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Dardzha Peninsula in western Turkmenistan: image taken February 11, 2001 by LANDSAT 7. Looking like a monstrous ogre with something gooey in its mouth, the Dardzha Peninsula in western Turkmenistan lies among the shallow coastal terraces of the Caspian Sea. Strong winds create huge sand dunes near the water, some of which are partly submerged. Further inland, the dunes transition to low sand plains.
Field Validation of satellite disturbance maps in Circeo National Park (Latium, Italy): ecological change and plants biodiversity relationships

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Abstract
Disturbance is defined as any change or perturbation, of biotic or abiotic origin, that can alter the ecological systems homeoeosis, and can be studied using change detection technique. In this study NDVI change detection was applied to investigate, within the Circeo National Park, those areas characterized by significant vegetation biomass modifications. Relationships among changed areas, stable areas and plants biodiversity were also analyzed with a new methodological approach that is to distinguish NDVI losses and gains as two different ecological events related to the processes of resistance and resilience. The final map of disturbance was used to verify within field data the relationships among plant biodiversity and both NDVI changes and stable areas.

Keywords: Change detection, Ecological change, NDVI, Plants biodiversity.

Introduction
Ecological systems are heterogeneous, showing a considerable complexity and variability in time and space [Li and Reynolds, 1994]. Variability and heterogeneity are described by all those events that can allow modification or change (e.g. disturbance) in ecosystem stability and resilience [Holling, 1992]. A disturbance is defined as a dynamic process caused by biotic or abiotic factors, that can disrupt the natural systems at all levels of hierarchy [cfr. Zurlini et al., 2006]. According to White and Pickett [1985], the disturbance is a “discrete event in time and space that alters the structure of ecosystems, communities, populations”, changing the substrate and the physical environment. The disturbance has not necessarily a negative valence or meaning, since by definition it does not destroy, but changed the context. The diversity-stability relationship has been a longstanding dispute in ecology [MacArthur, 1955; Elton, 1958; May, 1973; reviewed by McCann, 2000]. Empirical studies have found that the relationship between species diversity and ecosystem stability can be either positive [Griffiths et al., 2000, Muller et al., 2002], or negative [Pfisterer and Schmid, 2002], or neutral [Dukes, 2001; Griffiths et al., 2001; Liiri et al., 2002]. According to the theory...
of intermediate disturbance [Connell, 1978], Hobbs and Huenneke [1992] proposed that diversity of species is higher when the disorder shows intermediate frequency and intensity within their natural range of variation. Plant morphology tends to be well correlated with response to disturbance. Morphological types (e.g. biological forms) have been described as increaser, decreaser and neutral on regard to disturbance. Plant species furthermore respond to disturbance according to their biological attributes (disturbance enhance annuals forms and small stature). This approach to ecological change converge on a growth-form-based classification (annuals and short-lived perennials, perennial forbs) and response-specific attributes have been used to split plants group to particular disturbance regimes [Lavorel et al., 1997].  

The Normalize Vegetation Index (NDVI) [Rouse et al., 1974], computed by remote sensed processed images due to its characteristic of completeness is an excellent carrier of information both in landscape temporal changes studies [Griffith et al., 2002] and vegetation change assessment. In recent studies the NDVI change detection has been applied both to the monitoring of ecosystems carrying capacity [Zaccarelli et al., 2008], and ecological disturbance patterns identification [Millward and Kraft, 2004; Pettorelli et al., 2005]. Some of these studies focused on cumulative NDVI change without distinguish change regimes in its principal components: NDVI increase, decrease and stable areas. In this work we separately analysed NDVI increase, decrease and stable areas considering them different ecological functional states. We also applied the plants biological form classification method to verify the accuracy of NDVI change map by coupling map change to in field vegetation surveys (ground true). Our objectives were: (i) to analyze land-cover rates of change; (ii) to verify NDVI change map accuracy by in field surveys; (iii) to analysed plants biodiversity and biological form in response to NDVI changes.

Study area

The Circeo National Park is located in the province of Latina (Latium, Italy). The park is a protected area (since1934) of 8.440,00 hectares. This natural reserve is constituted by a variety of different habitats: transitional waters (the Fogliano, Caprolace and Sabaudia lakes), sandy dunes very rich in alophilic vegetation, Mediterranean and both meso and xero-thermophilic forests. Starting from 2004 the dune areas has been particularly protected from disturbance by building suspended catwalks to avoid the trampling of dunes vegetation (Fig. 1).

Materials and Methods

Remote sensing elaboration

Two Landsat TM5 images (dates July 1984 and July 2009) were used for the analysis. The 1984 image depicts the pre-disturbance condition, while the 2009 image depicts the post disturbance condition during which land use had changed appreciably. The 30 m resolution of Landsat images allows us to capture the study areas and the landscape variability over time. Prior to analysis restorations and rectification of images were performed to correct the geometry for errors and limitations in the sensor systems and to match a convenient geographic reference systems. Images radiance measurements were converted to exoatmospheric reflectance accounts for seasonal and latitudinal differences in solar illumination, using Markham and Barker [1986] algorithm.
Moreover, atmospheric corrections processing methods were used to reduce the degradation of images quality caused by atmospheric interference using a dark object subtraction approach [Chavez, 1996]. The NDVI index was calculated using:

\[ \text{NDVI} = \frac{(\text{IR}-R)}{(\text{IR}+R)} \]  \[1\]

This index relates the absorption spectrum of chlorophyll in the red (band 3, which corresponds to the range 0.63-0.69 µm) with a typical reflection in the near infrared which is strongly influenced by the type of leaf structure (band 4, which corresponds to the range 0.76-0.90 µm). NDVI is strongly related to variables of most ecological interest and it also reveals health and stress conditions of vegetation. The NDVI index is used as ecological response variable to identify support regions across scales where change is most likely (i.e. Resilience is low) [Law and Waring, 1994]. The NDVI index also represents a great information vector for landscape temporal modification studies [Griffith et al., 2002]. To perform images classification 30 ground true training regions (ROI) were collected directly by field surveys, then the Maximum Likelihood classification method was applied to obtain the study area land cover map. In a successive step the image difference technique was applied to NDVI maps derived from images using a pixel by pixel analysis.
pixel value subtraction [Coppin et al., 2004; Singh, 1989] [2]:

\[ D_{x_{ij}}^k = x_{ij}^k(t_2) - x_{ij}^k(t_1) + C \]  [2]

where: \( x_{ij}^k \) represent the pixel value of k band and i and J are respectively line and pixel number of the remote sensed image; \( t_1 \) and \( t_2 \) are the initial and final time of images acquisition and C is a constant to produce positive digital numbers. Difference data were selected for statistical significance by percentiles method: classes of change are defined by setting a threshold of change small enough to avoid random variations cover. The change thresholds were calculated using the tenth and the ninetieth percentiles of pixels distribution (10% increase in right tail and 10% decrease in left tail). The statistical threshold, appropriately prefixed, allows to assign each pixel to one of the following three classes: NDVI increase, no change (eg. stable areas), and NDVI decrease. The output of this procedure is the disturbance (or ecological changes) map (Fig. 2).

Figure 2 - The disturbance map. No-change areas white coloured, NDVI losses black coloured, NDVI gains gray coloured.
**GIS techniques**
Both the disturbance and the land cover classification maps were elaborated in GIS environment using the spatial analysis tools. In order to quantify the extent of the disturbed areas of a given land use type, both land use map and disturbance map were tabulated: the tabulation process output is a matrix in which to each class of land use is assigned the corresponding value of NDVI increase, decrease or the surfaces of stable areas (in terms of number of pixels). Change rates were estimated for all the land use classes as follow [3]:

\[ Cr[C,T]=\frac{S_C}{S_T} \times Y \times 100 \]  

Where \( S_C \) is the surface of changed area per class type and class of disturbance, \( S_T \) is the total class type surface calculated from the more recent classification map (2009), \( Y \) are the years of temporal interval (25 years) multiplied 100 to compute the percentage.

The following classes were selected to perform the field surveys analysis: Mediterranean forest of *Quercus ilex* L., prevalent [Blasi, 2005], dune areas, shoreline of Sabaudia and Caprolace salt lakes. The disturbance maps were also overlayed to the Circeo National Park orthophotos to select in field analysis areas by choosing NDVI losses, gains and stable areas pixels belonging to the sampling sites.

**Field data**
Three sampling sites were selected using disturbance map and changes data (Fig. 3). The first site was the Circeo promontory, a Mediterranean vegetated relieve with two distinct slopes: a sea mountainside called *Quarto Caldo* and, a land mountainside called *Quarto Freddo*. *Quarto Freddo* is characterized by Mediterranean forest with prevalence of *Quercus ilex* L. and some individuals of *Quercus suber* L. [Milanse et al., 1998]. The cape has a calcareous substrate and was interested by a fire event in 2006 [Blasi and Carranza, 1998]. These areas are also heterogeneous from the climatic point of view. In Circeo promontory were selected two sampling station belonging to increase area and stable areas of disturbance map. The second site was located in the edge zone between the sea dune area of Sabaudia and the homonymous lake, two sampling station representing NDVI increase and decrease were selected. The NDVI increasing zone was located in the seaside while the decrease zone was located in the lake-side forest. The third sampling site was identify close to the Caprolace lake and nearby its wetlands. NDVI increase and decrease were analyzed. Each sampling station was a square of 100x100 meters. Both phytosociological survey (canopy density, plants dominance, species identification, biological form) using Braun-Blanquet method [Braun-Blanquet, 1951, 1979] and quantitative analysis (total abundances of vegetal species per sampling station, diversity indices (Shannon Diversity Index- SHDI, total abundances, Shannon evenness. Simpson diversity) were performed. SHDI was calculated as follow [4] [Pielou, 1966]:

\[ \text{SHDI}= p_i \log p_i \]  

were \( p_i \) is the probability to find a specie in a n set of species. Species were identified using Pignatti [1982] plants classification manual. The biological forms were identified using
Raunkiær classification procedure [Raunkiær, 1934]. This method allows to assign each specie to the corresponding biological form (stage of plant development) using in field surveys to relieve plants morphological characteristic. Once considered the number of plant species and stage of their development is possible to obtain the flora biological spectrum which reflect the environmental characteristics and, not least, the degree of disturbance which interest (or interested) the studied area. Biological form is considered both an indicator of disturbance events and successional stages [Lavorel et al., 1997].

Figure 3- The selected surveys site.

Results
The estimated rates of change showed a good dynamism of the shrubbsland land cover class. Is interesting to underline that the coniferous mixed forests and deciduous oaks forests that are completely included in a central and isolated area of the Park (the plain forest) showed a low rate of change while, *Q. ilex* dominated forests that are widely diffused through the study area and particularly abundant in Circeo promontory appear more dynamic (Fig. 4). The field analysis confirmed that a great part of the shrubby areas identified by classification were plants juvenile stage of development due to post-disturbance recovery. In all the sampling stations a good correspondence was found among disturbance map and vegetation growth stage. The NDVI increased areas showed a post-disturbance recovery compared to stable areas. Forested areas of Circeo promontory in land mountainside, (stable area) had a very high canopy coverage (90%), with a predominance of arboreal biological forms and very poor undergrowth as a result of “competition for light” environmental forcing (a dense coverage involves necessary a poor penetration of light).
In the sea mountainside (NDVI increase area) the canopy coverage was of 70%, the predominant biological forms was those of shrubby and the undergrowth species were more represented. In this area a recovery post-disturbance dynamic was evident, with sparse and younger individuals characterized by early growth biological from (Tab. 1).

Table 1 - Circeo promontory phytosociological and plants morphological surveys. Symbol + those species whose coverage and presence was too little to quantify. Biological form according to Raunkiaer: P=Phanerophytes, Caesp= shrubby biological form, Scap=arboreal biological form, Ch= Camephytes, Frut =fruticosa. Other species not included in sampling station are: Smilax aspera L., Asparagus acutifolia L., Rubia peregrina L., Pteridium aquilinum (L.) Kuhn.

<table>
<thead>
<tr>
<th>Site Circeo Promontory</th>
<th>Land mountainside (Quarto Freddo) NDVI Stable area</th>
<th>Sea mountainside (Quarto Caldo) NDVI increase</th>
<th>Biological forms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plants coverage %</td>
<td>90%</td>
<td>70%</td>
<td></td>
</tr>
<tr>
<td>Number of species</td>
<td>6</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>Quercus ilex L.</td>
<td>5</td>
<td>3</td>
<td>P scap</td>
</tr>
<tr>
<td>Arbutus unendo L.</td>
<td>4</td>
<td>3</td>
<td>P caesp</td>
</tr>
<tr>
<td>Fraxinus ornus L.</td>
<td>1</td>
<td></td>
<td>P scap</td>
</tr>
<tr>
<td>Ostrya carpinifolia Scop.</td>
<td>1</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Olea europaea L.</td>
<td>+</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Rhamnus alaternus L.</td>
<td>+</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Pistacia lentiscus L.</td>
<td>+</td>
<td>1</td>
<td>P caesp</td>
</tr>
<tr>
<td>Phyllirea latifolia L.</td>
<td>+</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Erica arborea L.</td>
<td>1</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Juniperus phoenicea L.</td>
<td>+</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Cytisus villosus Pourret</td>
<td>1</td>
<td></td>
<td>P caesp</td>
</tr>
<tr>
<td>Ruscus aculeatus L.</td>
<td>+</td>
<td></td>
<td>Ch frut (small shrub)</td>
</tr>
</tbody>
</table>
In the second sampling station, adjacent to Sabaudia forested dune areas (sea side, NDVI increase), was recorded an advancement of the Mediterranean dune vegetation and a clear successional vegetation stage with the presence of pioneer species like *Carpobrotus acinaciformis* (L.) Bolus. as for a post-disturbance recovery. The areas of NDVI decrease close to the shores of the lakes instead, showed clear anthropogenic nature thinning effects (hiking trails, boat dock) that stood out sharply, forming an edge that separate clearly the deforested zone from the thicker forest (Tab. 2).


<table>
<thead>
<tr>
<th>Site</th>
<th>Sabaudia Lake dune area NDVI gains</th>
<th>Sabaudia Lake forested side area NDVI losses</th>
<th>Biological forms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant coverage %</td>
<td>70%</td>
<td>60%</td>
<td></td>
</tr>
<tr>
<td>Station width</td>
<td>100x100 m</td>
<td>100 X 100 m</td>
<td></td>
</tr>
<tr>
<td>Number of species</td>
<td>5</td>
<td>8</td>
<td></td>
</tr>
</tbody>
</table>

- *Quercus ilex* L. 3 70 *P* scap
- *Arbutus unendo* L. / + *P* caesp
- *Pistacia lentiscus* L. 5 14 *P* caesp
- *Pistacia terebinthus* L. / *P* caesp
- *Phyllirea angustifolia* L. 11 6 *P* caesp
- *Erica arborea* L. / 5 *P* caesp
- *Juniperus phoenicea* L. 24 15 *P* caesp
- *Juniperus oxycedrus* L. subsp. *Macrocarpa* 74 *P* caesp
- *Ruscus aculeatus* L. + (1) *Ch* frut (small shrub)
- *Pinus pinaster* Aiton *P* scap
- *Pinus pinea* L. *P* scap
- *Eucalyptus sp.*
- *Rhamnus alaternus* L. *P* caesp

In Caprolace Lake area NDVI losses corresponded to a wide deforested area, actually colonized by invasive and exotic species, the nearest NDVI gains hot spot was characterized by the massive uncontrolled development of *Vitis vinifera* L. plants (abandoned vineyards), *Robina pseudoacaia* L. (also note as black locust, native of United States and widely planted and naturalized elsewhere in temperate Europe is considered an invasive species), and *Eucalyptus globosus* Labill. (planted during the drainage works of Pontina lowland, 1939-1945, is considered an exotic and toxic for the freshwater macrobenthos (Tab. 3). The total abundances in species and individuals were similar with 106 vs 105 individuals respectively for NDVI gains and losses but species were different, with a prevalence of *Quercus ilex* L. in NDVI losses areas (arboreal form). SHDI was higher in NDVI losses areas, moreover the “type” of disturbance regimes followed this rule: not completely shaded area showed higher biodiversity because of light penetration. In The Caprolace lake area
abundances values were lower (64 individuals), but SHDI value was similar to the Sabaudia lake NDVI losses area (Tab. 4).

Table 3 - Caprolace lake phytosociological and plant morphological surveys. Biological form according to Raunkiær: P=Phanerophytes, Caesp= shrubby biological form, Scap=arboreal biological form, Ch= Camephytes, Frut =fruticosa. Other species not included in sampling station : Vitis vinifera L., Robinia pseudoacacia L., Rubus ulmifolius Schott, Ficus carica L., Quercus frainetto Ten.

Table 4 - Diversity indices calculated for salt lakes area. Indices were computed for different NDVI change class (gains and losses).
Discussion and conclusion
The field data showed a close relationship between remote sensing disturbance map and ground true. Assuming that, the biological form of a plant synthesizes the information related to its behaviour and adaptation mechanism, is consequent that the development of vegetation in an area is affected by the simultaneous multiple environmental factors. Specifically, fire events, cutting, storms and human activity plays a key role in the development of phytocoenoses, impoverishing biodiversity and promoting the prevalence of shrubby and arbustive biological forms. Plant morphology in study area was found to be well correlated with response to disturbance. Presumably, this pattern results from the correlation between plant size and several physiological attributes that provide adaptation to open environments, and from the direct relationship between plant size and resources accessibility. This characteristic can be used to analyse morphological changes in different disturbance regimes. [Duarte, 1995]. Another important aspect highlighted by this study was that, in field surveys, it makes possible to assess the disturbance source: in the sampling areas of Sabaudia and Caprolace lakes the disturbance was human-caused, while Circeo promontory was interested by natural disturbance regime due to wind storms in the sea-mountainside and deforestation caused by fire occurred in the past (2006). The SHDI values indicate that the biological diversity in forested ecosystem is promoted by those disturbance events that contributes to reduce canopy coverage. Biological forms are influenced both by forest coverage and disturbance patterns and are distributed consistently with the elaborated disturbance maps [Lavorel et al., 1997; Loreu, 1998]. Shrubby and young individuals forms were distributed in the open areas generated by biomass losses [Noble and Slatyer, 1997], while the high canopy coverage of stable areas seems to lead to a climax community, less dynamic and biologically poor. The recovery after disturbance was clearly evident in Circeo promontory, specifically in NDVI losses area interested by sea-storm, while in the fired portion of the forest the recovery was slower. The Sabaudia lake sea-side dune area was clearly interested by recovery coupled with stable area. In this case, the dune vegetation was in a successional stage, and was recorded the presence of secondary colonizer species. In particular, the presence of *Carpobrotus acinaciformis* (L.). *Carpobrotus a.* is a chamaephyte, mat-forming and succulent native to South Africa which were introduced as ornamentals and for erosion prevention and is a post-disturbance recovery indicator. This specie is actually widely naturalized on Mediterranean coastal rocks, cliffs and sandy dunes, and are considered a serious threat to several plant species and coastal habitats [Draper et al., 2003]. The altered species abundances following disturbances create opportunities for exotic species to successfully establish and subsequently naturalize into non-native environment. Such post-disturbance changes in abiotic and biotic environments may also promote a naturalized exotic species (or invading species) to become invasive through rapid colonization of the habitat sites by reducing the extent and size of resident plant species [Chakraborty and Li, 2010]. The importance of this study approach can be resumed in the following assertion: “from an ecological point of view the concept of stability do not equals biodiversity”. In synthesis, the results seems to highlight that stability is not always supported by high biological diversity and that change in ecological homerisize promote biodiversity via a more dynamic flux of species in disturbed areas. Naturally, those areas interested by anthropic disturbance (more intensive and persistent than natural disturbance) highlighted a species number increase due to the invasive flux of exotic and non-indigenous species that
degraded the ecosystem quality: not always biological diversity is synonymous of biological quality. The remote sensing-phytosociological coupled method approach purposed by this work, allowed both to distinguish the two main types of ecological change (NDVI gains and losses) and disturbance type (natural or anthropic). Accuracy of disturbance map was tested in field and revealed high correspondence. Starting from this procedure is possible to select “a priori” sampling sites subjected to different ecological regimes and processes by selecting the right pixels from NDVI ecological change maps and to distinguish the disturbance type using field surveys and plants biological forms classification.

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Received 17/01/2011, accepted 27/08/2011
SIGRI - an Integrated System for Detecting, Monitoring, Characterizing Forest Fires and Assessing damage by LEO-GEO Data

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Abstract
Forest fires are in the focus of the SIGRI pilot project (Integrated System for Fire Risk Management) funded by the Italian Space Agency (ASI). The project, started late in November 2008. It is due for completion by end-2011.
The EO part of the project is centred on (1) SAR borne observation in the X, C and the L-bands, from ASI and ESA platforms Cosmo-Skymed and Envisat; (2) on TIR/MIR/SWIR/NIR - and Red, where appropriate - observation by opto-electronic payloads operating at all spatial resolutions from 2006 onwards (SEVIRI, MODIS, HRVIR, HRG, TM, ASTER, LISS-III) and (3) upon SAR very high resolution (Cosmo SkyMed) and V-NIR observation by new commercial or dual-use satellites.
The system, of which the appointed user is the Italian Department of Civil Protection (DPC), is expected to deal at once with law enforcement (burn scar mapping), preparedness (risk mapping and urban interface fire contingency planning) and operational issues (fire detection and propagation prediction). It will be demonstrated in three operational theaters (northern Italy – Liguria, southern Italy – Calabria, and the island of Sardinia), all characterized by high frequency of occurrence of fires, but greatly differing in terms of fires style.
Keyword: fire, management, satellite, burned area, detection.

Introduction
Forest fires are the main threat to forests in the Mediterranean Region, as in Italy, where notwithstanding the high interannual variability of the phenomenon, in average (JRC, 2009) they kept steadily above ca. 7500 fires and ca. 40.000 hectares per year in the last decade. The management of this phenomenon by providing forecasts, performing detections and assessing damages, based on the use of advanced technologies (satellite data) is the objective of the SIGRI (Integrated System for Fire Risk Management) project. In particular, the objective of SIGRI is the development of products which can useful to the firefighting activities along all the phases which can be distinguished in the fire contrasting activity: forecast, monitoring/detection, counteract/propagation prediction, damage assessment/recover.
SIGRI builds upon four main axes:
a) to define, make and end-to-end demonstrate a functional architecture, accounting for all types of operational scenarios of fire-related emergencies at local, regional and national level, respectively;

b) to customize and implement into the system the whole set of unsupervised, fire-oriented EO techniques already consolidated at the start of final negotiations;

c) to explore, test, and implement into the system if appropriate, innovative unsupervised techniques for fire detection and burn scar mapping;

d) to provide the overall system with relevant, quantitative decision support functionalities, as the near-real-time straightforward modeling of fires in controlled environment under known boundary conditions.

