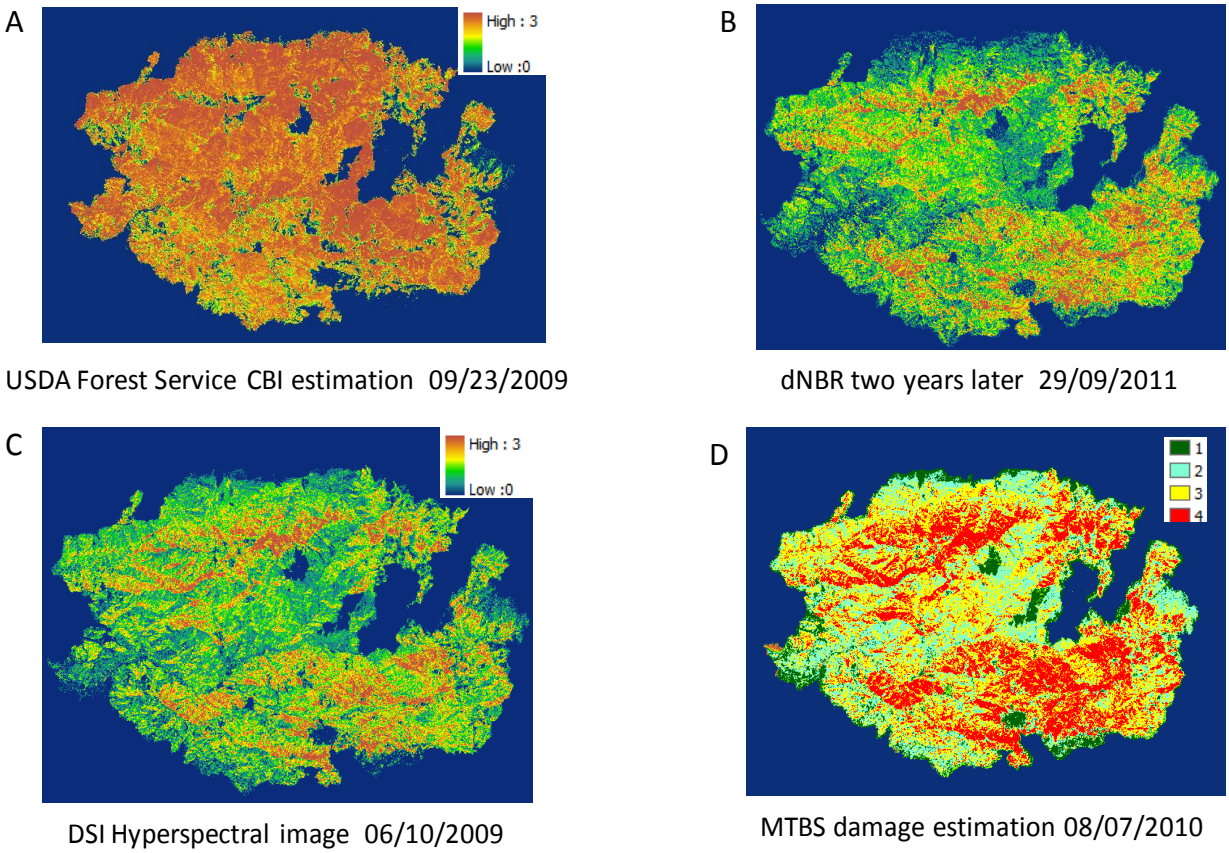

Figure 11. A) Severity map created by the USDA Forest Service; B) Two year later post-burn dNBR; C) Damage Severity Index; D) Severity map created by MTBS project.

Correlation coefficients were used to compare damage severity map to dNDVI and dNBR calculated two years after the fire. Correlation coefficients were determined for each of severity maps. The DSI index showed a correlation coefficient of 0.803 with dNDVI and of 0.737 with the dNBR computed as recalled above (by using an image acquired two years after the event), similar to the one provided by the MTBS method. The correlation coefficient of the USDA Forest Service CBI map was quite poor, as it can be noted by looking at the USDA severity map that assigns fairly uniformly a high damage to the whole burned area. Therefore, we can conclude that the results are satisfactory for the case under study, since it shows the improvement that the hyperspectral data could produce in damage severity assessment. In fact, hyperspectral method shows some advantage respect the other:

- doesn't require pre-event image.

- is fully automatic.
- doesn't require attending the following growing season after the event.

4. Conclusions

The paper is devote to illustrate the introduction of a new damage severity index (DSI) capable to quantify the damage caused to the vegetation from any kind of disastrous event (oil spill, land slide, floods, fire, etc.). Such index should exploit the information made available by the near future Italian hyperspectral satellite sensor PRISMA. After an initial definition of the index, based on the reflectance spectra collected 'in situ' during a couple of field campaigns, aiming at demonstrating the validity of the idea the introduction of a different expressions for the DSI were required in order to obtain a relationship practically applicable to the presently available (o available in the near future) satellite hyperspectral sensors. Finally, taking into account the characteristics of the PRISMA sensor and the field data a list of 6 indices well correlated with those vegetation parameters suitable to characterize its status were introduced. Such combination of indices was applied to a mosaic of AVIRIS images covering a big fire occurred on 2009 in California. The AVIRIS data were opportunely transformed for simulating the PRISMA channels. The results show the improvement that the hyperspectral information can provide in the estimate of the grade of damage caused by fires, helping in defining the different grade of damage in the burned area by using hyperspectral images acquired few weeks after the event. Of course the method needs further validation, and this can represent a problem due to the difficulty to find ground truth data. However, thank to a cooperation with the Sardinia Forest Corps (CFVA) this kind of information can become available soon.

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