Even if many project have been funded in the last years aiming at increasing the exploitation of satellite images in the management of forest fires (AFIS, PREVIEW, FIRE-M3, SENTINEL, etc.) no one has a so ambitious objective of developing a system capable to support firefighting in real time, mostly based on information provided by satellite images. In fact, most of these applications are not devoted to the early detection or monitoring of fires, and therefore, they are not suitable to support counteracting operations and event management. In fact, the main purpose of fire-detection applications (except in very rare cases) is that of carrying out a statistical study of the events and their possible environmental impact in terms of burnt area and variation of the optical characteristics of the atmosphere due to burning products (global-scale climate change). Fires occurring in the Mediterranean area are rarely significant in terms of burning products released in the atmosphere. Nevertheless, they have a dramatic impact on the extension of vegetated areas in regions with relatively scarce vegetation and on human lives and infrastructure.

This paper is devoted to introduce the SIGRI pilot project, that is a three years lasting project funded by the Italian Space Agency (ASI). Of this “pilot project”, initiated officially on November 2008, the main objectives and characteristics will be described.

**SIGRI Project generalities**

**Data and Methods**

The SIGRI pilot project will be developed in the mainframe of the project “Civil Protection from forest fires”, as a consequence it should take into account the institutional requirements, as: the normative aspects in forest fires matter [Gambardella et al., 2002], the distribution of responsibilities and competence of the authorities involved in the following activities: planning and management of the land, dangerousness forecast and risk assessment, prompt fire detection, monitoring and management of the fire event, damage assessment.

The principal user (reference user) of such a system would be the Italian Dept. of the Civil Protection (DPC). Therefore, the demonstrative system implemented during SIGRI will be structured in a way to be easily interfaced to the DPC infrastructures network and functional centers. Nevertheless, the system would be able to product information useful for supporting different user types having the role of responding, operationally, to the forest fire management according with the guideline and operational addresses indicated by DPC.

The system should provide products based on the use of EO data (Tab. 1) useful for being applied for managing the forest fire risk, for detecting fires, and mapping burned areas. Products Specifications will respond to user requirements from Italian DPC.

Fighting forest fires requires the availability of information and data to be used as a support
during all the year to the authorities in charge for the contrasting the forest fires. For this reason, three operational modalities which respond to the requirements of the different actors involved in the management of risk associated with the forest fires, have been identified that is, the prevention, the extinguishment, land management and damages assessment. Consequently, the demonstrative system of SIGRI would be operable according with the following modalities:

a) Mode STRATEGIC. This operational mode finds application out the fire season (SSI); the products generated will support the activities of planning and management of the territory for contrasting the fire events. In particular, maps of geospatial and temporal fire dangerousness, maps of vegetation ri-generation, maps of burned areas and a pre-fires-season map of fire risk will be produced.

b) Mode TACTICAL. It is applied during the fire season; the generated products are characterized by the high frequency of the updating and will provide support to the activity of detection, management and monitoring of the burning events.

c) Mode LEGISLATIVE. It finds application out of the fire season, its products regard mainly the development of an archive (cadastral) of the burned areas at the conclusion of the time period during with a fire occurrence is probable.

The development of the products to be provided by the project will be based, according with the requirements expressed by the DPC, on satellite sensor already available but taking into account EO satellite missions planned for the near future, too.

<table>
<thead>
<tr>
<th>Mission/ Sensor</th>
<th>Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cosmo-SkyMed</td>
<td>Burned areas maps at very high spatial resolution</td>
</tr>
<tr>
<td>IKONOS-2</td>
<td></td>
</tr>
<tr>
<td>QUICKBIRD</td>
<td></td>
</tr>
<tr>
<td>GeoEye-1</td>
<td></td>
</tr>
<tr>
<td>KOMPSAT 2</td>
<td></td>
</tr>
<tr>
<td>Pleiades (when available)</td>
<td></td>
</tr>
</tbody>
</table>
| SPOT-4 / 5 / IRS-P6-LISS3 Landsat 5 / TM | ▪ Land use maps  
▪ Vegetation indices  
▪ Burned areas map  
▪ Vegetation regeneration maps  
▪ Dynamics vulnerability maps |
| EO-1 / HYPERION or PRISMA | Dynamics vulnerability maps |
| TERRA e AQUA / MODIS | ▪ Hot Spot maps  
▪ Vegetation indices  
▪ Dynamics vulnerability maps |
| MSG SEVIRI      | Hot Spots maps |
| COSMO-SkyMed    | Burned areas maps  
ERS-SAR  
ENVISAT/ASAR  
SAOCOM/SIASGE (when available) | Dynamics vulnerability maps |

Table 1 - List of satellite sensors possibly used (or of interest) and the products expected by the SIGRI project.
**Demonstration phase**

The demonstration of the products generated in the framework of the SIGRI project will be carried out on test area selected in the following regions: Calabria, Sardinia and Liguria. The demonstration activities, in which ASI and DPC will be involved, aim at demonstrating the service functionality and the effective functioning of the end-to-end system. During the demonstration phase the products will be generated for each one of the test area. The areas, as shown in Fig. 1, correspond to: Imperia and Savona provinces (Riviera di Ponente, Liguria west coast), Locride province (Calabria) and Cagliari/Iglesias province (Sardinia). For these areas all the products foreseen for the specific system release will be provided.

![Figure 1 – Test areas. Definition of the test areas for the demonstration of the SIGRI system.](image-url)

**SIGRI research activities**

This paragraph is devoted to show aspects of the project mainly deserving a research activity.

**Fire Detection**

From the point of view of the fire detection, several studies have clearly assessed the capability of suitable algorithms to detect fires of very small size, compared with the satellite image pixel size, using the brightness temperature measured in the MIR and TIR spectral channels [Prince and Menzel, 1992; Flasse and Ceccato, 1996; Arino and Rosaz, 1999; Cuomo et al., 2001; Justice et al., 2002]. However the limited temporal revisit frequency of low earth orbit (LEO) satellites has prevented, up to now, the possibility of using satellite observations as a support to the real time counteraction of fire events. For this reason, given the improved characteristics of the SEVIRI sensor, notwithstanding its limited spatial resolution, it is interesting to explore the actual applicability of the MSG geostationary satellite, that is able to guarantee a 15 min. images temporal resolution.

The innovation, with respect to other forest fires detection methods based on geostationary or low orbit satellites, represented by the SFIDE (System for Fire Detection) algorithm, consists in the attempt to exploit the quasi-continuous Earth observation that SEVIRI provides to set up a wildfire automatic early detection system [Laneve et al., 2006a; Laneve and Cadau, 2006b].
The SFIDE algorithm tries to exploit the image high refreshing frequency guarantee by the SEVIRI sensor (15 min) for minimizing the sizes of the detectable fire. This objective is achieved by comparing temperatures variation between two consecutives images (acquired after 15 min one to the other). In normal conditions significant changes, representative of a fast dynamics, can be associated with the occurrence of a fire (volcano eruption) or the appearance of clouds. Small changes associated with the diurnal solar cycle or solar illumination conditions should be taken into account.

The research activity, in this case, aims:
- at improving the sensitivity limit of the fire detection algorithm maintaining a suitable rate of false alarms. This will be obtained by better defining the surface characteristics (emissivity, land cover), improving the cloud mask algorithm [Derrien and LeGleau, 2005; Laneve and Cadau, 2008], and introducing a much accurate description of the atmospheric effects;
- at increasing the reliability of the fire parameters (size, temperature, FRP) [Dozier, 1981; Roberts and Wooster, 2008; Laneve and Cadau, 2009] and at the development of new products (burned biomass, etc.) [Wooster et al., 2005].

**Burn Scar mapping in SIGRI**

The most effective, passive remote-sensing methods for detecting and mapping burn scars in vegetated areas, rely upon the observation of near-infrared (NIR) and short-wavelength infrared (SWIR) bands, with wavelengths comprised between 0.8 and 2.3 μm. A method to separate reflectance variation due to vegetation damages from changes due to other factors influencing the at-satellite reflectance, is that of identifying pseudo-invariant features to be used as reference targets in different scenes. Such invariants behave as Permanent Reflectors (PRs) ideally in three or more infrared bands, and allow (a) improving the robustness of the code developed and fine tuned from 2002, nicknamed MYME2 [Di Bartola et al., 2005; Hirn et al., 2007; Hirn and Ferrucci, 2008].

The research activities, in this case, aim at improving the already available algorithm for detecting burned areas by exploiting temporal series of radar images (phase and amplitude). In particular, the possibility to obtain maps compliant with the requirements of the Italian rules, by exploiting very high spatial resolution of the Cosmo-Skymed SAR images and testing different techniques, will be assessed.

**Fire risk maps**

Regarding the development of a daily map of fire risk/vulnerability index, among the indices already developed/proposed (FPI, FWI, etc.) worldwide [Burgan et al., 1998; Heidorn, 1998; Ventura et al., 2001; Lopez et al., 2002; Laneve and Cadau, 2007] the one under consideration should be characterized by the fact that it has to be based, at least partially, on satellite images. As consequence such an index would be based on the FPI (Fire Probability Index) recognized as an index able to identify those areas at risk of fire [Burgan et al., 1998; Laneve and Cadau, 2007]. The addition of further information like the presence of infrastructure, or areas of relevant importance will lead to define a fire vulnerability index. Based on: an ameliorate description of the vegetation type (fuel type), by using hyperspectral and radar images, and a satellite based estimate of the vegetation water content [Rothermel et al. 1986; Nelson, 2000; Ceccato et al., 2002] an improvement of the forecast based on the fire probability index would be obtained.
Conclusions
The present paper aims at presenting the objectives and expected products of the three-years-long pilot project called SIGRI, recently funded by Italian Space Agency. This project represents one of the 7 initiatives funded by ASI intended to enhance the utilization of satellite images for planning, managing and contrasting natural or anthropic hazardous events like wild fires, landslides, floods, sea and air pollution. A description of the project has been presented. Results of the research activity and of the operational application of the system will be presented in the next future, as they will be obtained.

Acknowledgements
This work has been carried out in the framework of the SIGRI pilot project funded by ASI, Contract no. I/052/08/0.

References


Received 15/01/2011, accepted 28/02/2011
Metodologie per l’individuazione di coperture in cemento-amianto mediante dati da remoto

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Riassunto
L’amianto rappresenta un problema ambientale di particolare gravità per i molteplici effetti nocivi che questo materiale provoca alla salute dell’uomo. In Italia la Legge n.257/92 ha messo al bando tutti i prodotti contenenti amianto e ha previsto il censimento da parte delle regioni degli edifici nei quali l’amianto è presente. L’obiettivo di questo lavoro consiste nello sviluppo di una tecnica speditiva ed affidabile per individuare, identificare e mappare le coperture in cemento-amianto con dati telerilevati del sensore iperspettrale MIVIS (Multispectral Infrared and Visible Imaging Spectrometer). Le immagini MIVIS sono state processate con le tecniche Minimum Noise Fraction (MNF) e Mixture Tuned Matched Filtering (MTMF) e classificate attraverso l’applicazione dell’algoritmo Spectral Angle Mapper (SAM). Lo studio è stato realizzato in un’area della provincia di Reggio Calabria (sud d’Italia).

Parole chiave: Cemento-amianto, dati MIVIS, MTMF, MNF.

Methodologies to identify asbestos-cement roofing by remote data

Abstract
Asbestos is a particularly serious environmental problem because of multiple harmful effects on human health. In Italy, law n.257/92 has banned all products containing asbestos and has provided by census regions where buildings were present. The objective of this study is to develop a quickly and reliable technique to detect, identify and map asbestos-cement roofing by MIVIS (Multispectral Infrared and Visible Imaging Spectrometer) hyperspectral data. MIVIS images have been processed by Minimum Noise Fraction (MNF), Mixture Tuned Matched Filtering (MTMF) techniques and classified by Spectral Angle Mapper (SAM) algorithm. This study has been carried out in an area of Reggio Calabria province (southern Italy).

Keywords: Asbestos-cement; MIVIS data; MTMF; MNF.

Introduzione
Negli ultimi anni il progresso della sensoristica ha permesso di sviluppare strumenti sempre più precisi per l’osservazione della Terra finalizzati all’analisi dell’ambiente urbano, industriale e naturale [Smith et al., 1994].
Una problematica di rilievo è rappresentata dalla presenza sul territorio nazionale di coperture in cemento-amianto, conosciuto anche con il nome di eternit [Marino et al., 2001]. Le coperture in cemento-amianto sono state utilizzate fin dai primi anni '90 per la costruzione di capannoni industriali, agricoli, pubblici ed abitazioni civili. Il cemento-amianto è un materiale che unisce robustezza a leggerezza, con le non trascurabili proprietà di facile lavorabilità e soprattutto di basso costo. Tuttavia, l’amianto (o asbesto) rappresenta un problema ambientale di particolare gravità ed entità per i molteplici effetti nocivi sulla salute dell’uomo. In Italia la legge 257/92 ha imposto la cessazione della produzione e dell’impiego dell’amianto.

Il monitoraggio delle superfici in cemento-amianto tramite tecniche di telerilevamento iperspettrale da piattaforma aerea rappresenta una valida alternativa ai metodi di censimento tradizionali basati sull’ispezione visiva delle superfici e prelievo in situ di campioni di copertura da analizzare successivamente in laboratorio [Busetto et al., 2003].

In particolare nel territorio italiano la classificazione del cemento amianto è stata spesso realizzata utilizzando dati iperspettrali acquisiti dal sensore MIVIS. Negli studi effettuati per la mappatura delle coperture in cemento-amianto la scena investigata veniva valutata qualitativamente attraverso l’analisi visiva dei singoli canali dei 4 spettrometri del sensore MIVIS [Fiumi et al., 1998; Fiumi et al., 2001; Fiumi et al., 2004]. Tale analisi portava alla conclusione che la qualità di alcuni canali (es. #59, #63) era al di sotto di un livello qualitativo tale da porre in questione il loro uso e per questo motivo veniva applicato un filtro ai canali dello Short Wave InfraRed (SWIR) ricadenti nel dominio spettrale 2,0-2,5 µm (#31 - #92) [Fiumi et al., 2004].

Inoltre, i canali dell’Infrarosso Termico (TIR, #93 - #102) non venivano presi in considerazione perché la temperatura di un edificio è solo in minima parte determinata dalle proprietà termiche dei materiali di cui è costituito, risultando, invece, prevalentemente influenzata dalle attività che in esso si svolgono [Fiumi et al., 1998; Fiumi et al., 2001; Fiumi et al., 2004]. Ricerche successive [Bassani et al., 2007] hanno dimostrato che le bande della regione spettrale del TIR risulterebbero fondamentali per la classificazione delle coperture in cemento-amianto.

Altri studi [Busseto e Micheletti, 2003] sottopongono le immagini calibrate ad una trasformazione MNF, che consente di migliorare la qualità della classificazione enfatizzando il rapporto Signal/Noise (S/N) [Amato et al., 2009].

L’obiettivo di questo lavoro è di sviluppare una tecnica speditiva ed affidabile per individuare, identificare e mappare le coperture in cemento-amianto.

Per individuare le strutture in cemento-amianto sono state effettuate analisi nelle quali vengono valutate l’utilità dei canali dello spettrometro dell’Infrarosso Medio e del Termico, i vantaggi dell’applicazione della trasformazione MNF e le ottimizzazioni delle procedure di classificazione utilizzando la tecnica MTMF che consente di individuare nell’immagine i pixel caratterizzati da una maggiore purezza spettrale [Boardman, 1998; Kruse et al., 2004]. Sull’immagine MIVIS è stata acquisita la firma spettrale di un singolo pixel relativo ad una copertura in cemento-amianto (identificato mediante un rilievo in situ) ed utilizzato per la MTMF. Il risultato di questa tecnica ha consentito di individuare, mediante fotointerpretazione e ricognizione in situ, altre coperture in cemento-amianto da cui estrarre i training sites per l’algoritmo SAM.

Infine, sono state confrontate due prove di classificazione (A e B): la prima considera differenti classi di copertura mentre la seconda la sola classe cemento-amianto.
Materiali e Metodi

*Area di studio e pre-elaborazioni delle immagini MIVIS*

La metodologia sviluppata è stata applicata ad una immagine MIVIS acquisita in data 31/10/2009 con una risoluzione al suolo di 3 m x 3 m su un’area di circa 16 km² sita nella provincia di Reggio Calabria (sud Italia).

E’ stata scelta questa area di studio perché caratterizzata dalla presenza di zone industriali, residenziali e terreni destinati all’attività agricola.

Il MIVIS è uno scanner modulare costituito da 4 spettrometri che riprendono simultaneamente, con un angolo istantaneo di vista di 2 mrad, le radiazioni provenienti dalla superficie terrestre nel Visibile, nell’Infrarosso Vicino, nell’Infrarosso Medio e nell’Infrarosso Termico per un totale di 102 bande (Tab. 1).

<table>
<thead>
<tr>
<th>Spettrometro</th>
<th>Regione dello spettro</th>
<th>Intervallo spettrale (µm)</th>
<th>Ampiezza bande (µm)</th>
<th>Numero bande</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Visibile - NIR</td>
<td>0,43 - 0,83</td>
<td>0,02</td>
<td>20</td>
</tr>
<tr>
<td>II</td>
<td>NIR - IR Medio</td>
<td>1,15 - 1,55</td>
<td>0,05</td>
<td>8</td>
</tr>
<tr>
<td>III</td>
<td>IR Medio</td>
<td>2,0 - 2,5</td>
<td>0,008</td>
<td>64</td>
</tr>
<tr>
<td>IV</td>
<td>IR Termico</td>
<td>8,2 - 12,7</td>
<td>0,4</td>
<td>10</td>
</tr>
</tbody>
</table>

L’immagine MIVIS è stata calibrata utilizzando l’algoritmo Internal Avarage Relative Reflectance (IARR) allo scopo di normalizzare i valori di radianza misurati nei diversi canali del MIVIS [Busetto et al., 2003].

Il rumore, presente nei dati telerilevati, riduce la possibilità di discriminare i differenti materiali presenti in una scena, in quanto causa una ridondanza dell’informazione acquisita dal sensore. Per ottenere classificazioni accurate di immagini iperspettrali, è quindi necessario rimuovere o quanto meno ridurre il rumore di cui sono affetti i dati [Xu et al., 2003]. A tale scopo, ben si presta la tecnica di processamento nota come MNF. La MNF consente di migliorare la qualità delle immagini [Green et al., 1988; Lee et al., 1990] massimizzando il rapporto S/N dei dati acquisiti, riducendone in questo modo il rumore. I vantaggi di tale metodo sono essenzialmente quelli di aumentare la separabilità spettrale delle differenti tipologie di materiali presenti nella scena analizzata e ridurre la dimensionalità dei dati, condensando l’informazione in un minore numero di bande (sintetiche) rispetto al numero originale.

Una maggiore separabilità spettrale aumenta la possibilità di identificare le classi di copertura presenti in una scena. Inoltre, la possibilità di lavorare con un numero ridotto di bande consente di ottimizzare i tempi di processamento dei dati.

La trasformazione MNF utilizzata in questo lavoro è quella implementata nel software ENVI [Green et al., 1988] e consiste nell’applicazione di due analisi della Principal Component Analysis (PCA). La prima PCA, sulla base della stima di una matrice di covarianza del rumore, decorrela e riscalda il rumore nei dati. Restituisce un dataset trasformato in cui il rumore ha varianza unitaria e non vi è correlazione tra le bande. Successivamente, l’applicazione di un’analisi standard della PCA genera delle nuove bande decorrelate [Bachari et al., 2004] e l’informazione è concentrata in un numero di
bande pari al 10% di quelle originali, mentre il dataset rimanente rappresenta per lo più rumore.

Al termine del processamento la trasformazione restituisce un nuovo set di bande (bande MNF) e l’MNF plot. Il plot rappresenta le bande MNF ed i corrispondenti autovalori: bande con elevati autovalori (maggiori di 1) contengono informazione, quelle invece con autovalori prossimi a 1 rappresentano per lo più rumore. Il dataset finale, da utilizzare nelle successive elaborazioni, è costituito dalle bande MNF a cui corrispondono immagini spazialmente coerenti ed autovalori elevati [Green et al., 1988].

La MNF è stata applicata sia sul dataset completo (102 bande dell’immagine MIVIS) che sulle bande relative ai 4 spettrometri separatamente considerando circa il 10% dei risultati della trasformazione. La scelta di utilizzare i 4 spettrometri separatamente si basa sull’ipotesi di poter discriminare più efficacemente l’informazione dal rumore.

Selezione dei training sites per la classificazione

L’individuazione dei training sites per la classificazione delle diverse coperture considerate nella scena MIVIS (cemento-amianto, laterizi, calcestruzzo, lamiere) è stata effettuata applicando la tecnica MTMF, implementata nel software ENVI. La MTMF è un metodo di mappatura spettrale basato sul Matched Filtering (MF), una tecnica di partial unmixing, che necessita come dati di ingresso bande restituite dalla trasformazione MNF.

La MF consente di stimare il grado relativo di sovrapposizione degli spettri dei pixel di un’immagine con quello considerato come riferimento, relativo al materiale che si vuole classificare. Enfatizza la risposta dello spettro di riferimento sull’intera immagine, attenuando quelle derivanti da firme relative a materiali differenti rispetto a quello da classificare [Boardman, 1998; Kruse et al., 2004]. Tuttavia tale tecnica (MF) può restituire dei falsi positivi, ovvero pixel erroneamente attribuiti alla tipologia di materiale cercato. Al fine di ridurre il numero di pixel classificati come falsi positivi, la MTMF aggiunge al risultato della MF una immagine di infeasibility [Boardman, 1998; Kruse et al., 2004]. L’infeasibility misura l’attendibilità del risultato ottenuto con la MF.

La MTMF, a partire dallo spettro di riferimento, restituisce quindi due immagini in livelli di grigio, una relativa alla MF e l’altra corrispondente alla infeasibility. I pixel a cui corrispondono elevati valori di MF e bassi valori di infeasibility sono quelli che, con maggiore probabilità, hanno una risposta spettrale simile a quella dello spettro di riferimento. Tale tecnica risulta essere particolarmente utile quando si dispone di un ridotto numero di firme spettrali e non si ha conoscenza diretta dell’ambito territoriale analizzato.

Sulle bande restituite dalla trasformazione MNF applicata all’immagine MIVIS è stata acquisita la firma spettrale di un singolo pixel utilizzato per la tecnica MTMF. Tale pixel appartiene alla copertura in cemento-amianto localizzata in situ e poi identificata sulla scena MIVIS.

Nel risultato della MTMF i pixel mappati correttamente, rispetto alla firma spettrale considerata, hanno un elevato valore di MF ed una bassa infeasibility. Tali pixel, evidenziati nell’area cerchiata dello scatter plot (Fig. 1a), rappresentano diverse coperture (Fig. 1b) e mediante rilievo in situ sono state selezionate solo quelle appartenenti alla classe cemento-amianto.
La stessa metodologia è stata applicata per selezionare le coperture relative a classi di materiale differente (cemento-amianto, laterizi, calcestruzzo, lamiere).
Da tutte le coperture individuate (cemento-amianto ed altre classi di materiale) sono stati scelti i pixel utilizzati come training sites per le successive classificazioni.

Classificazione dell’immagine
La classificazione delle immagini costituisce uno strumento fondamentale per il riconoscimento spettrale e/o geometrico degli oggetti presenti sulla scena esaminata [Harsanyi et al., 1994]. Le tecniche di classificazione discriminano i pixel dell’immagine in base al grado di somiglianza tra il loro comportamento spettrale e quello degli spettri di riferimento, ricavati dal training set oppure ottenibili da una libreria spettrale: ogni singolo pixel dell’immagine viene automaticamente assegnato alla classe verso la quale mostra la maggiore somiglianza spettrale.
In particolare, l’algoritmo della distanza angolare degli spettri (SAM) risulta particolarmente indicato nelle elaborazioni di immagini iperspettrali [Kruse et al., 1993].
L’algoritmo SAM si basa sul confronto angolare tra i vettori rappresentanti le proiezioni spettrali, nello spazio delle caratteristiche, delle classi di riferimento ed i singoli pixel da classificare. La similarità tra lo spettro di riferimento, ottenuto dalla media degli spettri forniti dai training sites per una certa classe $w_i$, e quello relativo ad ogni pixel è espressa come distanza angolare tra due vettori nello spazio n-dimensionale. L’algoritmo SAM attribuisce il pixel alla classe rispetto alla quale presenta la distanza angolare minore. Matematicamente l’algoritmo si basa sulla considerazione che il prodotto scalare tra due vettori $(u, v)$ è definito dalla equazione [1].

$$u \cdot v = \sum_{i=1}^{n} (u_i \cdot v_i) = uv \cdot \cos \alpha \quad [1]$$

dove $u_i$ e $v_i$ sono le componenti dei due vettori nell’iperspazio delle n bande, mentre $u$ e $v$ sono i moduli dei vettori. In base alla suddetta viene ricavato l’angolo $\alpha$ [2] che risulta essere una distanza angolare misurata in radianti il cui valore è compreso tra 0 e $\pi/2$:

$$\alpha = \arccos \frac{u \cdot v}{uv} = \arccos \left[ \frac{\sum_{i=1}^{n} (u_i \cdot v_i)}{\sqrt{\sum_{i=1}^{n} u_i^2} \cdot \sqrt{\sum_{i=1}^{n} v_i^2}} \right] \quad [2]$$

Nella classificazione SAM l’angolo di separazione tra i “vettori spettrali” non è influenzato dalle diverse condizioni di illuminazione dei pixel. In questo lavoro la SAM è stata applicata per individuare sulla scena tutti i pixel con caratteristiche spettrali simili a quelli riconosciuti come cemento-amianto. L’immagine MIVIS è stata classificata per mezzo di tale algoritmo e questa procedura è stata applicata sui seguenti dataset utilizzando un numero di training sites pari a 600 pixel per ogni classe di materiale:

1) 102 bande MIVIS (MIVIS);
2) Bande MIVIS, escludendo quelle visivamente più rumorose (N) e quelle dell’Infrarosso Termico (TIR) denominate N-TIR;
3) Bande risultanti dalla trasformazione MNF applicata al dato MIVIS (MNF);
4) Bande risultanti dalla trasformazione MNF applicata al dato MIVIS, escludendo le bande rumorose e quelle del termico (MNF/N-TIR);
5) Bande risultanti dalla trasformazione MNF applicata, separatamente, al dataset di ciascuno dei 4 spettrometri. Le bande MNF, selezionate per ogni spettrometro, sono state accorpate e considerate per la classificazione (MNF 4 SP).

Questi diversi dataset sono stati scelti al fine di confrontare e verificare quale tra di essi produce i risultati migliori in termini di classificazione.

Per ogni singolo dataset sono state eseguite due diverse prove:
- prova A - come training sites per la classificazione sono stati utilizzati pixel appartenenti alla classe cemento-amianto e ad altre diverse tipologie di coperture “altri materiali”: laterizi, calcestruzzo, lamierie presenti nella scena;
prova B - sono stati usati i training sites appartenenti alla sola tipologia di copertura cemento-amianto.

**Verifica dell’Accuratezza**

La verifica dell’accuratezza delle classificazioni è stata eseguita considerando per ogni tipologia di copertura un numero di pixel pari a 600, diversi dai training sites, distribuiti casualmente nell’area di studio ed assegnati alle differenti classi di copertura mediante fotointerpretazione di fotografìi aerei con risoluzione spaziale di 0,25 m/pixel.

Nella prova A l’accuratezza è stata calcolata valutando gli errori di Commissione (CO) ed Omissione (OM) in termini di percentuale e di pixel. Per la sola classe cemento-amianto vengono riportate la Producer’s Accuracy (PA) e la User’s Accuracy (UA) espresse in percentuale e in pixel in base ai test sites.

Nella prova B avendo una sola classe (cemento-amianto) è stata considerata la Producer’s Accuracy, che coincide con la Overall Accuracy. Pertanto il termine di confronto tra le due prove per la classe cemento-amianto risulta essere la Producer’s Accuracy.

Inoltre è stato effettuato un confronto tra il numero di coperture in cemento-amianto censite nell’area di studio con verifiche a terra rispetto al numero di coperture classificate.

**Risultati**

Confrontando le diverse classificazioni (Tab. 2, Tab. 3 e Tab. 4) si evince che in entrambe le prove (A e B) i valori più elevati in termini di accuratezza si ottengono dai dataset ai quali è stata applicata la tecnica MNF. Le classificazioni dei dataset MIVIS e N-TIR presentano valori meno accurati ed un’ulteriore perdita di accuratezza si registra quando nelle elaborazioni non si considerano le bande più rumorose (N) e quelle del TIR (Fig. 2).

Nella prova A gli errori di Commissione e di Omissione per le classi “cemento-amianto” ed “altri materiali” diminuiscono quando si prendono in considerazione le bande rumorose e quelle dell’Infrarosso Termico e migliorano sensibilmente quando si considera il dataset MNF 4 SP (Tab. 2).

In dettaglio, analizzando la classe cemento-amianto, i valori di Producer’s Accuracy e di User’s Accuracy confermano che applicando la tecnica MNF ai 4 spettrometri separatamente (MNF 4 SP) si ottengono risultati più accurati (Tab. 3).

La prova B, nella quale è stata considerata la sola classe cemento-amianto, non solo conferma l’efficacia della tecnica MNF applicata ai 4 spettrometri separatamente ma restituisce anche valori di Producer’s Accuracy più elevati (Tab. 4). Infatti, in questo caso, l’accuratezza è pari al 97% (Fig. 3): su 600 pixel scelti come test sites, 582 sono stati classificati correttamente, mentre 18 pixel (3%) rientrano nel non classificato.

La verifica in situ delle coperture censite, confrontata con quelle individuate dalla classificazione MNF 4 SP, ha prodotto i seguenti risultati: di 110 coperture censite, 107 sono state identificate correttamente e 3 non sono state individuate per motivi legati alle differenti condizioni di illuminazione, alla presenza di vegetazione ed alle ridotte dimensioni delle coperture.

Tali risultati confermano l’ipotesi che la tecnica MNF applicata ai 4 spettrometri separatamente consente di discriminare più efficacemente l’informazione dal rumore per ciascuno dei 4 gruppi spettrali (Tab. 1), rispetto alla trasformazione MNF applicata
alle 102 bande, così da enfatizzare l’informazione contenuta in ogni gruppo spettrale. In particolare si è visto che escludendo il gruppo dei canali del TIR si ottenevano risultati con accuratezza peggiore, confermando che l’informazione derivante dalle bande del Termico ha un peso rilevante per la classificazione delle coperture in cemento-amianto.

Tabella 2 – Risultati della classificazione (prova A): errori di Commissione (CO%) e di Omissione (OM%) per le classi cemento-amianto ed altre coperture.

<table>
<thead>
<tr>
<th>Prova A</th>
<th>ALTRI MATERIALI</th>
<th>CEMENTO-AMIANTO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO%</td>
<td>OM%</td>
</tr>
<tr>
<td>MIVIS</td>
<td>3,23</td>
<td>33,82</td>
</tr>
<tr>
<td>N-TIR</td>
<td>64,76</td>
<td>68,91</td>
</tr>
<tr>
<td>MNF</td>
<td>4,20</td>
<td>22,43</td>
</tr>
<tr>
<td>MNF/N-TIR</td>
<td>37,50</td>
<td>83,19</td>
</tr>
<tr>
<td>MNF 4 SP</td>
<td>0,00</td>
<td>4,42</td>
</tr>
</tbody>
</table>

Tabella 3 – Risultati della classificazione (prova A): Producer’s Accuracy (PA) ed User’s Accuracy (UA) per la classe cemento-amianto.

| Prova A: classe cemento-amianto | |
|-------------------|----------------|-
| Data-set | PA % | UA % | PA | UA |
| MIVIS   | 48,5% | 97,98 | 291/600 | 291/297 |
| N-TIR   | 23% | 60,53 | 138/600 | 138/228 |
| MNF     | 81% | 97,01 | 486/600 | 486/501 |
| MNF/N-TIR | 42,5% | 83,33 | 255/600 | 255/306 |
| MNF 4 SP | 91,5% | 96,83 | 549/600 | 549/567 |

Tabella 4 – Risultati della classificazione (prova B): Producer’s Accuracy (PA) per la classe cemento-amianto.

| Prova B: classe cemento-amianto | |
|-----------------|----------------|-
| Data-set | PA% | pixel class/pixel test |
| MIVIS   | 63.50% | 381/600 |
| N-TIR   | 45% | 270/600 |
| MNF     | 95% | 570/600 |
| MNF/N-TIR | 83,50% | 501/600 |
| MNF 4 SP | 97% | 582/600 |
Figura 2 – Confronto dell’accuratezza della classe cemento-amianto nelle due diverse prove (A e B).

Figura 3 – Classificazione MNF 4 SP sulla scena MIVIS.
Conclusioni
Il progresso delle tecniche di remote sensing ha permesso di sviluppare strumenti sempre più precisi per il monitoraggio del territorio e l’utilizzo di immagini acquisite da sensori remoti ha consentito di ridurre i tempi ed i costi del censimento delle coperture in cemento-amianto.
In tale contesto l’applicazione di tecniche di trasformazione come la Minimum Noise Fraction ad immagini iperspettrali ad elevata risoluzione spaziale permette di migliorare la qualità dell’immagine in termini di riduzione del rumore e di discriminare, in maniera puntuale, le superfici in eternit rispetto alle altre tipologie di materiali presenti sul territorio.
In questo lavoro è stata proposta una metodologia speditiva ed affidabile per l’individuazione e la mappatura di coperture in cemento-amianto sfruttando le potenzialità della trasformazione MNF applicata al dataset MIVIS (102 bande) e ai 4 spettrometri del sensore MIVIS separatamente.
I risultati ottenuti indicano che la MNF applicata separatamente ai canali dei 4 spettrometri consente di enfatizzare ulteriormente la separabilità spettrale dei materiali che ricorrono nella scena MIVIS e quindi avere una classificazione più accurata per la classe cemento-amianto.
Inoltre il lavoro ha evidenziato che la classificazione ad una classe (prova B) consente di ottenere una maggiore accuratezza rispetto a quella relativa a più classi (prova A).
Alla luce dei risultati ottenuti tale metodologia sarà applicata allo studio di altre tipologie di materiali, cercando di sfruttare le specifiche caratteristiche spettrali di ciascuno.

Bibliografia


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in the urban areas. Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and data Fusion over Urban areas, Rome, Italy, November 8-9th.


Ricevuto 10/06/2010, accettato 17/12/2012
Introduction to the special issue

Dear Readers,
this is the special issues part II dedicated to contributions to the 14th National Conference of Federation of Scientific Associations for Territorial and Environmental Information (ASITA) held in Brescia on November 9-12 2010. Part I was published in June 2011 within the Volume 43 (2).
These selected papers deal with remote sensing applied to different disciplines, from environmental resources to disaster management. In addition, techniques for data pre-processing are addressed as well.
Capaldo et al.(a) present a new proprietary matching strategy for DSMs generation while Capaldo et al.(b) have investigated the stereo imagery orientation for COSMO-SkyMed and TerraSAR-X High Resolution SAR using a radargrammetric orientation model and a Rational Polynomial Coefficients tool.
A comparison between couples of CO emission datasets computed from satellite observations obtained from sensors of different types is shown by Migliaccio et al.
Deidda and Sanna present a module developed in interactive data language and embedded in the ENVI menu system aimed at the pre-processing of high resolution satellite images for sea bottom classification. Tarantino examines the potentiality of medium spatial resolution thermal infrared data in monitoring spatial and temporal distribution of sea surface temperature.
Pirotti et al. present a review on laser scanner applications for forest and environmental sciences. Medium resolution LiDAR data are used by Clementel et al. to carry out statistical models for estimating forest timber volume. De Agostino et al. present the results of an experimental study aimed at the rock face surveys using terrestrial LiDAR techniques.
Baiocchi et al. have used panchromatic images to study the detection capabilities for post seismic application. Ajmar et al. have used MODIS archive images to derive flood extents in developing countries. Perez et al. present the studies performed and their contribution to the improvement of the ITHACA drought Early Warning System, which is mostly based on satellite data.
We thanks all the reviewers for their contribution, they ensured the quality of this special issue in publishing high content quality. Special thanks to our colleagues from the Editorial office, Francesca Bottalico, Chiara Lisa and Silvia Fiorentini for their continuous and efficient work.

With our best regards,

Gherardo Chirici and Davide Travaglini
Editors
DSM generation from high resolution imagery: applications with WorldView-1 and Geoeye-1

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Abstract
In this paper we present and discuss some results obtained with a new proprietary matching strategy for DSMs generation, which is implemented in the SISAR software developed at the Area di Geodesia e Geomatica – Università di Roma “La Sapienza”. In order to assess the accuracy of the new strategy, some tests were carried out, using a stereo pair of Augusta coastal zone (Sicily, South Italy) acquired from WorldView-1 and one of the first available GeoEye-1 stereo pairs, which was acquired over Rome. The results show that an accuracy at the level of about 2 m is achievable in open areas with both WorldView-1 and GeoEye-1 stereo pairs, whereas higher errors are displayed in urban areas. For WorldView-1 the results are still acceptable, being the accuracy at the level of 3 meters, but for GeoEye-1 the DSM extracted over a very dense urban area are much worse, with an accuracy at the level of 8-10 meters. Nonetheless, the new matching strategy has been proven effective, performing always better if compared with the one implemented in a well known and largely used software as PCI-Geomatics.

Keywords: Digital Surface Models, Matching, WorldView-1, GeoEye-1, Rational Polynomial Coefficients.

Introduction
Digital Surface Models (DSMs) have large relevance in many engineering, land planning and environmental applications for a long time. At present, the data required for the DSMs generation can be acquired by several sensors/techniques, among which airborne LiDAR, aerial photogrammetry, optical and radar spaceborne sensors play the major role. In this respect, the availability of new high resolution optical spaceborne sensors offers new interesting potential for DSMs generation, among which low cost (in comparison with aerial imagery, if small areas, for example included into one scene, are concerned), speed of data acquisition and processing and relaxed logistic requirements, quite important for the areas where the organization of aerial flights can be difficult for a variety of reasons. Thanks to the very high resolution and the good radiometric quality of the most recent satellite imagery, it seems possible to extract DSMs comparable to middle scale aerial products; anyway, it has to be underlined that the DSM accuracy level is strictly related both to the quality of the stereo image orientation and to the effectiveness of the matching strategy.
Two different types of orientation models are usually adopted: the physical sensor models (also called rigorous models or geometric reconstruction) and the generalized sensor models. The first one is based on a standard photogrammetric approach, where the image and the ground coordinates are linked through the collinearity equations, so that the involved parameters have a physical meaning [Westin, 1990; Toutin, 2004; Poli, 2005; Crespi et al., 2009; Crespi et al., 2011]. On the contrary, the generalized models are usually based on the Rational Polynomial Functions (RPFs), which link image and terrain coordinates through the Rational Polynomial Coefficients (RPCs) and an eventual additional transformation based on GCPs [Tao and Hu, 2001, 2002; Fraser and Hanley, 2003; Hanley and Fraser, 2004; Crespi et al., 2009].

For matching, it is well known that several approaches have been developed in recent years. In all of them, the main step is to define the matching entity, that is a primitive chosen in the master image to be looked for in the slave image(s); basically, we can distinguish two techniques, the Area Based Matching (ABM) and the Feature Based Matching (FBM). In ABM methods, a small image window represents the matching primitive and the main strategies to assess similarity are cross-correlation and Least Squares Matching (LSM). FBM methods use, as main class of matching, basic features that are typically the easily distinguishable primitives in the input images, like corners, edges, lines, etc. [Gruen 1985; Tang et al., 2002; Jacobsen, 2006; Nascetti, 2009]. In addition, new pixel based matching strategies with cost function using dynamic programming techniques were proposed during last decades [Birchfield and Tomasi, 1998, 1999]; recently, the quite promising technique of semi-global matching was proposed and applied to aerial imagery [Hirschmüller, 2008; Hirschmüller and Scharstein, 2009].

In the last year, a new tool for the image matching based on geometric constraints in the object space and ABM has been included in the SISAR software, which is a scientific package devoted to the high resolution image orientation, developed at the Area di Geodesia e Geomatica – Università di Roma “La Sapienza” [Nascetti, 2009]. In order to evaluate the potentiality of the new matching strategy and the accuracy of the extracted DSMs, some tests were carried out. In details, two stereo pairs acquired by WorldView-1 and GeoEye-1 satellites have been used to compare the DSMs generated with the new strategy to those derived using the well known commercial software OrthoEngine v.10.2 (PCI Geomatics).

The implemented matching strategy is object of a pending application for patent supported by the Università di Roma “La Sapienza”, so that it cannot be disclosed and presented in details; this is the main reason why here we just focus on test results.

**WorldView-1 and GeoEye-1 Stereo pair Orientation**

The panchromatic in-track stereo pair collected by WorldView-1 (product type Basic Stereo Pairs - Level 1) has been acquired in June 2008 and covers an area of about 200 km² over the Augusta municipality (Sicily, South Italy); one of the two images has been collected in “forward” mode (North to South) with off-nadir angle of 18 deg, the other one in “reverse” mode (South to North) with off-nadir angle of 20 deg (Fig. 1); both images have a mean spatial resolution (Ground Sample Distance – GSD) of 0.55 m and the B/H ratio is equal to 0.70.
The panchromatic in-track stereo pair collected by GeoEye-1 (product type GeoStereo - Level 2) has been acquired over Rome in December 2009 at 8:00 a.m. with sun height of 24 deg, and both images have been collected in “reverse” mode; they have a mean GSD of 0.50 m (Fig. 2) and the B/H ratio is equal to 0.57.

The two stereo pairs have been orientated with OrthoEngine and with SISAR using both rigorous and RPCs models.

As regards the tests with the rigorous models, the WorldView-1 stereo pair has been orientated using 9 Ground Control Points (GCPs) out of 16 available Ground Points (GPs); 10 GCPs out of 29 available GPs have been used for the GeoEye-1 stereo pair. All the GPs, both for Augusta and Rome stereo pair, were surveyed by geodetic class GPS receivers in RTK mode; their mean horizontal and vertical accuracies are between 10 and 20 cm respectively.

The orientation with RPCs model, using RPCs supplied together metadata file, has been carried out without GCPs and with 1 and 3 GCPs, necessary to compute the shift and affine transformations respectively [Tao and Hu, 2001, 2002; Fraser and Hanley, 2003; Hanley and Fraser, 2004]. It is important to highlight that for the WorldView-1 stereo pair the GPs which may be used as GCPs are uniformly distributed on the whole images (Fig. 1), whereas for the GeoEye-1 stereo pair they are located in the North-West image corner (Fig. 2), so that only this area has been analyzed.

The orientation accuracies obtained with SISAR and OrthoEngine software were evaluated on a set of the Check Points (CPs) in East and North direction and in the ellipsoidal height (Tab. 1). As regards the SISAR rigorous model applied to the WorldView-1 stereo pair, it is around 0.3 – 0.6 m in the horizontal components and 1 m in the height, whereas OrthoEngine supplies horizontal accuracies close to 1.5 m and much worse in the height (around 3.5 m), may be due to a not correct modeling of different acquisition mode of the two images (forward and reverse). The orientation accuracy level for GeoEye-1 images is again slightly better for SISAR than for OrthoEngine (1 m for SISAR vs 1.5 m for OrthoEngine in all components).
Concerning the orientation with the RPCs model, it has to be underlined that OrthoEngine v. 10.2 does not supply a tool for the visualization of CPs accuracy; consequently both the stereo pairs have been orientated with SISAR only (Tab. 1). The orientation accuracy without GCPs is worse than the ones with 1 and 3 GCPs, respectively obtained applying a shift and an affine transformation in order to remove the systematic errors of the metadata RPCs. The best one is obtained with 1 GCP and is around 1 GSD for the horizontal components (0.55 m for WorldView-1 and 0.5 m for GeoEye-1) and around 3 GSD in the height; it supplies results quite similar to those achieved by the SISAR rigorous model using much more GCPs.

Table 1 - Orientation results of WorldView-1 and GeoEye-1 stereo pairs using rigorous and RPCs models.

<table>
<thead>
<tr>
<th>Sensor</th>
<th># GCPs</th>
<th>RMSE CP [m]</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SISAR</td>
<td>OrthoEngine</td>
<td>SISAR</td>
<td>OrthoEngine</td>
<td>SISAR</td>
</tr>
<tr>
<td></td>
<td></td>
<td>East</td>
<td>North</td>
<td>H</td>
<td>East</td>
<td>North</td>
</tr>
<tr>
<td>WorldView-1</td>
<td>9</td>
<td>0.61</td>
<td>0.32</td>
<td>1.08</td>
<td>1.55</td>
<td>1.65</td>
</tr>
<tr>
<td>GeoEye-1</td>
<td>10</td>
<td>0.50</td>
<td>0.87</td>
<td>1.14</td>
<td>1.24</td>
<td>0.71</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sensor</th>
<th># GCPs</th>
<th>RMSE CP [m]</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SISAR</td>
<td>OrthoEngine</td>
<td>SISAR</td>
<td>OrthoEngine</td>
<td>SISAR</td>
</tr>
<tr>
<td></td>
<td></td>
<td>East</td>
<td>North</td>
<td>H</td>
<td>East</td>
<td>North</td>
</tr>
<tr>
<td>WorldView-1</td>
<td>0</td>
<td>3.47</td>
<td>1.53</td>
<td>6.21</td>
<td>Not available</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.53</td>
<td>0.33</td>
<td>1.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.51</td>
<td>0.49</td>
<td>1.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GeoEye-1</td>
<td>0</td>
<td>3.81</td>
<td>3.59</td>
<td>4.58</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.54</td>
<td>0.62</td>
<td>1.45</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.04</td>
<td>0.56</td>
<td>1.51</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Therefore, even the orientation with just 1 GCP appears able to exploit the largest part of the geometric potentialities of WorldView-1 and GeoEye-1 as regards the 3D geometric reconstruction, what is of relevance for practical applications when the GCPs number has to be kept as lower as possible for obvious budget constraints.

**Image matching and DSM generation**

It is well known that the critical issue for image matching is the definition of a strategy to search the corresponding points within the considered images. Moreover, the two already mentioned classical techniques (ABM and FBM) do not appear suited to manage complex morphologies (for example urban areas) as imaged in satellite scenes. Therefore, we proposed an advanced matching method, based on a coarse-to-fine hierarchical solution with an effective combination of geometrical constrains and an ABM algorithm; some ideas in this direction were already presented in [Zhang and Gruen, 2006], but our approach is different and original.

Our matching algorithm is based on affine transformations which drive the ABM, performed by cross-correlation and LSM. Several affine transformations are used at different heights, estimated starting from some Ground Points at corresponding heights whose image coordinates are computed from suitably generated RPCs with a proprietary procedure [Crespi et al., 2009]. In such a way the image matching has been combined with image orientation in order to increase its effectiveness and reliability and the final accuracy of the derived DSMs.

As regards the commercial software OrthoEngine used for results comparison, the image matching technique used is not declared; nonetheless, on the basis of a visual inspection of the results, it is possible to argue that a disparity determination via dynamic programming is applied [Birchfield and Tomasi, 1998, 1999], since typical signatures of such a strategy (“stripes”) are visible.

The matching algorithm implemented in SISAR were tested both over the WorldView-1 and the GeoEye-1 stereo pairs. For the accuracy analysis of the extracted DSMs some tiles were selected, in order to investigate the effect of different land covers on the accuracy (Fig. 2; Fig. 3).

![Figure 3 - Augusta area - Selected tiles in (a) open and (b) urban area.](image-url)
The extracted DSMs have been compared with the reference DSMs through program DEMANAL, developed by Prof. K. Jacobsen – Leibniz University Hannover, allowing for a full 3D comparison to remove possible horizontal biases too. The height differences are computed by a bilinear interpolation of the reference DSM at the position of the DSM under analysis. For the DEMANAL convention, the bias is negative when the generated DSM is above the reference DSM. For each selected area of the extracted DSM, the bias, the precision (that is the standard deviation $\sigma$) and the accuracy (that is the Root Mean Square Error RMSE) at 95% probability level (LE95) have been computed.

**Wordview-1 Augusta area results**

Two tiles of the DSM generated from the Augusta stereo pair (Fig. 3), one regarding an open area and the other mainly including an urban area were selected in the South-East part of the image, where the LiDAR ground truth is available. For these tiles, the DSMs were extracted at a spatial resolution of 2x2 m, orientating the stereo pair with the rigorous models and using 9 GCPs. They were compared with the reference DSM, with a spatial resolution of 1.5x1.5 m and an accuracy of 10 cm (Tab. 2).

| Table 2 - WordView -1- Results of DSM accuracy assessment in open and urban areas. |
|---|---|---|---|
| **open area [m]** | DSM | bias | $\sigma$ | RMSE H |
| OrthoEngine | -0.04 | 1.79 | 1.79 |
| SISAR | -0.76 | 1.50 | 1.68 |
| **urban area [m]** | DSM | bias | $\sigma$ | RMSE H |
| OrthoEngine | -1.02 | 4.57 | 4.68 |
| SISAR | 0.11 | 3.06 | 3.09 |

The accuracy level achieved by both programs OrthoEngine and SISAR is around 1.7 m in open area, although the SISAR DSM displays an higher bias (approximately 70 cm); on the contrary, SISAR reaches an accuracy of 3 m in the urban area, where building shapes and heights are enough correctly reconstructed, whereas the accuracy of OrthoEngine DSM is remarkable lower, around 4.7 m. Also a visual inspection of the derived DSM evidenced a significant blurring effect, which prevents the separation of closely located buildings. Some city blocks are clearly matched as undistinguished stains; moreover the white holes display remarkable wrong elevations due to the matching errors (the errors are at level of hundreds meters) (Fig. 4).

Examples of height profiles are shown in Figure 5 and in Figure 6 in order to highlight the performances of the SISAR matching algorithm over built-up areas. In the profile 1 the shape of the DSM recovered from SISAR (Fig. 5c) is comparable with the LiDAR ground truth (Fig. 5a), whereas positive errors are shown for OrthoEngine (Figure 5b). The profile 2 displays a critical zone for both software, but it is possible to highlight the better behavior of SISAR software once more.
GeoEye-1 Rome area results

The accuracy evaluation of GeoEye-1 DSMs was carried out by comparison over Rome area with a ground truth derived by a 3D vector map at 1:2000 scale (mean horizontal accuracy 30 cm, mean accuracy in the height 40 cm).

For each software three DSM tiles with resolution of 2x2 m (two over urban areas and one over an open area in Figure 2.b) have been extracted, orientating the stereo pair with RPCs without GCP and with 1 and 3 GCPs respectively; comparisons between the generated DSMs and the reference one in the three different zones have been performed.

The reference DSM used in the urban area has a cell size equal to 1x1 m, obtained by interpolation of the known points complemented with the shape file of the buildings; on the contrary, the reference DSM in the open area has a cell size of 10x10 m, just obtained by interpolation of points with known heights.

In the open area the level of accuracy is around to 3.5 m if no GCPs are used both with OrthoEngine and SISAR, due to a remarkable vertical bias (around 3 m). On the
contrary, an accuracy around 2 m is achieved even when 1 GCP only is used to enhance the geolocation, whereas the use of 3 GCPs with bias correction by a 2D affine transformation do not lead to a significant improvement. For both programs the standard deviation remains approximately constant, independently from the geolocation. In the urban area Tile A the best DSM results are obtained with SISAR in all cases, but the overall accuracy is much worse: the RMSE H ranges between 14 m with OrthoEngine and 10 m with SISAR. Also in this case the bias reduces just with 1 GCP, whereas the precision remains approximately constant, again with better results for SISAR. The same situation happens in the urban area Tile B, where the differences among the two programs are more marked in terms of bias (differences in range from 6-7 m to 4-5 m) and less marked in terms of standard deviation (differences in range from 1.5 m to 2 m) (Tab. 3).

In order to better investigate the reasons of such a coarse results and the different behaviors of the two programs over urban areas, a shape file of buildings has been overlaid to the generated DSMs. In the SISAR DSM the streets among the buildings are better reconstructed (Fig. 7b); on the contrary, streets and buildings are rather indistinguishable in the OrthoEngine DSM (Fig. 7a).

Figure 6 - Augusta area - Buildings profile 1, LiDAR (a), OrthoEngine (b) and SISAR (c).
Figure 6 - Augusta area - Buildings profile 2, LiDAR (a), OrthoEngine (b) and SISAR (c).

Figure 7 - Rome area - (a) OrthoEngine and (b) SISAR DSM.
Table 3 - GeoEye-1 - Results of DSM accuracy assessment in open and urban areas.

<table>
<thead>
<tr>
<th>DSM</th>
<th>Open area [m]</th>
<th>Urban area Tile A [m]</th>
<th>Urban area Tile B [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 GCP</td>
<td>1 GCP</td>
<td>3 GCPs</td>
</tr>
<tr>
<td></td>
<td>bias</td>
<td>σ</td>
<td>RMSE H</td>
</tr>
<tr>
<td>OrthoEngine</td>
<td>-2.92</td>
<td>1.85</td>
<td>3.45</td>
</tr>
<tr>
<td>SISAR</td>
<td>-2.91</td>
<td>1.85</td>
<td>3.45</td>
</tr>
<tr>
<td>SISAR</td>
<td>-6.67</td>
<td>7.85</td>
<td>10.30</td>
</tr>
</tbody>
</table>

Also, from the error map it can be seen that the errors of the SISAR DSM (black areas in Fig. 8a) are mainly due to the presence of trees, not mapped in the 3D vector map at 1:2000 scale.

Figure 8 - Rome area - (a) Error distribution map and (b) urban tile A screenshot.
In this respect, if the generated DSMs are checked over buildings only (inside the building footprints given by the reference map (Fig. 7), much better (even if not satisfactory enough) results are achieved, with an accuracy around 5 m and a bias of 1.5 m. In fact there are some errors shown by white areas (Fig. 8a) due to lower height of the matched buildings; probably this kind of errors are strictly related to algorithm parameters, not yet optimally set.

Conclusions
In this work the geometric potentiality of WorldView-1 and GeoEye-1 stereo pairs and the accuracy assessment of generated DSMs, extracted using a minimum number of GCPs, have been evaluated. Tests on the Augusta and Rome areas were carried out with the commercial software OrthoEngine and with the scientific software SISAR.
The orientation with the RPFs model based on given RPCs with bias correction just by 1 GCP appears able to exploit the largest part of the geometric potentialities of WorldView-1 and GeoEye-1 for the 3D geometric reconstruction (around 1.5 m), reaching accuracies similar to those achieved by the SISAR rigorous model using much more GCPs. This is relevant for practical applications, when the number of GCPs has to be kept as low as possible.
Further, concerning the DSMs generation, two test areas (one open area and one urban area) have been extracted from the WorldView-1 stereo model (2x2 m spatial resolution) and compared with a LiDAR reference DSM (1.5x1.5 m spatial resolution, mean accuracy 10 cm). The accuracy level achieved by SISAR is around 1.7 m in open areas and 3 m in urban areas, where building shapes and heights are enough correctly reconstructed. In this last case, the accuracy of OrthoEngine DSM is significantly lower (4.7 m), whereas similar quality has been achieved in open areas.
GeoEye-1 DSM (2x2m spatial resolution) have been geenerated in three test areas (one open area and two urban areas) and compared with a reference DSM derived from a 3D vector map at 1:2000 scale (1x1 m spatial resolution in urban area, 10x10 m spatial resolution in open area; mean horizontal accuracy 30 cm, mean height accuracy 40 cm). In the open area the results are similar for the two programs, with an accuracy close to 2 m. In the urban area the accuracy level is much worse and not comparable to Worldview-1 urban results, being around 11 m for OrthoEngine in tile A and slightly worse (13 m) in tile B; the best results have been obtained with SISAR, with accuracies of 8 m in tile A and 10 m in tile B respectively.
The results obtained with GeoEye-1 stereo pair seem not to be representative of the full potential of the sensor (better represented by the results gained over open areas), as influenced by the highly complex morphology of the Rome downtown and the discrepancies of the ground truth.
The main and still open problem is obviously related to the matching strategy, in order to reach a better reconstruction of the texture of buildings and streets, presently not sufficiently delineated.
An optimization of the matching algorithm parameters, an original interpolation methods (necessary to grid irregular data) and a noise filtering are likely to improve the results, as well as the possible integration of the concept of semi-global matching.
In this respect, the discussed results (with particular regards to those obtained over urban
areas) need to be considered preliminary and further investigations with the two software, and possibly other ones too, are necessary in the future.

Acknowledgements
The WorldView-1 and GeoEye-1 stereo pairs was made available by e-Geos S.p.A., Rome (Italy), in the frame of a collaboration agreement; the Authors are indebted to e-Geos S.p.A. for this.
The Authors thank very much Prof. K. Jacobsen for making available the DEMANAL software.

References


**Received 14/02/2011, accepted 17/12/2011**
A radargrammetric orientation model and a RPCs generation tool for COSMO-SkyMed and TerraSAR-X High Resolution SAR

Paola Capaldo, Mattia Crespi, Francesca Fratarcangeli, Andrea Nascetti and Francesca Pieralice

Abstract
The topic investigated in this paper is the stereo imagery orientation with regards to the SAR imagery in zero-Doppler geometry acquired by COSMO-SkyMed and TerraSAR-X in Spotlight mode. A rigorous orientation model, based on geometric reconstruction, had been already implemented in the scientific software SISAR; starting from this model, a tool for the Rational Polynomial Coefficients (RPCs) generation has been developed. The results of the orientation tests, performed using both rigorous and RPCs models, clearly show that the generated RPCs exploit the geometric potentialities of SpotLight stereo pairs as regards 3D surface reconstruction at the same accuracy level (about 3 meters) of the rigorous model.

Keywords: High Resolution SAR, Radargrammetry, orientation, COSMO-SkyMed, TerraSAR-X, RPCs generation.

Introduction
For a long time Digital Surface and Elevation Models (DSMs, DEMs) have large relevance in many engineering and environmental applications. DSMs generation from satellite stereo pair offers some advantages, among which low cost, speed of data acquisition and processing, availability of several commercial software and algorithms for data processing. In particular, DSMs generation from SAR data offers the significant advantage of possible acquisition during the night and in presence of clouds.

Two different methods may be utilized to extract absolute or relative elevations from SAR imagery, interferometry and radargrammetry. Actually, due to the low resolution in amplitude supplied by the spaceborne radar sensors available until now (at the level of tens of meters), usually the first approach has been used, being aware that interferometry may suffer for lack of coherence.

At present, the importance of the radargrammetric approach is rapidly growing due to the new high resolution imagery (up to 1 m GSD) which can be acquired by COSMO-SkyMed, TerraSAR-X and RADARSAT-2 sensors in SpotLight/Ultrefine mode. In this sense, it seems useful to underline that the two approaches should be considered complementary, in order to obtain the best (accurate and complete) products [Crosetto and Pérez Aragues, 1999].

The radargrammetric approach was first used in the 1950s; then, as mentioned, it was less and less used, due to the quite low resolution in amplitude of radar imagery, if compared
to their high resolution in phase; nevertheless, some researchers have investigated the radargrammetric DSMs generation from SAR data acquired by the various available sensors: several results about data acquired by lower resolution satellite, like RADARSAT-1 and ERS1/2, have been published in [Toutin and Gray, 2000; Méric et al., 2009]. Only quite recently some investigations were developed about the potentialities of the new-generation high resolution SAR sensors, as RADARSAT-2 [Toutin and Chénier, 2009], TerraSAR-X [Raggam et al., 2010] and COSMO-SkyMed [Perko et al., 2011].

As regards the radargrammetric orientation model, we considered the model proposed in the classical book of Leberl [Leberl, 1990], customized for zero-Doppler SAR imagery; then, the defined and implemented model performs a 3D orientation based on two range and two zero-Doppler equations.

Based on this rigorous orientation model, a tool for the RPCs generation has been implemented in SISAR software, similarly to the one already developed for optical sensors [Crespi et al., 2009]. The possibility to generate RPCs sounds of particular interest since, at present, the most part of SAR imagery is not supplied with RPCs, although the Rational Polynomial Functions (RPFs) model is available in several commercial software packages.

Some experiments performed on COSMO-SkyMed and TerraSAR-X Spotlight stereo pairs are here illustrated and discussed, and the performances of the RPCs model are compared both with those of our rigorous model and of the well-known Toutin’s model implemented into the commercial software PCI Geomatica v. 10.3.

The radargrammetric orientation model

The radargrammetric approach performs a 3D reconstruction based on the determination of the sensor-object stereo model, in which the position of each point on the object is computed by the intersection of (at least) two radar rays with two different look angles. In this respect, the optimum stereo imagery configuration for the radargrammetric applications is when the target is observed in opposite-side view; however it may cause large geometric and radiometric disparities with complex morphologies, hindering the image matching, which is the second fundamental step for DSMs generation after the imagery orientation. A good compromise is to use a same-side configuration stereo pair with a base-to-height ratio (B/H) ranging from 0.25 to 2 [Méric et al., 2009] in order to increase the efficiency of the image matching.

Before defining the radargrammetric orientation model, we shortly recall the fundamentals of a slant range projected SAR image.

The image coordinate system is 2D and describes the position of a point in an image: the origin is in the upper left corner, the position is pointed out by its line (J) and sample (I); the line number increases downwards and the sample number increases toward the right. The line number J is related to the acquisition time, measured along the flying direction of the satellite, called azimuth direction; the sample number I is related to the slant range of each point, that is the distance between the satellite and the imaged point on the ground. Correspondingly, the pixel shape is rectangular, since we have two different pixel spacing: the line spacing (LS) in azimuth direction, and the column spacing (CS) in slant range direction.

The fundamental radargrammetric equations for zero-Doppler SAR imagery at the basis of the orientation model read:
\[\begin{align*}
\mathbf{r} \cdot (\mathbf{S} - \mathbf{P}) &= 0 \quad [1] \\
\|\mathbf{S} - \mathbf{P}\| &= RS_P
\end{align*}\]

where:

a) \(\mathbf{P}\) is the 3D position of a point P on the object;
b) \(\mathbf{S}\) is the 3D satellite position and is the 3D satellite velocity vector when the point P is imaged in zero-Doppler projection;
c) \(RS_P\) is the slant range related to the point P.

The first equation of [1] represents the condition of zero-Doppler projection: the target is acquired on a heading that is perpendicular to the flying direction of the satellite; the second equation of [1] is the slant range constraint.

The equations [1] can be rewritten in an explicit form within a local cartesian coordinate system, with the origin in the image centre (known from metadata), the x-axis pointing to East, the y-axis pointing to North and the z-axis pointing up along the local normal to the ellipsoid. To this aim, we have to consider that the orbital arc related to the image acquisition in SpotLight mode is quite short (about 10 Km), so that it can be modelled with a circular arc; its parameters are estimated by least squares adjustment using the orbital state vectors available in the metadata with a RMSE fitting at few meters level.

Therefore, the equations [1] take the form:

\[\begin{align*}
V_{XS} \cdot (X_S - X_P) + V_{YS} \cdot (Y_S - Y_P) + V_{ZS} \cdot (Z_S - Z_P) &= 0 \\
\sqrt{(X_S - X_P)^2 + (Y_S - Y_P)^2 + (Z_S - Z_P)^2} - (D_S + CS \cdot I) &= 0 \quad [2]
\end{align*}\]

where:

a) \(X_S, Y_S, Z_S\) are the coordinates of the satellite in the local coordinate system (time dependent);
b) \(X_P, Y_P, Z_P\) are the coordinates of the generic Ground Control Point (GCP) in the local coordinate system (time independent);
c) \(V_{XS}, V_{YS}, V_{ZS}\) are the cartesian components of the satellite velocity in the local coordinate system (time dependent);
d) \(D_s\) is the so-called near range, the acquisition parameter related to the range measure;
e) \(CS\) is the column spacing;
f) \(I\) is the column position of point P on the image.

Moreover the time of acquisition of each GCP can be related to its line number \(J\) through the linear function involving other two acquisition parameters, the start_time (ST) and the pulse repetition frequency (PRF):

\[t = ST + \frac{1}{PRF} \cdot J \quad [3]\]

The nominal values of ST, PRF and \(D_s\) are available in metadata file; they can be refined in the least squares solution of the orientation problem if necessary.
RPCs model and coefficients generation

The Rational Polynomial Functions (RPFs) model is a well-known method to orientate optical satellite imagery. It is well-known that the RPFs model relates the object point coordinates (latitude $\phi$, longitude $\lambda$ and height $h$) to the pixel coordinates $(I, J)$ in the form of ratios of polynomial expressions [4] whose coefficients (RPCs) are often supplied together with imagery:

$$I = \frac{P_1(\phi, \lambda, h)}{P_2(\phi, \lambda, h)} \quad J = \frac{P_3(\phi, \lambda, h)}{P_4(\phi, \lambda, h)} \quad [4]$$

The number of the RPCs obviously depends from the polynomial order (usually limited to the third one), so that each of them takes the generic form:

$$P_n = \sum_{i=0}^{m_1} \sum_{j=0}^{m_2} \sum_{k=0}^{m_3} t_{ijk} \phi^i \lambda^j h^k \quad [5]$$

with $0 \leq m_1 \leq 3; 0 \leq m_2 \leq 3; 0 \leq m_3 \leq 3$ and $m_1+m_2+m_3 \leq 3$ where $t_{ijk}$ are the RPCs.

In case of third order polynomials, the maximum number of coefficients is 80 (20 for each polynomial); actually, it is reduced to 78, since the two equations [4] can be divided for the zero order term of their denominators.

The image and ground coordinates in equation [4] are usually normalized to (-1, +1) range in order to improve the numerical accuracy, using the simple formula:

$$T_n = \frac{T - T_{\text{offset}}}{T_{\text{scale}}} \quad [6]$$

where $T_n$ are the normalized coordinates, $T_{\text{offset}}$, $T_{\text{scale}}$ are the normalization parameters available in the metadata file and $T$ is the generic original ground or image coordinate $(T=I, J; \phi, \lambda, h)$. Moreover, since residual biases may affect RPCs provided with each image, the orientation can be refined on the basis of some GCPs; usually a 2D shift (2 parameters) or a 2D affine (6 parameters) transformations are estimated with the model:

$$I_n = A_x + I_x \cdot A_1 + J_x \cdot A_2 + \frac{P_1(\phi_n, \lambda_n, h_n)}{P_2(\phi_n, \lambda_n, h_n)} \quad [7]$$

$$J_n = B_x + J_x \cdot B_1 + I_x \cdot B_2 + \frac{P_3(\phi_n, \lambda_n, h_n)}{P_4(\phi_n, \lambda_n, h_n)}$$

where $(I_n, J_n)$ and $(\phi_n, \lambda_n, h_n)$ are the normalized image and ground coordinates and $(A, B)$ are the unknowns accounting for possible image shift and drift.

Therefore, quite few GCPs are necessary to obtain a refined RPFs orientation, which has been already demonstrated able to reach the accuracy level of a rigorous model based one in case of optical imagery [Tao and Hu, 2001, 2002; Hanley and Fraser, 2004].

Overall, the use of the RPFs model is common in several commercial software, at least for three important reasons:

a) the implementation of the RPFs model is standard, unique for all the sensors and
much more simple that the one of a rigorous model, which has to be customized for each sensor;
b) the performance of the RPFs model, using a refinement transformation if needed, can be at the level of the ones from rigorous models;
c) the usage of the RPFs model requires zero or, at most, quite few GCPs, if refinement transformations are used, so that the cost for ancillary information is remarkably reduced with respect to rigorous models, which often require at least 10-12 GCPs for optical images to supply a stable orientation.
For these reasons, the use of RPCs could be conveniently extended also to SAR imagery. Therefore, considering that only RADARSAT-2 supplies imagery with RPCs file, the RPCs generation tool already implemented in SISAR for optical imagery has been extended to comply with COSMO-SkyMed and TerraSAR-X imagery.
RPCs can be calculated by the users via a least squares estimation directly from GCPs, or generated on the basis of rigorous orientation sensor models.

Nevertheless, the first methodology (also called terrain-dependent) is not recommended for two relevant reasons. At first, it is likely to cause large deformations in areas far from the GCPs and it is very weak and vulnerable in presence of outliers. Further, it is not convenient, since the number of required GCPs could be very high: for example, at least 39 GCPs are necessary if RPCs up to the third order are looked for.
In the second methodology, RPCs can be generated according to a terrain-independent scenario [Tao and Hu, 2001, 2002; Hanley and Fraser, 2004], using a known physical sensor model; this is the standard for some sensor managing companies, which supply through imagery metadata a re-parametrized form of the rigorous sensor model in term of RPCs, generated from their own secret physical sensor models.
The developed and implemented procedure to generate RPCs within SISAR is presented hereafter. Three are its main steps:

a) at first the image is orientated through the already established rigorous orientation model on the basis of chosen GCPs;
b) further, a 2D image grid covering the full extent of the image is established and its corresponding 3D object grid with several layers slicing the entire terrain elevation range is generated (Fig. 1); the horizontal coordinates \((\phi, \lambda)\) of a point of the 3D object grid are calculated from a point \((I, J)\) of the image grid using the computed rigorous orientation at a fixed selected height \(h\);

c) finally, the RPCs are estimated in a least squares solution, having as input the coordinates of the 2D image grid points and of the 3D object grid points. The coarsest spacing both for 2D and 3D grids definition is dependent on the need to generate enough grid points for the RPCs estimation, considering that each correspondence between a 2D image grid point and a 3D object grid point supplies a couple of linearized RPFs equations:

\[
\begin{align*}
I_a + b_a \lambda_a L_a + b_b \lambda_b L_b - b_c h_c L_c - a_x - a_0 \lambda_x - a_x \phi_x - \ldots - a_n \lambda_n - a_0 h_n = 0 \\
J_x + d_x \lambda_x L_x + d_y \phi_y J_y + d_z h_z J_z - c_0 - c_x \lambda_x - c_y \phi_y - \ldots - c_n \lambda_n - c_0 h_n = 0
\end{align*}
\]

where \((a_x, b_x, c_x, d_x)\) are the RPCs to be estimated; on the other hand, there is an incompressible error due to the accuracy of the rigorous model, so that very fine 2D and 3D grid spacings are useless.

Since the equations [8] are independent, the least squares estimations are performed separately for the two image coordinates \((I_n, J_n)\):

\[
\begin{align*}
A_i x_i + y_i &= 0 \\
A_j x_j + y_j &= 0
\end{align*}
\]

where \((A_i, A_j)\) are the design matrices (including products between image and ground coordinates), \((x_i, x_j)\) are the unknown parameters (RPCs) and \((y_i, y_j)\) are the known terms (image coordinates); for the first equation [9] we have:

\[
A_i = \begin{bmatrix}
A_{1,1} & \cdots & A_{1,k}
\end{bmatrix} \rightarrow 1^a GCP
\]

\[
X_i = \begin{bmatrix}
a_0 \\
a_1 \\
\vdots \\
a_k
\end{bmatrix}
\]

\[
Y_i = \begin{bmatrix}
I_{1,1} \\
I_{1,2} \\
\vdots \\
I_{1,k}
\end{bmatrix} \rightarrow 1^a GCP
\]

\[
A_i = \begin{bmatrix}
I_a \phi_a - I_x \lambda_x L_x h_x - I_y \lambda_y L_y h_y - I_z \lambda_z L_z h_z + 1 - \phi_x - \lambda_x - h_x & \ldots & \phi_x - \lambda_x - h_x
\end{bmatrix}
\]

and similarly for the second one.

Now, it has to be stressed that previous investigations with optical imagery clearly underlined that many RPCs are highly correlated, so that the least squares problem is
basically overparametrized; in order to avoid instability due to high correlations, leading to a pseudo-singular design matrix, usually a Tikhonov regularization is adopted, adding a damping factor to the diagonal of the normal matrix.

On the contrary, we decided to avoid overparametrization just selecting the actually estimable RPCs (“parsimony principle”) [Box et al., 1994; Dermanis et al., 2000]. The Singular Value Decomposition (SVD) and QR decomposition are employed to evaluate the actual rank of the design matrix and to perform this selection; the remaining RPCs need to be constrained to zero.

In details, we adopted a SVD-based subset selection procedure due to Golub, Klema and Stewart [Golub and Van Loan, 1993; Strang and Borre, 1997] that proceeds according the main following steps:

a) The SVD is computed and used both to calculate the approximate values of RPCs to normalize the design matrix A and to determine its actual rank r; the threshold used to evaluate r is based on the ratio between the maximum and the allowed minimum singular values; reference values are $10^{-4} \div 10^{-5}$ [Press et al., 1992]

b) An independent subset of r columns of A is selected by the QR decomposition with column pivoting: $AP=QR$. In a system of linear equations $(Ax=b)$, if A has a rank r, the QR decomposition produces the factorization $AP=QR$ where R is:

$$R = Q^T AP = \begin{bmatrix} R_{11} & R_{12} \\ 0 & 0 \end{bmatrix} \rightarrow r$$

$$\downarrow \quad \downarrow$$

$$r \quad m - r$$

and Q is orthogonal, $R_{11}$ is upper triangular and not singular and P is a permutation matrix. At the generic $i^{th}$ step of the QR factorization in the matrix A the 2-norm of every column is computed and if the 2-norm of $i^{th}$ column of $A_1$ is longer than the 2-norm of $k^{th}$ column of $A_2$, the two columns are interchanged. Consequently the same columns of matrix P are interchanged too. The permutation matrix P is calculated so that the columns of the matrix $B_i \in \mathbb{R}^{m \times r}$ in $AP=[B_1 \ B_2]$ are “sufficiently independent”; $B_1$ has a number of columns equal to rank of A.

c) $B_1$ is the matrix extracted from A and used to solve the linearized RPFs equations [8] in the least squares sense, computing the only estimable r RPCs.

Moreover, the statistical significance of each estimable RPC is checked by a Student T-test and the estimation process is repeated until all RPCs are significant.

Results presentation and discussion
Data set
The data available for the experiments were COSMO-SkyMed and TerraSAR-X SpotLight imagery.

As regards COSMO-SkyMed, we considered two images forming a stereo pair over the area of Merano (Northern Italy, approximately 10 Km x 10 Km) (Fig. 2, Tab. 1); the images belong to the Level 1A (SCS) category products, that is focused data in complex format, in slant range and zero-Doppler projection.
Figure 2 - COSMO-SkyMed image of Merano (left) and Ground Points distribution (right).

Figure 3 - TerraSAR-X image of Hannover (left) and Ground Points distribution (right).

The two scenes of Merano were acquired along descending orbits by two different COSMO-SkyMed satellites (CSK1 and CSK2), with incidence angles of 25.9 and 42.3 degrees respectively, forming a same-side configuration stereo pair, with a B/H equal to 0.3. The stereo pair was orientated considering 20 Ground Points (GPs), used both as GCPs and CPs; their horizontal coordinates were derived from cartography (scale 1:5000) whereas the heights came from a LiDAR Digital Terrain Model (mean elevation accuracy of 0.25 m); both these data are free available from the website of the Provincia Autonoma di Bolzano (http://www.provincia.bz.it/-/urbanistica/cartografia/cartografia\-.asp).

As regards TerraSAR-X, we had three images acquired over the town of Hannover (Northern Germany) (Fig. 3, Tab. 1); all images are High Resolution SpotLight products with an extension of 10 Km x 5 Km.

Two images were acquired along an ascending orbit, the other one along a descending orbit. In this case it was possible to choose various image combinations, in order to form different stereo pairs; we selected a same-side stereo pair (first and second image) with a B/H equal to 0.15 and an opposite-side stereo pair (first and third image) with a B/H equal to 1 (Tab. 1). On the Hannover images 20 GPs were been selected, whose coordinates have been derived from a LiDAR DSM.
### Table 1 – COSMO-SkyMed and TerraSAR-X imagery features.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Area</th>
<th>Acquisition date</th>
<th>Mean Incidence angle [deg]</th>
<th>Orbit</th>
<th>Look Side</th>
</tr>
</thead>
<tbody>
<tr>
<td>COSMO-SkyMed</td>
<td>Merano</td>
<td>30/11/2009</td>
<td>25.9</td>
<td>Desc</td>
<td>Right</td>
</tr>
<tr>
<td></td>
<td>Merano</td>
<td>02/02/2009</td>
<td>42.3</td>
<td>Desc</td>
<td>Right</td>
</tr>
<tr>
<td>TerraSAR-X</td>
<td>Hannover</td>
<td>05/12/2007</td>
<td>33.8</td>
<td>Asc</td>
<td>Right</td>
</tr>
<tr>
<td></td>
<td>Hannover</td>
<td>10/12/2007</td>
<td>44.9</td>
<td>Asc</td>
<td>Right</td>
</tr>
<tr>
<td></td>
<td>Hannover</td>
<td>29/12/2007</td>
<td>31.8</td>
<td>Desc</td>
<td>Right</td>
</tr>
</tbody>
</table>

**Figure 4 - Same area on the ascending TerraSAR-X images (left) and on the descending one (right).**

It has to be pointed out that the identification of GPs on the SAR image is usually much more difficult than in the case of optical imagery, so that an average error of 1-2 pixels (if not larger) has to be considered [Raggam et al., 2010].

Further, additional problems came out for the GPs identification on the opposite-side Hannover stereo pair. In fact, in this case, only 13 GPs are visible on both images, since the areas illuminated in the first image are in the shadow in the third one. As shown in Figure 4, the two images, acquired on opposite-side looking, are significantly different. The used GPs were selected in open areas, visible and well illuminated by the satellite on both looking sides.

**Accuracy results of radargrammetric model**

To test the effectiveness of the implemented RPCs generation tool, at first the reference results were computed: the stereo pairs were orientated with the SISAR rigorous orientation model, varying the number of GCPs and the model accuracy was evaluated for each configuration. In order to obtain significant results from the statistical point of view, for a given number of GCPs, different tests were carried out, using independent sets of GCPs, selected under the condition of a homogeneous distribution over the areas covered by the stereo pairs. For Merano stereo pair, the horizontal accuracy is at level of 3.0 - 4.0 m, and the vertical one is around 3.0 m; in Table 2 the accuracy is evaluated in terms of RMSE on CPs residuals (RMSE CPs), and the average, the median and the standard deviation of the RMSE obtained in the several tests carried out using independent sets of GCPs are shown.
As regards the model performance varying the independent sets of GCPs, the software shows a stable behaviour and the increase of GCPs number does not improve the results remarkably. In this respect, no more than 9 GCPs were considered, also because the number of the CPs would have been too small for computing a RMSE CPs significant from a statistical point of view.

As regards the TerraSAR-X data, we had a same-side and an opposite-side stereo pair. In Table 3 the accuracy achieved in the orientation tests with Hannover same-side stereo pair are presented: the horizontal and vertical accuracy are both at level of 2.5 - 3.5 m; again the software shows a stable behaviour and the increase of GCPs number does not improve the results remarkably.

<table>
<thead>
<tr>
<th># GCPs</th>
<th># Ind. Sets</th>
<th>RMSE CPs COSMO-SkyMed Merano</th>
</tr>
</thead>
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<td></td>
<td></td>
<td>North</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>2.78</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>2.55</td>
</tr>
<tr>
<td>9</td>
<td>2</td>
<td>2.78</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th># GCPs</th>
<th># Ind. Sets</th>
<th>RMSE CPs TerraSAR-X Hannover same-side</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>North</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>2.71</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>2.38</td>
</tr>
<tr>
<td>9</td>
<td>2</td>
<td>2.17</td>
</tr>
</tbody>
</table>

Finally, the results of the orientation of the opposite-side stereo pair are presented in Table 4. Considering only the two orientation tests, there is not a preferable configuration between the same-side and the opposite-side, since both get the same accuracy level (around 3.0 m).

As regards the commercial software OrthoEngine v. 10.3 (PCI Geomatica), in which the model developed by T. Toutin is embedded, just the best results are presented in the Table 5.

<table>
<thead>
<tr>
<th># GCPs</th>
<th># Ind. Sets</th>
<th>RMSE CPs TerraSAR-X Hannover opposite-side</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>North</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>1.97</td>
</tr>
<tr>
<td>6</td>
<td>2</td>
<td>2.04</td>
</tr>
</tbody>
</table>
Table 5 – Results of OrthoEngine v. 10.3 for Merano and Hannover stereo pairs.

<table>
<thead>
<tr>
<th># GCPs</th>
<th>RMSE CPs COSMO-SkyMed Merano</th>
<th>RMSE CPs TerraSAR-X Hannover same-side</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>North [m]</td>
<td>East [m]</td>
</tr>
<tr>
<td>9</td>
<td>2.21</td>
<td>3.40</td>
</tr>
</tbody>
</table>

Only the accuracy level obtained with 9 GCPs is displayed, since the OrthoEngine v. 10.3 is able to orientate the SAR image with radargrammetric model using 8 GCPs at minimum [PCI Geomatics, 2009].

The results related to COSMO-SkyMed and TerraSAR-X same-side stereo pairs are displayed, whereas the TerraSAR-X opposite-side stereo pair was not considered, because only 13 GPs (then 6 or 7 GCPs at most) were available.

The height accuracy is at the same level of SISAR for Merano stereo pair, but slightly worse for Hannover.

**Accuracy results of RPCs model**

At first, it has to be underlined that different RPCs sets were generated on the basis of the mentioned different GCPs independent sets already used to compute the reference results with the rigorous orientation model. In all these cases, the RPCs generation tool estimated only about 20 coefficients, instead of the 78 coefficients generally employed in the third order RPFs, avoiding the overparametrization and selecting only the estimable and significant parameters as mentioned before.

The generated RPCs were used in order to orientate the stereo pairs and the results of RPCs applications are presented in Table 6: the accuracy level is just close to the one achieved by the rigorous orientation model, what proves the effectiveness of the RPCs generation tool implemented in SISAR.

It was already mentioned that a common drawback of the generalized RPFs model, when the coefficients are estimated according to a terrain-dependent approach, is the high dependence on the actual terrain relief and the inability to reconstruct complex morphologies. On the other hand, RPCs generated according to a terrain-independent approach should provide the sensor orientation, enabling the correct reconstruction of the acquisition geometry and modelling image distortions related to the elevation of the scene. Our goal is now to show in a simple way that the RPCs generated by the tool implemented in SISAR are able to model the typical SAR distortions in presence of a complex morphology.

To study the effects of the topography, simulation tests were performed. In details, the elevation of a chosen GP has been modified adding different height shifts Δh, and the corresponding image coordinate variations were computed applying the RPCs model (Tab. 7). Considering that the column spacing is around 0.4 m, the increase in I coordinates is consistent with the increase in elevation, whereas the line coordinate does not vary significantly, since the GP coordinates are not modified in azimuth direction. These results remark that the generated RPCs model well reflects the physical acquisition of the SAR image even with rough morphology.
Table 6 – Results of the SISAR RPCs model for all images using different RPCs generated with the independent sets of GCPs.

<table>
<thead>
<tr>
<th>Stereo pair</th>
<th># GCPs</th>
<th># Ind. Sets</th>
<th>Average [m]</th>
<th>Median [m]</th>
<th>Standard Deviation [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>North</td>
<td>East</td>
<td>Up</td>
</tr>
<tr>
<td>CSK Merano</td>
<td>3</td>
<td>8</td>
<td>2.79</td>
<td>4.23</td>
<td>2.63</td>
</tr>
<tr>
<td>TSX Hannover</td>
<td>5</td>
<td>4</td>
<td>2.28</td>
<td>2.85</td>
<td>3.07</td>
</tr>
<tr>
<td>Opposite</td>
<td>3</td>
<td>4</td>
<td>1.99</td>
<td>2.76</td>
<td>3.21</td>
</tr>
</tbody>
</table>

Table 7 – Effect on the image coordinates with respect to the elevation variations as accomplished by the SISAR RPCs model.

<table>
<thead>
<tr>
<th>ΔH [m]</th>
<th>I [pix]</th>
<th>J [pix]</th>
<th>ΔI [pix]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>6682.3</td>
<td>7272.6</td>
<td>0.0</td>
</tr>
<tr>
<td>5</td>
<td>6667.9</td>
<td>7272.6</td>
<td>-14.4</td>
</tr>
<tr>
<td>10</td>
<td>6653.5</td>
<td>7272.6</td>
<td>-28.8</td>
</tr>
<tr>
<td>50</td>
<td>6538.4</td>
<td>7272.5</td>
<td>-143.9</td>
</tr>
<tr>
<td>100</td>
<td>6394.5</td>
<td>7272.3</td>
<td>-287.9</td>
</tr>
<tr>
<td>300</td>
<td>5818.7</td>
<td>7271.8</td>
<td>-863.6</td>
</tr>
</tbody>
</table>

Acknowledgements
The COSMO-SkyMed stereo pairs were made available by e-Geos S.p.A., Rome (Italy), in the frame of a collaboration agreement; the Authors are indebted to e-Geos S.p.A. for this. The TerraSAR-X stereo pairs have been provided in the framework of the international project “Evaluation of DEM derived from TerraSAR-X data” organized by the ISPRS (International Society for Photogrammetry and Remote Sensing) Working Group VII/2 “SAR Interferometry”, chaired by Prof. Uwe Soergel – Leibniz University Hannover. Moreover the Authors thank very much Sysdeco Italia S.r.l., who supplied a temporary license of the OrthoEngine v. 10.3 software.

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resolution satellites imagery orientation. Chapter 4 In: Li D., Shan J., Gong J. (Eds.), Geospatial Technology for Earth Observation data. Springer.

Received 14/02/2011, accepted 20/06/2011
CO emission datasets and maps from Remote Sensing: spatial and statistical comparison at different levels

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Abstract
CO emissions due to biomass burning can be represented as raster maps computed from satellite observations obtained from sensors of different types, on board of different platforms, exploiting algorithms which combine input data in different ways. Hence, different CO emission “products” are available and it is important to define comparison tools among datasets, considering that no ground truth is available for these data. Comparisons between couples of CO emission datasets have been performed implementing statistical tools in GIS environments. Interpreting the results of the comparisons, it became apparent that the information carried by the different datasets available can be very dissimilar, thus reflecting the high level of variability connected with the determination of the approach used to estimate the product and of uncertainty of the parameters entering the computation of the CO emission datasets.

Keywords: CO emissions, GIS, dataset comparison, map comparison.

Datasets and raster maps of CO emissions and GIS tools for their comparison
The case that has been studied and is presented here regards the comparison between maps of CO emissions due to biomass burning and derived from Remote Sensing. Thanks to satellite sensor acquisitions global and updated information about CO emissions is available, delivered by different service providers. Two approaches are generally used for estimating emissions from biomass burning using satellite data. The bottom-up approach derives CO emissions from the estimates of burnt areas and by applying specific parameters for each land cover class (fuel load, burning efficiency and CO emission factors) based on the multiplicative model provided by [Seiler and Crutzen, 1980]. The top-down approach relies on measurements of CO concentration in the troposphere made available by satellites to derive CO surface emissions [Pétron et al., 2004; Arellano et al., 2006].
Because of a lack of ground truth, one effective support for data interpretation is represented by product inter-comparison [Boschetti et al., 2004; Jain, 2007; Stroppiana et al., 2010]. In this work, which has been developed in the framework of the INTERMEDE BBSO (Inter-comparison of methods to derive global burnt biomass from satellite observations) project, some indices for the products inter-comparison are presented and preliminary results at different geographical levels are shown.
The considered satellite derived maps of CO emissions are in raster format, cover the whole Earth surface at the spatial resolution of $0.5° \times 0.5°$ or of $1° \times 1°$ and are produced with a
monthly temporal evolution for the year 2003. The datasets corresponding to such raster maps which have been taken into account in the course of the research are five: ATSR [Mieville et al., 2010], VGT [Michel et al., 2005; Liousse et al., 2010], MODIS [Chin et al., 2002; Giglio et al., 2006], ITO-PENNER [Ito and Penner, 2004] and PETRON [Petron et al., 2004]. The PETRON dataset has been derived with a top-down approach whereas the others are based on a bottom-up model. For more details about such products, see Table 1.

Table 1 – Original resolution for the global data and per land cover of the CO emission products studied.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>ORIGINAL RESOLUTION for global data</th>
<th>ORIGINAL RESOLUTION known per land cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATSR</td>
<td>1° × 1°</td>
<td>Monthly</td>
</tr>
<tr>
<td>VGT-COR</td>
<td>0.5° × 0.5°</td>
<td>Daily</td>
</tr>
<tr>
<td>MODIS</td>
<td>1° × 1°</td>
<td>Monthly</td>
</tr>
<tr>
<td>ITO-PENNER</td>
<td>1° × 1°</td>
<td>Monthly</td>
</tr>
<tr>
<td>PETRON</td>
<td>0.5° × 0.5°</td>
<td>Monthly</td>
</tr>
</tbody>
</table>

The top-down approach relies on the estimation of the burned area, which can be derived from the detection of biomass burning from different satellite sensors. Moreover, in the datasets considered here, the satellite images are used to detect different surface conditions related to biomass burning: either active fires (i.e. the flaming front of the fire) or burned areas (the surface affected by the fire).

Besides, the land cover map used as a reference during the project is GLC2000 - Global Land cover 2000 [Bartholomé and Belward, 2005]. A more detailed description of the aim of the project, of the datasets analyzed and of some results can be found in [Carrion et al., 2010]. An example of map representing CO emissions at a global level is reported in Figure 1.

During the project, ad hoc tools have been generated at Politecnico di Milano by means of the ESRI suite ArcGIS 9.3, in particular using the Model Builder application (see e.g. Fig. 2) in order to develop models and the Spatial Analyst extension for its advanced functionalities on raster data.

Besides, the Python 2.5 scripting language was exploited to integrate specific ArcGIS functions, thus allowing to repeat flows of operations in an efficient way. As an example, using these tools monthly or seasonal averages can be automatically computed for every chosen CO emission dataset at global or regional level, producing the corresponding histograms and storing the results. Graphs and charts can be afterwards generated from such results also by integrating the functionalities of the open-source Matplotlib library.

During the course of this research 50 tools have been realized, including both ArcGIS models and Python scripts; these instruments have been collected in a toolbox in order to facilitate the portability among different users or computers. A simple graphic interface has been prepared for each tool, to make the data input easier and also to suggest possible default
values. Besides, during the tool run-time a window displays the operations in progress. For each tool an extensive documentation in HTML format has been included, containing text, pictures and diagrams, which are accessible to the user at any time [Carrion et al., 2010].

Figure 1 – Example of a raster map representing a dataset of CO emissions at spatial resolution of $1^\circ \times 1^\circ$: the case is that of VGT [Liousse et al., 2010], month May 2003; units are tons of CO.

Figure 2 – Example of a “model” realized by the ESRI ArcGIS ModelBuilder application; in this case, the flux of operations describes the creation of an “agreement map”.
At a later stage of the research free/open source software was exploited, namely GRASS 6.4.0 RC6, also for the sake of comparing proprietary and free/open source types of software for this specific application. Already existing and newly developed GRASS modules were employed to compute statistical indices for the CO emission datasets. All the analyses which will be presented in the following paragraphs have been carried on by exploiting the GIS tools described in this section of the paper.

**Statistical indices for the comparison of datasets of CO emissions**

When carrying on studies on CO emissions and using datasets representing this kind of information, a very important question is how it is possible to validate a single dataset: the answer to this question is not trivial, since there is not a “ground truth” available in this particular case. As a consequence, the necessity arises (as the next logical and possible step) to compare two datasets in order to highlight similarities and differences in their behaviour. In order to keep this analysis on the quantitative level it is possible to base these comparisons on the computation of statistical indices: this allows to define the level of “agreement” between couples of datasets obtained from remotely sensed data collected by means of different sensors and from different platforms, exploiting algorithms that are not completely identical.

The statistical indices computed in order to quantify this level of “agreement” for the different couples of CO emission products are described in the following.

Linear correlation coefficient $\rho_{xy}$ between two datasets $X$ e $Y$, where $\sigma_{xy}$ is the covariance between the two datasets, while $\sigma_x$ e $\sigma_y$ are the standard deviations; $\rho_{xy}$ is a non-dimensional index and its values range between -1 and 1, see for example [Mood et al., 1974]:

$$\rho_{xy} = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$  \[1\]

Agreement Coefficient $AC$ proposed by [Ji and Gallo, 2006], which measures the level of agreement between two datasets $X$ and $Y$, under the hypothesis that both datasets are equally subject to measurement errors; $X_i$, $Y_i$ represent the values of the corresponding pixels in the two datasets, while $\bar{X}$ e $\bar{Y}$ are the average values; this index is non-dimensional and its values are upper bounded by 1 (perfect agreement between the two datasets):

$$AC = 1 - \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}(|X_i - \bar{X}| + |X_i - Y_i|)(|X_i - \bar{X}| + |Y_i - \bar{Y}|)}$$  \[2\]

Mielke’s Measure of Agreement $\rho$, described by [Ji and Gallo, 2006], based on the mean square error of the two datasets $X$ e $Y$, where $X_i$, $Y_i$ represent the values of the corresponding pixels in the two datasets; also this index is non-dimensional and its values are upper bounded by 1 (perfect agreement between the two datasets):
Robinson’s Coefficient of Agreement $A$, described by [Ji and Gallo, 2006], which measures the distance between point $(X_i, Y_i)$ and the line $X = Y$, where $X_i, Y_i$ represent the values of the corresponding pixels in the two datasets; $\overline{Z}$ is the average value of $\overline{X}$ and $\overline{Y}$; also this index is non-dimensional and its values are bounded by 0 and 1 (perfect agreement between the two datasets):

$$A = 1 - \frac{\sum_{i=1}^{n} (X_i - Z)^2 + \sum_{i=1}^{n} (Y_i - Z)^2}{\sum_{i=1}^{n} (X_i - \overline{Z})^2 + \sum_{i=1}^{n} (Y_i - \overline{Z})^2} \quad [4]$$

The linear correlation coefficient $\rho_{XY}$ (Equation [1]) can be computed by means of the r.covar tool included in the GRASS software package. The computation of the other three indices (Equations [2], [3], [4]) has been implemented by developing the new tool r.compare in the GRASS 6.4.0 RC6 environment. This tool has been written in C language and provides the users with an easy interface for data entry and for the visualization of the relevant documentation in HTML format.

One remark is in order. The use during the research of the above described indices could be argued, also because some of the possible choices may be controversial. The choice of the indices described above represents a way of providing a measure of the products’ correlation. However, other measures of comparison of couples of CO emission datasets at a spatial level have been also used and presented [Migliaccio et al., 2011; Zambrano et al., 2011].

**Comparisons between CO datasets and maps at a global and continental level**

At a global level, the specific comparison between different CO emission datasets was essentially carried on by computing new raster maps which represent the “agreement” between CO emission values over single cells covering the earth surface. Assuming that all products have the same accuracy in detecting CO due to biomass burning, each cell of this raster represents a value corresponding to the number of datasets that detect CO emission in that particular cell (Fig. 3). This type of synthetic representation highlights the spatial agreement between the datasets and it does not take into account the difference between the cell values as provided by the dataset [Migliaccio and Pinto, 2009].

The example of agreement map in Figure 3 highlights some global spatial patterns, which are typical of biomass burning in agricultural and forested regions of Russia and Siberia and in the savannas of the southern continents (South America, Africa and Australia). Indeed in these regions most of the datasets agree on pointing out the presence of fires as source of CO emissions.
Figure 3 – Example of agreement map: month May 2003.

The agreement map is also associated with an “agreement table”, in which each record represents the detection of a cell as “active” (i.e. a cell emitting CO) by a particular subset of CO emission products. The size of a specific subset is a way to “measure” the agreement between CO emission datasets; in fact 0 implies that no dataset represents the cell as an active one, 5 implies that all datasets represent the cell as an active one (disregarding the quantity of emitted CO). All values in between have an obvious meaning. As an example of possible results that can be drawn from this type of table see the Agreement Table of May 2003 (Tab. 2).

From the first three records of Table 2 (which is a selection from the records of the complete agreement table, that has also been ordered by frequency) it can be observed that:

- the most frequent combination (involving about 50% of cells) is the one for which Petron shows CO emissions, while the other products do not show any emission; the reason for this could be that the Petron dataset has been computed with an original 2.1° x 2.8° resolution and afterwards it has been interpolated at 0.5° x 0.5° [Pétron et al., 2004];
- the second most frequent combination shows that, in May 2003, the VGT and Petron datasets single out CO emissions at the same time for 17% of cells, since Petron and VGT datasets indentify a larger number of CO sources compared to the others;
- finally, all the CO emission datasets agree in defining a cell as “active” in only about 5% of the cases showing a weak spatial agreement between the datasets.
In practice, the production of agreement maps and tables allows highlighting similarities and differences between the spatial distribution of CO emission as shown by the datasets at a very general level. It is then possible to quantify the level of agreement between couples of CO emission datasets by computing the above described statistical indices (Equations [1] to [4]). This has been done both at global and at continental level. The extent of the geographical windows for the continental analysis has been defined as reported in Table 3.

Table 2 – Agreement Table of May 2003 for a total number of 17520 cells which are seen as “active” by at least one CO emission product.

<table>
<thead>
<tr>
<th>N. CELLS</th>
<th>%</th>
<th>ATSR</th>
<th>IT_PE</th>
<th>MODIS</th>
<th>PETRON</th>
<th>VGT</th>
<th>AGREE</th>
</tr>
</thead>
<tbody>
<tr>
<td>8494</td>
<td>48.48</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>3035</td>
<td>17.32</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>967</td>
<td>5.52</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>847</td>
<td>4.83</td>
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<td>1</td>
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<td>1</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>721</td>
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<td>500</td>
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<td>1</td>
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<tr>
<td>491</td>
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<td>439</td>
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<td>1</td>
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<td>1</td>
<td>4</td>
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<td>172</td>
<td>0.98</td>
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<td>143</td>
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<td>0</td>
<td>1</td>
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<td>1</td>
<td>4</td>
</tr>
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<td>130</td>
<td>0.74</td>
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<td>0</td>
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<td>104</td>
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<td>0</td>
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<td>1</td>
<td>3</td>
</tr>
<tr>
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<td>0.58</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>96</td>
<td>0.55</td>
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<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>25</td>
<td>0.14</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>0.07</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>0.05</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>0.03</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td>4</td>
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<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>0.02</td>
<td>1</td>
<td>0</td>
<td>0</td>
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<td>1</td>
</tr>
<tr>
<td>3</td>
<td>0.02</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>0.02</td>
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<td>0</td>
<td>0</td>
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<td>1</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>
It has to be underlined that both globally and for the continental windows these indices reveal a very low level of agreement for all couples of datasets and for all the months of the year, with only a few cases when the results are better. In general the outcome of the computations has shown that the datasets which better correspond to each other and for which the statistical indices have higher values are ATSR, MODIS and VGT, in particular for the month of January 2003 and in the Africa window.

A way of confirming these results by means of a different statistical tool is to produce scatter plots for each couple of CO emission products and for each month of the year. This can be done either at global or at continental level. A scatter plot can suggest various kinds of correlations between variables, and in particular a line of best fit can be drawn in order to study the correlation between the variables. In the case under study, a scatter plot can be useful since we are interested in quantifying how much two datasets representing the same type of information are in agreement with each other: the “perfect” agreement would be represented in the scatter plot by all points aligning on the $Y = X$ line.

As an example of the use of scatter plots, let us consider the case of the active cells defined as such by the CO emission products for the month of February 2003 in the African area. These active cells are plotted in the small map shown in Figure 4 and show fires typical of the savannas of Northern Africa. For these cells, the scatter plots have been computed and they are also shown in Figure 4.

From the figure it can be seen that the points in all diagrams tend to be irregularly distributed, showing no particular behavior (or trend), except maybe in the cases of the couples of MODIS & VGT and ATSR & MODIS which show a certain level of agreement (i.e. the points tend to be more close to the $Y = X$ line). Those couples where the PETRON dataset is taken into account show a scatter plot with points clustered along the y-axis; this effect is due again to the low resolution of this dataset with respect to the others which leads to a higher number of cells with emissions greater than zero. Therefore cell by cell comparisons, which rely on a high spatial agreement between the datasets, provide worse results when the PETRON dataset is involved. As a matter of fact, in the following paragraphs these correspondences will be confirmed by the values of the statistical indices.

However, a remark about the scatter plots for the couples of CO emission products is here in order. The situation depicted by Figure 4 can be quite different if we examine the couples of CO emission products for the other months of the year. This means that no systematic behavior could be found, and couples of products showing similar behavior for one specific month could show a very different behavior for other months. Biomass burning is in fact a phenomenon characterized by a high variability from place to place mainly as a function of the land cover characteristics and conditions at the time of fire occurrence.

<table>
<thead>
<tr>
<th>Window</th>
<th>$\lambda_{\text{min}}$</th>
<th>$\lambda_{\text{max}}$</th>
<th>$\phi_{\text{min}}$</th>
<th>$\phi_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>North America</td>
<td>-180</td>
<td>-50</td>
<td>30</td>
<td>75</td>
</tr>
<tr>
<td>Europe</td>
<td>-30</td>
<td>45</td>
<td>26</td>
<td>71</td>
</tr>
<tr>
<td>Northern Asia</td>
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<td>180</td>
<td>26</td>
<td>71</td>
</tr>
<tr>
<td>South America</td>
<td>-117</td>
<td>-33</td>
<td>56</td>
<td>30</td>
</tr>
<tr>
<td>Africa</td>
<td>-30</td>
<td>63</td>
<td>-50</td>
<td>26</td>
</tr>
<tr>
<td>South-East Asia</td>
<td>63</td>
<td>180</td>
<td>-50</td>
<td>26</td>
</tr>
</tbody>
</table>
Comparisons between CO datasets and maps at a sub-continental level
Since the analyses carried on at global and continental level highlighted a quite poor spatial agreement for all couples of CO emission datasets, it was decided to investigate whether a better level of agreement could be found for the same couples of datasets at a sub-continental level. In particular, areas of limited extension were chosen where the agreement between datasets appeared to be more pronounced by a visual inspection of maps such as the one shown in Figure 5. In fact this figure represents the map of active cells for all five CO emission datasets for the month of February 2003. The darker is a specific cell, the highest is the number of CO emission datasets that indicate that cell as an active one. For such areas as the ones identified in the map of Figure 5 it is interesting to verify the level of agreement of the CO emission datasets by computing the statistical indices of Equations [1] to [4]. The results of the computation of these indices for the month of February 2003 over the African area, limited by $-35^\circ \leq \phi \leq 4^\circ$ and $9^\circ \leq \lambda \leq 42^\circ$, are reported in Table 4; they have been obtained by means of the r.covar and r.compare GRASS tools.
From the table it can immediately be seen that the couples MODIS-VGT and ATSR-MODIS show a better level of correlation than the other couples of datasets, and that they also show high values for the Mielke’s Measure of Agreement. These datasets are in fact derived from the same set of coefficients to describe fuel loads, burning efficiency and emission factors for each land cover class of the common GLC2000 map. Moreover, these results are consistent with the scatter plots of Figure 4. Another consideration is that the Robinson’s Coefficient of Agreement has very similar values for all couples of datasets.
Conclusions
At the moment the research on the characterization and cross-comparison of datasets of CO emissions caused by biomass burning has proceeded for a time span of more than two years. The time spent studying such data gave us the opportunity to gain some insight on the phenomenon and to draw some comments, though they may not be the conclusive ones, which regard two aspects of the work carried on so far.

One aspect concerns the implementation of statistical tools in a GIS environment. At the moment, exploiting the ESRI ArcGIS 9.3 suite, a toolbox has been prepared which allows to carry on a number of statistical analyses on the datasets both from the numerical and from the mapping/graphic point of view. Working on the comparisons between maps of CO emissions in a GIS environment has proved to be a very effective way of proceeding, besides being an intuitive one since CO emission datasets intrinsically correspond to raster maps. Another advantage is represented by the possibility to repeat the same flow of operations in an extensive way for a large number of different geographical areas or of different time periods. Moreover, the GIS-based tools make easier the extension of the analyses to additional datasets, which could be made available to the scientific community in the future. Besides, the flexibility of these tools easily allows to exploit them also in other research fields where raster data are involved.

At the moment, more tools are being integrated as their usefulness is recognized and attention is devoted to make the procedures easy to follow also for non-specialist GIS users.

The second aspect regards the interpretation of the results of the comparison of CO emission datasets, computed by means of the GIS toolbox. At a global or even continental level a weak agreement between couples of datasets has been found out, although several measures of agreement have been tried and computed. When limiting the geographic extent of the area for which the analysis is performed below the continental level, it is possible to highlight similarities in the behavior of couples of datasets. However, similarities observed for one region seem not to be consistent for the other regions. From the results presented here the couples of datasets which show the best agreement are MODIS-VGT and ATSR-MODIS; indeed, these datasets are all derived from a common land cover map (GLC2000) and a common set of parameters in the equation for deriving the amount of CO emitted from biomass burning for each 0.5°x0.5° cell.

It is anyway apparent that the information carried by the different CO emission datasets available can be very dissimilar reflecting the high level of uncertainty of these types of products. The sources of uncertainty are connected with all the parameters entering the computation of the CO emission datasets and with the approach used for deriving each product (bottom-up or top-down). The differences among the VGT, ATSR and MODIS datasets, which use common parameters for describing the vegetation and common emission factors, mainly come from the estimation of the amount of burned area in each 0.5°x0.5° cell. These estimates can in turn vary as a function of the geometric and spectral characteristics of the sensor and of the observed phenomenon (active fires or burned areas). Note that, for example, the ATSR dataset relies on active fires detected at night-time; in some ecosystems, these fires can represent only a sample of the daily total fire activity and therefore could lead to an underestimation of the total burned area. In general, the sources of the observed differences could come from any of the parameters involved in the computation of the emissions: the use of global-wide land cover classes, the assumption of average biomass amounts and conditions in space (wide land cover classes) and time (constant through the
year) and the use of constant emission factors. The fire research community has now been focusing on the use of a new approach based on the estimation of the Fire Radiative Energy (FRE). In fact, the energy radiated by an active fire can provide information on the total fuel combusted by the fire [Wooster et al., 2005] thus overcoming limitations of the models based on the estimation of the area burned and on land cover dependent parameters. Proceeding with the work, some issues that still need to be clarified will be addressed. First of all the question arises if it is possible to compare the results given by the different agreement measures, and how or, if it is possible, to summarize these results in a single measure. Two key issues need to be explicitly addressed in the future: i) to quantify the agreement of the seasonality provided by the datasets and ii) to investigate how the land cover distribution can explain the differences observed among the CO datasets. Both are important information for the scientific community working on the development of models of atmospheric circulation which use emissions from fires as input data.

References


Received 8/02/2011, accepted 16/08/2011
Pre-processing of high resolution satellite images for sea bottom classification

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Abstract
In order to monitor the coastal-sea environment it is necessary to check variations of the coastal line as well as the sea bottom. There are techniques for using remote sensing as a technique for the extraction of bathymetric information. However, these techniques require preliminary radiometric image processing in order to fulfill the model constraints. More precisely, atmospheric effects must be removed together with the water column correction in order to achieve radiometric values that are only representative of the sea depth and to homogenize the upwelling response from different bottom types. If sun-glint is present, the effect of the sun beams reflecting on the sea surface, it has to be corrected by a special procedure. This work is concerned with pre-processing the images, via the development of a module in IDL (Interactive Data Language). This module was subsequently embedded in the ENVI menu system. The model was applied to Ikonos and WorldView-2 scenes, representing respectively the Poetto beach near the city of Cagliari and the littoral of Marina di Altidona (the Marches, Italy). The results of pre-processing were evaluated using an unsupervised classification.

Keywords: Ikonos, WorldView-2, bottom classification, bathymetry, model, pre-processing.

Introduction
In order to determine the bathymetry in the area of Poetto beach in Cagliari (Italy), the same research team built their research upon the application of the Jupp method to the Landsat images [Deidda, 2008]. This area is under study due to a phenomenon of widespread erosion, which in the last sixty years has reduced the beach to the point being in serious need of beach nourishment, this was carried out in 2002. The research results, although applied to medium-resolution images (Landsat TM5), were so promising as to induce us to use images with higher spatial and radiometric resolution (Ikonos, WorldView-2 and ADS40 sensors), in order to produce a greater scale digital model of the sea bottom.

The application of the bathymetry extraction model to these images was split up into three phases:
1. pre-processing of the multispectral images and the implementation of the corresponding procedures in IDL;
2. designing and building of a ROV for fast bathymetry measurements in order to calibrate the models;
3. calibrating and validating the entire system.
Currently, only the first phase of the project has been completed. Herein, we will describe the pre-processing procedure used upon Ikonos and WorldView-2 images which represent, respectively, an area along the coastline of Cagliari and that of Marina di Altidona (the Marches, Italy). Table 1 and Table 2 compare respectively the characteristics of the sensors and those of the two scenes.

### Table 1- Satellites characteristics.

<table>
<thead>
<tr>
<th></th>
<th>Ikonos II</th>
<th>WorldView-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor resolution</td>
<td>1 x 3.20 m</td>
<td>0.5 x 2 m</td>
</tr>
<tr>
<td>Spectral range</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coastal Blue</td>
<td>----</td>
<td>400-450 nm</td>
</tr>
<tr>
<td>Blue</td>
<td>450-530 nm</td>
<td>450-510 nm</td>
</tr>
<tr>
<td>Yellow</td>
<td>----</td>
<td>585-625 nm</td>
</tr>
<tr>
<td>Green</td>
<td>520-610 nm</td>
<td>510-580 nm</td>
</tr>
<tr>
<td>Red</td>
<td>640-720 nm</td>
<td>630-690 nm</td>
</tr>
<tr>
<td>Red Edge</td>
<td>----</td>
<td>705-745 nm</td>
</tr>
<tr>
<td>NIR 1</td>
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<td>770-895 nm</td>
</tr>
<tr>
<td>NIR 2</td>
<td>----</td>
<td>860-1040 nm</td>
</tr>
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<td>11 bits per pixel</td>
</tr>
<tr>
<td>Swath Width</td>
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<td>16.4 km at nadi</td>
</tr>
<tr>
<td>Revisit time</td>
<td>~ 3 days</td>
<td>~ 1 day</td>
</tr>
<tr>
<td>Orbital altitude</td>
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<td>770 km</td>
</tr>
<tr>
<td>Nodal crossing</td>
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</tbody>
</table>

### Table 2 - Scenes properties.

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</tr>
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<tr>
<td>Columns</td>
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<td>5836</td>
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<td>Product type</td>
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<td>Standard</td>
</tr>
<tr>
<td>Percent cloud cover</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Pre-Processing
The image pre-processing we have implemented applies the following operations consecutively:

- Atmospheric correction
- Sun-glint correction
- Water column correction
- Sea bottom classification

The algorithms which carry out the sun-glint and water column corrections were operated in the IDL language. The two modules were added to the ENVI software menu system under “Topography”.

The sun-glint problem and ENVI implementation
Mapping the sea bottom features may be seriously impeded by the sun-glint on the sea surface. Unfortunately, this phenomenon in ideal conditions (clean sky, shallow water and high image resolution) is too strong to make it possible to acquire remote sensing images. Typically, the sun-glint appears as stripes of white along the crests of the waves, on the side of the wind direction and near the shore. These white stripes prevent visual recognition of the sea bottom features and compromise their classification.

Although in sun-glint areas the signal acquired appears to consist almost entirely of light reflected on the water surface, the upwelling radiance component may be retrieved. A study by Hedley et al. [2005] presents a method for removing the sun-glint component from visible wavelength bands by using the Near Infrared one. Based on this method, a module for the correction of the sun-glint phenomenon was written in the IDL.

The method for “deglinting” an image may be explained as follows:

1. The NIR (Near Infrared) signal is composed entirely of sun-glint and a spatially constant ambient component, without the spatially variant benthic one.
2. The amount of sun-glint in the visible bands is linearly correlated to the signal in the NIR band.

The first statement is justified by the fact that water is highly opaque in the NIR wavelengths [Mobley, 1994], thus even shallow waters have a very low upwelling radiance in the NIR band regardless of the bottom type. This method assumes a constant ambient signal level (MIN\text/subscript\_{NIR}), which is subtracted from each pixel of the image during the process.

Although the minimum of the NIR signal in deep waters should be zero, in practice it has a value higher than zero (MIN\text/subscript\_{NIR}). In particular, if the image is not atmospherically corrected, this residual or “ambient” signal corresponds to the NIR diffusion in the atmosphere.

The assumption that the relationship between the NIR signal and the amount of sun-glint in the visible bands is linear, is acceptable because the actual refraction index is approximately the same for the NIR and visible wavelengths. The method thus proceeds by defining the linear relationship between the NIR signal and the amount of sun-glint in each visible band. This information, combined with the infrared signal in each pixel, is used to calculate the amount which must be subtracted from each band in order to remove the effect of the sun-glint on the pixels.

The linear relationship between the NIR signal and each visible band is calculated by
means of a linear regression. In order to obtain an interval from low to high sun-glint, one or more areas of consistent signal are interactively selected on the image. The module then calculates the linear regression of the point cloud obtained by plotting the values of the visible bands on the Y axis, and those the Near Infrared band on the X axis. If the slope of the regression line for the $I$ band is $b_i$, then the sun-glint may be removed from every pixel of the $I$ band image by applying the following equation:

$$
R'_i = R_i - b_i \cdot (R_{NIR} - MIN_{NIR}) \quad [1]
$$

Where

- $R'_i$ is the pixel signal without sun-glint
- $R_i$ is the pixel signal in $I$ band;
- $b_i$ is the regression slope;
- $R_{NIR}$ is the pixel value in the NIR band;
- $MIN_{NIR}$ is the ambient signal level.

The operations related to the image processing were implemented according to the phases of the method developed by Hochberg et al. [2003] and modified as published by Hedley et al. [2005].

The module was tested on both the Ikonos and the WorldView-2 images. In particular, the WorldView-2 scene was processed first of all by using the four “traditional” bands (Red, Green, Blue and Near Infrared 2) and then by using the new Coastal band in place of the Blue one. Figures 1, 2 and 3 show a comparison of the original (left) and the de-glinted (right) images for the three cases under study. In the figure 1, the original image contains a considerable amount of sun-glint. In the corrected image the white stripes are removed and the image appears smoothed out. In the figure 2 and 3 the original image did not have the same mount of sun-glint as the previous one, thus the effects of the de-glint process were less pronounced. On the other hand the latter two images show that using the coastal band instead of the blue band has no noticeable effects on the results.

Figure 1 - Sun-glint correction on the Ikonos scene.
Water Column Correction (Lyzenga method) and ENVI implementation

Light, on its ideal path, starting from its source (the sun), reaches the sea bottom by travelling through two different layers: the atmosphere and the water column. Both influence the radiance values collected by the sensor, but if these values have to represent the surfaces on which the light reflects, the image needs to be pre-processed. There are various software modules dedicated to atmospheric correction (FLAASH in ENVI and ATCOR in PCI, etc.), but there are no packages available for water column correction. For want of these modules, the operations of sea bottom classification are strongly conditioned by radiance values, which are not really representative of the actual reflecting surfaces.

Conceptually, this method is based on the assumption that the radiance reflected by the bottom is a linear function of bottom reflectance and an exponential function of the water depth [Lyzenga, 1981]. The relationship between $K_i$, radiance and depth is described by the equation:

$$L_i = L_{si} + a \cdot r \cdot e^{(-2K_i z)} \quad [2]$$

where $L_i$ is the apparent pixel reflectance in band $i$, $L_{si}$ is the averaged apparent reflectance for deep water in band $i$ minus $2\sigma$, $a$ is a constant value, $r$ is bottom reflectance, $K_i$ is the attenuation coefficient for $i$ band and $z$ is the depth.
The attenuation coefficient $K$ is an important correction factor for the water column: it models the effect of absorption and scattering in the water on the radiance collected by the sensor. In order to establish a linear relationship between radiance and depth, the radiance values (after atmospheric correction) must be transformed by using the natural logarithm. Since the values in the homogeneous substrates are constant, when plotting two bands versus each other, the pixel values will lie on a straight line. The deviations of the values with respect to the line will only be due to variations in depth. The slope of the line represents the ratio between the attenuation coefficients of the two bands.

It is impossible to follow this approach, because there are too many unknown quantities in the equation: the value of $a$, the attenuation coefficient for each band and the water depth for each pixel. Lyzenga [1978, 1981] proposed a method that does not need the calculation of the three parameters, bypassing the obstacle he used information from multiple bands. The module we implemented in ENVI follows Lyzenga’s approach in order to generate a depth-invariant index.

The Lyzenga approach follows three steps:
1. linearization of the depth/radiance relationship;
2. calculation of the attenuation coefficient between pairs of bands;
3. generation of the depth-invariant bottom type index.

In literature these three steps are represented by Figure 4 where two types of bottom are considered (sand and seagrass).

![Figure 4 – Construction of the depth-invariant index](image)

Arrow 1 represents the passage from the exponential function to the linearized one. Arrow 2 represents the passage to the ratio between the two bands, which results in a straight line. While, if a different kind of bottom is considered this passage will be represented by a parallel line. Since the second type of bottom will not have the same reflectance as the first one, therefore its line will be placed either above or below the first one. The slope of the two lines is the same, because the ratio of the attenuation coefficients $k_i/k_j$ only depends on the band wavelengths and on the transparency of the water. Therefore arrow 3 represents the comparison between different
bottom types. The bottom type index may be obtained by extrapolating the interception of each line; thus the y axis becomes the bottom type axis. Not all the pixel values for a given bottom type are perfectly placed on the line, because of natural variations in the bottom reflectance, due to the transparency of the water and sensor noise. Whilst running, the module asks the operator to select, on the multispectral image, two samples of the same bottom type at different depths (the package was implemented taking into consideration only the Red, Green and Blue channels; the Near Infrared was not considered due to the low penetration in water of that wavelength). The analytical approach followed in the IDL implementation of the module is based on the parametric equation of the line: \( Y = mX + q \), where \( m \) is the slope of the regression of \( y \) on \( x \) and \( q \) is the intercept. Expressing the equation in terms of the intercept, we have \( q = Y - mX \); thus, 

\[
\text{depth - invariant index} = \ln(L_i) - \left[ \frac{k_i}{k_j} \right] \ln(L_j) \]  \[3\]

where:
- \( L_i \) and \( L_j \) represent the radiance of the pixel respectively in the I and J bands;
- \( K_i \) and \( K_j \) are the attenuation coefficients for the i and j bands.

Being \( L_i \) and \( L_j \) known quantities (since they are the radiance values in the i and j bands respectively), the problem is determining the ratio \( k_i/k_j \) between the attenuation coefficients. This is obtained by finding the regression line which minimizes the mean square deviation measured perpendicular to the line itself. (Using a conventional least-squares regression would yield different results depending on which band was used as the independent variable and which as the dependent one.) [Lyzenga, 1978; Green et al., 2000].

The ratio is thus calculated by using the following equation:

\[
\frac{k_i}{k_j} = \frac{\sigma_{ij}^2 - \sigma_{ji}^2}{2\sigma_{ij}^2} + \sqrt{\left[ \frac{\sigma_{ii}^2 - \sigma_{ij}^2}{2\sigma_{ij}^2} \right]^2 + 1} \]  \[4\]

where \( \sigma_{ii} \) is the variance in the i band; \( \sigma_{jj} \) the variance in the j band; \( \sigma_{ij} \) the covariance between the i and j bands.

The IDL module is based on this expression. The module calculates a depth-invariant index image for each pair of spectral bands and produces a combined image output of the three depth-invariant images (each obtained from a pair of bands). The depth-invariant bands may be used for visual analysis in place of the original bands. The result of the process is shown in Figures 5, 6 and 7 respectively for both the Ikonos scene and the WorldView-2 one (using the two different band combinations).

In each image, the original scene is on the left and the processed one is on the right. The result of the processing on the Ikonos scene emphasizes the differences between the bottom types, highlighting in particular the edge of the Posidonia. As in the Ikonos case, also with the WorldView-2 image the method makes the bottom type more apparent. Unlike the sun-glint processing, using the coastal band produced visually different results from the blue one. The following classification will show whether this difference is only visual or it is meaningful in terms of information carried.
Figure 5 – Water column correction: Ikonos scene.

Figure 6 – Water column correction: WorldView-2 scene using RGB NIR2 bands.

Figure 7 – Water column correction: WorldView-2 scene using RGC NIR2 bands.
Classification operations on the images after the pre-treatment

The experiments conducted up to now in the application of the Jupp model for extracting bathymetric information from satellite images have indicated that it is necessary to isolate the different types of sea bottom, if the objective is to make the sensor response representative of depth only. In order to verify the effectiveness of the corrections produced by the implemented modules, the images used in the experiment were thus processed with a classification procedure. In this phase, we wanted to measure the “natural” propensity of the pixel radiance values to allow them to fall into classes which were more representative of the real bottom types. For this purpose, we used the Unsupervised K-Means classifier. Figures 8, 9 and 10 show the results of the operation for the Ikonos and WorldView-2 (RGB and RGC) images: on the left the classification performed on the original image; on the right the same classification performed on the image pre-processed image with sun-glint and water column corrections. In all these cases K was set to 3.

Figure 8 – Results of the classification on the original and processed Ikonos image. In this and the following images the colors represent the classes automatically separated by the unsupervised classification.

Figure 9 – Results of the classification on the original and processed WorldView-2 (RGB) image.
While on the original image, the classifier cannot discriminate any classes from either Ikonos or WorldView-2 image sensors, on the pre-processed one it isolates the requested classes. In particular in the classified Ikonos pre-processed image, the class corresponding to the sandy bottom (blue in the image) is revealed at last.

Moreover, in order to determine whether the use of the Coastal band from the WorldView-2 data set produces an improvement in the classification, this operation was performed on the depth-invariant images calculated both from the RGB NIR2 and the RGC NIR2 bands. As in the Ikonos case, we used the K-means unsupervised classifier, with values of K set to 3, 4 and 5. In a visual analysis, the results of the classification show no evident difference between RGB NIR2 and the RGC NIR2, as shown in Figures 11 and 12.
In order to have a quantitative measure of the differences, the statistics of the image difference between the RGC-based and RGB-based classifications for the same value of K have been calculated. These statistics are shown in the following Table 3, where the columns show respectively the minimum, maximum, mean and standard deviation of the difference between the two classification images.

### Table 3 – Statistics of the differences between the classifications.

#### RGC K=3 - RGB K=3

<table>
<thead>
<tr>
<th>Basic Stats</th>
<th>Min(DN)</th>
<th>Max(DN)</th>
<th>Mean(DN)</th>
<th>Stdev(DN)</th>
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<td>Band 1</td>
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<td>0.000336</td>
<td><strong>0.102082</strong></td>
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</table>

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<th>Total(pixel)</th>
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#### RGC K=4 - RGB K=4

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Also shown are the histograms of the three differences. In practice, the number of the pixels that are different from zero allows us to evaluate numerically the differences between the classifications. In all three cases, we have over 97% of equal pixels, with a maximum standard deviation of 0.15.
Conclusions
The processing of image data with the sun-glint and water column corrections makes a classification of sea bottom types possible. Following this processing, the natural propensity of the pixels to fall into separate classes is maintained when increasing the number of classes (K). Furthermore, the use of the Coastal band does not seem to provide a substantial increase in the amount of information for the case under examination. This is demonstrated by the value of the standard deviation of the image differences, which varies between 0.10 (for K = 3) and 0.14 (for K = 5). Instead, we expect it to be useful when applied to the Jupp method for bathymetry extraction.

While the lack of data about the actual bottom types has not allowed us to evaluate the accuracy of the classification in this phase (we are still pursuing that line of research), the current results prefigure the possibility of obtaining more accurate results when applying a supervised classification is applied. Also, the correct detection of the “sand” class would allow us a precise determination of the boundary of the Posidonia growth. The multi-temporal analysis of that boundary would be particularly useful in the study of coastal erosion.

Thus the implemented modules thus form, together with the bathymetry calculation module already implemented in ENVI by us, form a tool set for the treatment of water images, able to detect the coastal dynamics over an historical series of data.

Acknowledgments
We would like to thank Planetek Italia for kindly providing the WorldView-2 sample scene. This research was co-financed by the Autonomous Regional Government of Sardinia (Regione Autonoma della Sardegna) with funds from the “PO Sardegna FSE 2007-2013” and the Regional Law 7/2007 “Promotion of scientific research and technological innovation in Sardinia”.

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Received 12/02/2011, accepted 04/07/2011
Monitoring spatial and temporal distribution of Sea Surface Temperature with TIR sensor data

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Abstract
This study was primarily aimed at verifying the potentiality of medium spatial resolution Thermal Infrared (TIR) data in monitoring environmental aspects strictly correlated to SST (Sea Surface Temperature), such as industrial cooling water discharges and the increase in seawater temperature over time, at two coastal sites in the Apulia region (Italy). TIR data acquired by LANDSAT ETM+ and ASTER satellite instruments were used to observe SST and provide insight into its spatial variability, in this case totally lacking information from conventional in situ measurements. The spatial information obtained, clearly mapped for its visual interpretation, can significantly contribute to improving general surface near-shore water quality monitoring.

Keywords: Thermal Infrared; LANDSAT ETM+; ASTER; Sea Surface Temperature.

Introduction
A significant population percentage lives in low elevation coastal areas and is directly at risk from sea-level rise, coastal erosion, stronger storms and other seaward hazards induced by climate change [McGranahan et al., 2007]. The remaining coastal areas undergo intense anthropogenic effects. The continuous increase and additive effect of various pollution sources lead to a progressive eutrophication and microbiological contamination of water, making it substantially more difficult to use for human needs [Kaplan et al., 2003]. As a consequence of the increasing threat to our environment, it is important to organize coastal water area monitoring, and create corresponding systems, including the most recent aerospace platforms [Bondur, 2005].

Thermal infrared (TIR) sensors have been successfully deployed at global scale on operational meteorological satellites for over 30 years to provide images of cloud top and sea surface temperatures (SST). Since TIR radiance depends on both the temperature and emissivity of the target, and the emissivity will vary as the land cover changes, it is difficult to measure land surface temperatures. On the other hand, the emissivity of water is known and nearly constant (98%), approaching the behaviour of a perfect blackbody radiator [Klemas, 2009]. Considering that the TIR radiance measured over the oceans will primarily vary with SST, an accurate determination of SST (± 0.5 ºC) can be performed through some atmospheric corrections [Ikeda and Dobson, 1995]. Accurate long-term SST observations are important to a wide range of oceanographic studies and global-scale events, e.g. to investigate western boundary currents, such as the Gulf Stream and Kuroshio, or to monitor...
El Niño events of major upwelling areas and the elevated SSTs damaging coral reefs which support a large diversity of sea life.

At local scale, TIR data can aid identifying a severe environmental phenomenon which may extend for only a few kilometres studying estuary and coastal thermal plumes: thermal pollution resulting from power plant and industry discharges of water used in cooling processes. Aquatic life gets affected as the thermal pollution lowers dissolved oxygen and increases respiration rates, killing an ever-increasing quantity of fish in their positive feedback cycle. The density and viscosity of water also decrease as temperature increases. This results in a faster settling of suspended solids. The rate of evaporation significantly increases too as temperature increases, resulting in a greater wastage of water in the form of its vapour.

The Thematic Mapper (TM) on the LANDSAT -5 satellite, launched March 1, 1984, and the Enhanced Thematic Mapper Plus (ETM+) on the LANDSAT -7 satellite, launched April 15, 1999, provide a single 10.5-12.5 μm TIR band. The main differences between these two technologies are related to spatial resolution and Noise-Equivalent Temperature Difference (NEΔT), respectively 120 m and NEΔT of ≤ 0.30 at 280 K for the LANDSAT -5 and 60 m and NEΔT of 0.22 at 280 K for LANDSAT -7 [Barsi et al., 2003]. The launch of LANDSAT ETM+ was followed by the introduction of the first Earth Observing System (EOS) platform, subsequently named Terra, which included the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) with five thermal infrared spectral bands, each with a spatial resolution of 90 m and NEΔT of ≤ 0.3 K at 280 K [Yamaguchi et al., 1998].

The capability of these new instruments allows to develop new applications with thermal infrared data in order to address new issues that could not be addressed with earlier instruments [Steissberg et al., 2005]. LANDSAT sensors proved to be useful in studying inland water processes [Rogers et al., 1976] and the clarity and color of water associated with changes in sediment input or the amount of chlorophyll [Choubey, 1998]. Thermal infrared data can be processed to look at changes in the surface temperature associated with upwellings or changes in circulation [Schladow et al., 2004; Steissberg et al., 2005]. Gibbons and Wukelic [1989] demonstrated the potential use of LANDSAT-4 and 5 TIR imageries in estimating SST in coastal thermal plumes. Xing et al. [2006] integrated LANDSAT-5 and LANDSAT-7 TIR data to detect the thermal pollution of cooling water discharge from the Daya Bay nuclear power station. Ahn et al. [2006] derived detailed SST maps through LANDSAT-5 and 7 sensors, with enhanced information about the plume shape, dimension and direction of dispersion of waste water, in order to study the thermal impact of warm water discharged from Younggwang nuclear power plant on the coastal marine ecosystem. Teggi [2010] proposed a method for improving the spatial resolution of ASTER TIR data aimed at mapping small bodies of water or near coasts.

This paper is the first step to investigate the potential of medium resolution satellite TIR data in monitoring SST anomalies due to various environmental pollutants at two Apulian coastal sites, Brindisi and Taranto respectively (Fig. 1). The analysis was implemented on single LANDSAT and multi-date ASTER data in a remote sensing image processing software environment [ITT, 2009]. Due to the lack of contemporaneous ground surveying, the resulting maps were qualitatively compared with the SST measurements published by the Maritime Department of the Italian Agency for the Environmental Protection and Technical Services (APAT).
Data and methods

**Study case 1. The coastal water area of Brindisi**

The first analysis was conducted on one LANDSAT ETM+ TIR data set (acquisition date: July 6th, 2001) from the Southern coast of Brindisi which hosts ENEL “Federico II” power plant (Fig. 2). The plant complex includes 4 sections divided by polycombustible thermoelectric power of 660 MW each, which came into service between 1991 and 1993. This plant made Brindisi a leader in the production of electricity in Italy. The area considered suffers from severe environmental problems, not only in terms of atmospheric pollution from coal combustion but also of sea bed degradation near the heat water discharges of local cooling ponds [Akella et al., 2009].

To improve the accuracy of thermal pollution identification in TIR sensor data, the high-resolution panchromatic data (15 m) was co-georeferenced (reference system UTM 33
– WGS 84) in order to verify the coastal line coincidence in both the images.

LANDSAT ETM+ and ASTER sensors acquire surface temperature data and store it as 8 bit Digital Numbers (DNs). In order to convert these DNs to temperature data, the procedure was subdivided into two phases, the first for data calibration and the second one for radiometric temperature identification [Zhang et al., 2008].

Radiometric calibration was preliminarily carried out to derive thermal radiance \( L_{\text{sensor}} \). The Digital Number (DN) values of band 6 were converted into spectral radiance \( L (\text{w} \times \text{m}^{-2} \times \text{sr}^{-1} \times \mu\text{m}^{-1}) \) using the following equation:

\[
L_{\text{sensor}} = \text{gain} \cdot DN + \text{offset} \quad [1]
\]

This is also expressed as:

\[
L_{\text{sensor}} = L_{\text{min}} + ((L_{\text{max}} - L_{\text{min}}) / 255) \cdot (DN - L_{\text{min}}) \quad [2]
\]

where \( L_{\text{max}} \) and \( L_{\text{min}} \) are the spectral radiance values for band 6 at digital numbers 1 or 0 and 255, respectively. Moreover, it is known that band 6 of LANDSAT ETM+ is always acquired in low (L) and high (H) gain states. Band 6L provides an expanded dynamic range and lower radiometric sensitivity and can measure temperatures in between \(-70 \degree \text{C}\) and \(+90 \degree \text{C}\), whereas band 6H has higher radiometric sensitivity (although it has a more restricted dynamic range) and can measure temperatures in between \(-30 \degree \text{C}\) and \(+60 \degree \text{C}\). For band 6L, \( L_{\text{min}} = 0.0, L_{\text{max}} = 17.04 \); for band 6H, \( L_{\text{min}} = 3.2, L_{\text{max}} = 12.65 \). The values for all these parameters were obtained from data header files.

Next, the spectral radiance \( L_{\text{sensor}} \) was converted into at-sensor brightness temperature \( T \) in Kelvin. The conversion formula is given by:

\[
T_{\text{sensor}} = \frac{K_2}{\ln \left( \frac{K_1}{L_{\text{sensor}}} + 1 \right)} \quad [3]
\]

where \( T \) is the at-sensor brightness temperature in K; \( K_1 \) (666.09 K) and \( K_2 \) (1282.71 K) are calibration constants.

The resulting temperature map was not technically considered as a proper SST map, because it also needed to be atmospherically corrected, using either a model or calibration with in situ data. In this case raw LANDSAT TIR data were not atmospherically processed due to the lack of ground based temperature measurements at the time of the satellite overpassing the instruments mounted on the stations located across the study area. The accuracy and precision of deriving surface temperatures from LANDSAT TM band 6 data have already been assessed in a study by Schneider and Mauser [1996], who employed a full atmospheric model to convert at-satellite radiance to an accurate measure of water leaving radiance (and thus water temperature) at a lake in Germany for which extensive in situ water temperature data were available. On average (across 31 images), atmospheric correction increased satellite-derived temperatures by 1.33 K between 9:00 and 11:00 h, the standard crossing times of LANDSAT satellites. Humes et al. [2005]
proved that TM-derived temperature was slightly higher than the ground-based temperature (approximately 1.5 °C). With most current satellite observations at 1 km pixel scale, significant variations in near surface meteorological conditions may be observed, depending on surface conditions. Methods using satellite data indicate at least a ≈ 3 K uncertainty in the estimate of SST when compared to standard weather station observations [Goward et al., 1994; Prince et al., 1998]. Thus, we may expect to slightly underestimate temperatures when corrections are not made, although the exact error shall depend upon specific atmospheric conditions.

In this case study, to effectively improve the visual interpretation of SST variations in the processed image, the Linear Stretching function was lastly applied (Fig. 3). A linear stretch clipped off a portion of the histogram tails and then effectively increased the dynamic range by stretching the remaining histogram over the full 0–255 data range. The pixel values in the lower portion of the histogram were automatically set to 0 and the values in the upper portion of the histogram clipped were set to 255.

![Figure 3 – Map showing the spatial distribution in °C of Sea Surface Temperature (SST) near the power plant “Federico II” of Brindisi (acquisition date: July 6th, 2001).](image)

**Study case 2. The coastal water area of Taranto**

The coastal water area in the Gulf of Taranto (Ionian Sea) was investigated in this study because of its complex environmental system. It consists of a coastal marine area between two sea basins known as “Mar Grande” and “Mar Piccolo”. Mar Grande is characterized by the presence of important naval and industrial activities. This sea area is connected to the basin of Mar Piccolo by two narrow channels, the so-called “Navigabile” and “Porta Napoli” channels. Mar Piccolo washes the Northern town area of Taranto. It is an inner, semi-enclosed basin with a 21 km² surface area, divided into two inlets, called first and second inlet, which have a maximum
depth of 13 and 8 m, respectively. Its marine ecosystem features a number of lagoons, strongly modified by human activities. Being a semi-enclosed basin, it is affected by water exchange mainly due to its moderate tidal range, which does not exceed 30-40 cm [De Serio et al., 2007]. The source of pollution in Mar Piccolo mainly originates from urban effluents, discharges from local industries, spillages from vessels, harbour operations, and presumably atmospheric transport [Mossa, 2006]. In addition, a large industrial settlement (the most important steelworks in Europe) and a petroleum refinery also affect the neighbourhoods of Taranto, while small rivers and freshwater springs drain the surrounding agricultural soils in the basin of Mar Piccolo [Pisoni et al., 2004; Cardellicchio et al., 2007].

The analysis of this study area was carried out on the multi-date TIR bands of ASTER sensor data (acquisition dates/time: August 11th, 2000 – time 10:07; June 18th, 2006 - time 9:46; August 24th, 2007- time 9:46).

In the preprocessing phase the In-Scene Atmospheric Correction (ISAC) algorithm [Young et al., 2002] was applied, only considering at-aperture radiance data to estimate the upwelling radiance and transmissivity of the atmosphere.

\[ L_{\text{obs}} = \tau \cdot B(T) + L_u \] \[ 4 \]

In eq. [4] \( L_{\text{obs}} \) is the observed at-aperture radiance, \( \tau \) is the transmission of the atmosphere, \( B(T) \) is the Planck function, and \( L_u \) is the upwelling radiance due to the atmosphere. Figure 4 shows the atmospheric transmission and upwelling spectra related to the five TIR ASTER bands for every single acquisition date, using the Thermal Atmosphere Correction function of the ENVI image processing [ITT, 2009].

Next, the brightness temperature of each pixel from the pixel radiance was derived. For such purpose, digital number (DN) values of thermal infrared bands were converted into spectral radiance \( L_s \) \( (\text{W} \times \text{m}^{-2} \times \text{sr}^{-1} \times \mu\text{m}^{-1}) \) using the following equation:

\[ L_{\text{sensor}} = \text{gain} \cdot (\text{DN} - 1) \] \[ 5 \]

where \( \text{gain} \) is different in different bands:

\( \text{gain}(10) = 0.006882, \text{gain}(11) = 0.006780, \text{gain}(12) = 0.006590, \text{gain}(13) = 0.005693, \text{gain}(14) = 0.005225. \)

Secondly, spectral radiance was converted into brightness temperature by means of the following equation

\[ T_{\text{sensor}} = \frac{c_2}{\lambda_c \ln \left( \frac{c_1}{\lambda_c (L_{\text{sensor}} + 1)} \right)} \] \[ 6 \]

where:

\( c_1 = 1.191 \times 108 \, \text{Wm}^{-2}\text{sr}^{-1}\mu\text{m}^{-1}, \) \( c_2 = 1.439 \times 104 \, \mu\text{m K}, \lambda_c \) is the wavelength in \( \mu\text{m}. \)

In the final phase, the apparent emissivity image was obtained by normalizing the radiance of each pixel to the Planck’s curve that was generated from the pixel with the
maximum brightness temperature at an emissivity value of 0.98 (a reasonable hypothesis for water) [Schmugge et al., 2002].

The resulting SST showed substantial concordance with the ground based temperature measurements taken at the time of the satellite overpassing the mareographic station (SM3810 model) located at the pier St. Eligio in Taranto’s harbor. Such measurements were published by the Maritime Department of the Italian APAT. At 10:00 h, the crossing time of ASTER satellites, the measured temperatures were: August 11th, 2000 – 24.5 °C; June 18th, 2006 - 22.0 °C; August 24th, 2007- 27.2 °C.

Lastly, to make previous image treatments more effective and enhance the interpretation of SST variations in the processed image, the Linear Stretching function was implemented in this study case, too.

Figure 4 – Plots of the resulting atmospheric transmission and upwelling spectra related to the five TIR ASTER bands.
Results and conclusions
The final data from both study cases were interpreted in order to better understand the environmental processes affecting both areas.

The SST values derived from LANDSAT thermal data were divided in two distinct zones (zone 1 and zone 2) in the coastal area of Brindisi, with 20.51 °C \((T_1)\) and 23.25 °C \((T_2)\) values as mean temperatures (Fig. 5). The rate of change in temperature \(\Delta T\) between zone 1 and zone 2 was then calculated, normalizing the difference between \(T_1\) and \(T_2\).

\[
\Delta T(\%) = \frac{(T_1 - T_2)}{T_2} \times 100 = 13.26\% \quad [7]
\]

The resulting SST spatial distribution combined with the obtained increase in temperature \(\Delta T\) between zone 1 and zone 2 demonstrated the effectiveness of this image data analysis in upwelling thermal anomalies in sea water.

As to SST spatial and temporal distribution in the Gulf of Taranto’s study area, a qualitative analysis of the time series processed from ASTER showed a progressive increase of temperature, especially for 2007 data (Fig. 6). The resulting image showed a significant SST rise for the second inlet of Mar Piccolo, correlated to its weak currents, resulting in attenuated mixing and dispersion. As for the first study case, the prevalence of temperature anomalies can’t but emphasize the vulnerability of the coastal area studied.

The examination of results as presented in this study shows the effectiveness of satellite...
methods and technologies in thermal monitoring of coastal areas subjected to intense atrophic activities. The SST maps derived from both TIR LANDSAT and ASTER sensors captured fundamental properties such as minimum and maximum temperatures, dates of temperature extremes, and rates of change in temperature, all useful in understanding estuarine and coastal processes which could hardly be recognized through lower spatial resolution.

![Figure 6](image)

Figure 6 – The SST changes identified on the multi-date TIR ASTER data (2000, 2006 and 2007) in the marine coastal area between Mar Grande and Mar Piccolo – Taranto.

In order to provide reliable information on favorable and unfavorable environmental conditions and in the water area studied, permanent monitoring should be maintained on major ground based parameters (current fields, wind speed and direction, air temperature, etc.). Such monitoring should be performed by processing and analyzing remotely sensed data and comparing it with the results of in-situ measurements. When new satellite techniques aimed at generating, organizing, storing, and analyzing spatial information are combined with watershed, estuarine and coastal ecosystem models, coastal managers and scientists have sufficient means to assess the impacts of alternative management practices.

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Received 27/01/2011, accepted 14/07/2011
Laser Scanner Applications in Forest and Environmental Sciences

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Abstract
Potential forest-related information can be obtained from processing data obtained from laser scanning sensors making this technology extremely useful for forest management and environmental assessment. It is thoroughly documented in recent literature how specific forest characteristics can be estimated at stand, plot and single tree level using laser scanner surveys at corresponding scales. The high resolution models of the canopy surface and of the bare earth (terrain), as well as the information obtained related to the structure of the volume between these two surfaces, concur at offering a more complete source of information not only for direct forestry-related applications, but also for connected disciplines such as hydrology, engineering, forest disturbances analysis and ecological assessment.

Having accurate and spatially distributed information over the above mentioned aspects give land assessment and management added value data to work with. Correct utilization of laser scanner data can lead to the assessment of many characteristics usually obtained by ground surveys. Ground-plots require significant expenditure in terms of human effort, economical investment and can be distributed on large areas only in limited number. The following paper shows the efforts which are being undertaken by scientific research towards testing laser scanner applications for forest and environmental sciences.

Keywords: Terrestrial Laser scanning (TLS), LiDAR, Forest Attributes, Ecological Assessment, Geomorphology.

Introduction
Laser scanner sensors measure distances between the sensor emitting the laser pulse and the surface which is intercepted by the laser’s light cone, thus returning the 3D coordinate of the position of that point on the surface. The frequency of the pulse emission is such that a large number of points are recorded per survey, therefore the dataset is usually referred to as point cloud. If the obstruction by the surface is only partial, as it is likely in the case of leaves in forest canopy, the pulse can penetrate, to a certain degree, and return a ground surface hit (Fig. 1a). The resulting dataset is a point cloud representing all surfaces which were intercepted by the laser light cone with their reflectivity. A laser scanner sensor can be used to equip satellite vectors, airborne vehicles or static mounts on the ground. When on the air it is usually referred to as airborne laser scanner (ALS), whereas on the ground it is
referred to as terrestrial laser scanner (TLS). LiDAR (Light Detection and Ranging) is the term which refers to using “time-of-flight” of the laser pulse as measuring system as opposed to other approaches such as structured light or interferometry. There is abundant literature relative to the principles of laser scanning technology [Crosilla and Galetto, 2003; Crosilla and Dequal, 2006; Heritage and Large, 2009], to applications to various fields [Tarolli et al., 2009; Vosselman and Maas, 2010] and to forestry in particular [Pirotti, 2009; Maas, 2010]. Nowadays certain laser sensors also provide the full return waveform, by digitizing the return pulse in a discrete time domain. This provides a full-waveform for the user to analyze, where the peaks represent the surfaces which cause reflection (Fig. 1b).

![Figure 1 – a). Discrete return laser scanner on airborne platform, b) full-waveform laser scanner with schema of return pulse shape [from Pirotti, 2009].](image)

Depending on sensor characteristics and survey method the points have a certain density and positional accuracy. The former can vary depending on pulse repetition rate; to give an idea, today’s sensors can give up to $2 \times 10^6$ measurements per second with an accuracy of 25 mm at a range of 150 m. The accuracy is referred to as the measurement accuracy, whereas the actual positional accuracy is usually around 10-20 cm at a flying altitude of 1000 m due to errors from position and orientation of the sensor/platform system. These characteristics are very important for many applications related to environmental assessment and earth modelling. Having a precise digital terrain model (DTM) and digital surface model (DSM) is fundamental for hydrology and geomorphology applications, as well as for assessing accessibility and terrain characteristics for mechanization in forest operations. The difference between the elevation of each pixel in the DTM and in the first return DSM gives the digital canopy model (DCM – synonymous of CHM). The relationship between the DCM and tree/canopy structure is well documented in literature - Popescu and Wynne [2004], Barilotti et al. [2007]. The penetration ability of the laser permits to have also information of objects between the canopy top and the ground surface, thus providing important information which can be used to derive forest structure and even information on single-tree metrics if the point density is
Forestry applications deal with the correlation between lidar-derived metrics and forest characteristics. The survey methods and resulting processing methods depend on the sensor used and on the point density [Dubayah and Drake, 2000].

**Laser scanner for forestry applications**

The characteristics which are useful for forest management are usually surveyed by planning ground plots which are representative of the study area. Many of these characteristics can be inferred from laser scanner data obtained from aerial or ground surveys, depending on what specific metrics are of interest.

**Terrestrial laser scanning**

Terrestrial laser scanning provides high resolution models of trees limited to smaller areas compared to ALS. It is a well suited technology for detailed modelling tasks. The limiting factors are the density of trees, the presence of undergrowth, the morphology of the terrain and the limited area which can be scanned at each scan station. Many scan stations are necessary when large areas are to be covered. Obstruction due to undergrowth or other objects is a critical factor. The main metrics which can be collected from a TLS survey are tree positions, diameter at breast height (DBH), tree heights, stem profiles and stem models (Fig. 2). Measurements can be done directly on the model, or statistical software (e.g. R) can be used for fitting shapes to the points automatically deriving forest inventory parameters [see Maas et al., 2008]. Bienert et al. [2006] have shown that 95% of trees can be detected on clean forest and DBH could be defined with an accuracy of 1.5 cm as well as tree heights with an accuracy of 80 cm. Maas et al. [2008] reported a similar accuracy on DBH (1.8 cm), but a worse accuracy on tree height measurement (2.07 m) when comparing LiDAR with hand-held tachymeter measures. This can be a promising technique for gathering information on small-scale plots as a way to bridge the gap between classic inventory techniques and airborne laser scanning surveys.

![Figure 2 – Examples of results from terrestrial laser scanner of single trees. Measurements are possible directly from the points (from Lingua and Pirotti [2009] - courtesy of CIRGEO).](image)

The objective of our future research is to test methods for automatic extraction of dendrometric and structural information by segmenting points in different interest classes (i.e. stem, leaves, ground, low vegetation) and isolating points returned by noise. New
possibilities from sensors with real-time full-waveform analysis – thus multiple returns from a single pulse – are being investigated. An accurate point classification can lead to better modelling of stems, which can be done by fitting mathematical shapes such as tetrahedrons or cones.

**Aerial laser scanning**

Using orbiting or airborne vehicles equipped with a laser scanner sensor permits to cover very large areas with varying point resolutions depending on the sensor’s pulse frequency and the speed and flying height of the vehicle. Full-waveform and discrete return sensors give different data products, but both give data of interest for establishing relationships between forest metrics and laser metrics. In both cases the fundamental aspect is the possibility to record the geometric information of the canopy surface, of the ground, and of elements in between these two layers (i.e. the forest structure). Figures 3 and 4 give a representation of this type of information. The objective of research is to find optimal models for extracting metrics of interest for forestry-related applications (i.e. forest inventory, biomass assessment, single-tree detection). The metrics considered are above ground biomass, wide-area stem volume estimation, DBH, canopy density, tree height distribution and tree position. It is not our intention to report all methods which have been successfully investigated for each metric, but indications on methods can be found in [Dubayah and Drake, 2000; Maas, 2010] about LiDAR for forest application in general, [Hollaus, 2009] for stem volume estimation, [Persson et al., 2002; Barilotti et al., 2007] for tree position detection and canopy structure, [Hyyppä et al., 2004] for forest measurements. It can be inferred from literature that most practical investigations have been done in northern European countries, Canada and the U.S.

![Figure 3 – High density point cloud profile over forest area.](image)

Processing full waveform requires more steps than processing discrete return data because the digitized waveform has to be processed to extract information and points. This process requires a filter to decrease noise and Gaussian models to detect the peaks and their characteristic width and amplitude (see [Vosselman and Maas, 2010] for a review
of methods and [Pirotti, 2011] for a review of forest-related applications). The number of points which can be extracted from a waveform depends on the method used, but it typically provides twice the amount of points as opposed to discrete return sensors [Reitberger et al., 2009]. The waveform can also be processed directly by extracting indices on the shape of the waveform itself [Pirotti et al., 2010], but this still as to be tested on different case studies. Research on this topic focuses on assessing which are the most applicable methods to waveform processing for extracting forest metrics. Not only which methods give best results, but also considering the method’s processing time and degree of complexity for end users.

Figure 4 – Results of processing full-waveform data – on the left part is the representation of waveform peaks in 3d space, on the right side is a raster representation of waveform metrics correlated to canopy density.

**Laser scanner for ecological assessment**

Models relating species to habitats or biotic communities to biotopes are among the most important tools for natural resources planning and environmental assessment. Such models are based on data varying in precision and reliability according to the available resources and the study area extent. Professionals and scientists have traditionally relied on field data, digital terrain models, site conditions (soil, water, geology, climate, vegetation) or on remote sensed data: aerial photos or, more rarely, satellite images. LiDAR makes possible to obtain, on continuous and wide surfaces, important parameters of the stand structure that, usually, are the most time consuming to measure on the field. Canopy cover density and other canopy structure metrics surveyed on the field can be easily related with the canopy height obtained from a DCM grid made up of 1-25m² pixels. The availability of georeferenced field data should permit to find the relations between them and the remote sensed LiDAR data, and to verify the possibility to adopt DCM as a surrogate of field measured data. The relations and the variance proportion of the field
surveyed data explained by the LiDAR data could be found by a simple linear regression. In an English study [Hinsley et al., 2002; Hill et al., 2004] about two species of tits (*Parus major* L. and *P. caeruleus* L.) the mean height calculated with LiDAR in 54 x 54 m plots centred on the surveyed nests, were associated with an index of reproductive success proportional to the habitat quality. This relation was extended over the whole forest to predict the habitat quality. The same criteria can be applied to realize habitat suitability maps for the management of animal and plant communities, like Graf et al. [2009] made for Capercaillie (*Tetrao urogallus* L.). The availability of data from combined sensors, (e.g. LiDAR and hyperspectral imagery), gives the possibility to add to stand structure variables also the stand composition [Bradbury et al., 2005]. A case study of integration between multispectral and LiDAR data in an Italian protected area is described in Dal Ponte et al. [2008]; the author concludes that the elevation value of the first LiDAR return is very effective for the separation of species with similar spectral signatures but different mean heights, and propose a novel classification system, based on different possible classifiers that were able to properly integrate multisensor information.

The fundamental role of the microhabitat heterogeneity for the community diversity is well known, especially for birds [Roland, 1976]. The DCM permits to calculate the spatial variability of the values, at habitat level, of some important attributes related to a taxon presence and abundance. From the DCM is possible to gain several information, also at landscape scale, like the boundary between woodland and not woodland land uses, or between different ecosystems, therefore quantifying with GIS the ecotone length, that could be a determinant of the animal species selection. Moreover, the height variability on the horizontal space, at spatial resolutions appropriate for the parameterization of the species-habitat relations, can be gained from LiDAR. Figure 5 shows an example of heterogeneity mapping of tree canopy on a horizontal space, which could be useful to characterize the habitat of species affected by the forest stand structure variability, like the Hazel grouse (*Tetrastes bonasia* L.) [Åberg et al., 2003].

If the sensor can record not only the first and last return (necessary for extracting the DCM), but also intermediate returns, it is possible to obtain indices of vertical structural stand complexity that could be used as indices of habitat quality, as Clawges et al. [2008] have done for birds. However, the complete analysis of all the vegetation layers is possible only with full waveform LiDAR, that permits to map vegetation topography under the canopy and crown heights to within 1 m [Turner et al., 2003]. Beside the elevation, the record of several back pulses of the FW sensors, makes it possible to estimate the density of vegetation at different heights and a 3-d profile of the vertical stand structure. Hyde et al. [2006] demonstrated that the FW LiDAR sensors are capable to estimate, without the help of other sensors, the tree canopy cover and biomass, and have adopted the data from a 9-11 m footprint, as a base to draw a map of stand structure at landscape scale of animal habitats. Similar studies were conducted to predict bird species richness [Goetz et al., 2007], density [Clawges et al., 2008] or habitat quality [Goetz et al., 2010]. Usually, these studies tend to identify, like the discrete data, first, the relations between the habitat quality and the measures derived from LiDAR data (density, mean height, canopy cover, biomass, etc.) then the relations between the latter and the field surveyed data, to verify their accuracy, which is normally good, even in ecosystems with rough and complex terrains [Hyde et al., 2005].
LiDAR-derived high resolution digital models for forest operation management

LiDAR has revolutionized the survey of accurate and high resolution elevation data over large areas. This adds value to the analytic competence of foresters to evaluate and design forest road networks and to plan forest operations.

As reported by White et al. [2010], the LiDAR data analysis offers several advantages for mapping road features. The detection of forest road under canopy was approached by
considering the road as a continuous, linear voids in near-ground vegetation. The voids were identified using three-dimensional LiDAR points clouds [Lee et al., 2005]. More precisely, David et al. [2009] deals with road and pathway detection in a complex forested mountainous area by distinguishing automatically and semi-automatically the forest road seeds. As a consequence the full pathways were then defined and vectorized. The LiDAR point clouds were successively generated for each point of the pathways to estimate more accurately the road widths.

Table 1 - Some studies that used stand structure data from discrete LiDAR for the analysis of forest habitats [after Sitzia, 2009]. A synthesis of studies in non forest ecosystems can be found in Vierling et al. [2008].

<table>
<thead>
<tr>
<th>Authors</th>
<th>Species</th>
<th>Location</th>
<th>Extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hinsley et al. [2002]</td>
<td>Great tit (<em>Parus major</em> L.) and Blue tit (<em>Parus caeruleus</em> L.)</td>
<td>Monks Wood, Cambridgeshire (UK)</td>
<td>157 ha</td>
</tr>
<tr>
<td>Broughton et al. [2006]</td>
<td>Marsh tit (<em>Poecile palustris</em> L.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nelson et al [2005]</td>
<td>Delmarva fox squirrel (<em>Sciurus niger cinereus</em> L.)</td>
<td>Delaware (USA)</td>
<td>6452 km²</td>
</tr>
<tr>
<td>Graf et al. [2009]</td>
<td>Capercaillie (<em>Tetrao urogallus</em> L.)</td>
<td>Swiss Prealps (CH)</td>
<td>17.7 km²</td>
</tr>
</tbody>
</table>

At application level, the use of a LiDAR resolution between 2 and 3 points per square meter – with the relative derived DTM – is ideal for several basic analysis that can be carried out by forester using common GIS tools.

The length, the centerline and the longitudinal profile of the forest roads can be easily detected just by interpreting the digital terrain model and the digital canopy model. White et al. [2010] reports on results of a comparison of the accuracy of road gradients calculated from a high resolution DTM (cell size 1 m) derived from LiDAR data with 2 points per square meter and road gradients derived by traditional DTM (cell size 10 m). The road gradients were calculated every 10 m segment of a forest road in a mountainous area located in Trento Province (Northeastern Italy). Unexpected values (gradient higher than 30%) were observed on the road gradients extracted from the traditional DTM. Instead the gradient derived by the high resolution DTM reported values with a not significant difference form the value calculated on the field. Also by comparing the two results, the gradient derived by the 10 m DTM are significant higher than the gradient derived by the high resolution DTM (Fig. 6).

The cable line layout for log extraction can be also previously studied by interpolating the DCM to identify the highest group of trees and by interpolating the DTM to determine the terrain profile. The extracted point of interest such as support and anchor trees can be then plotted as layer in a computer aided design file (CAD) to study the layout of the line or they can be exported into a spreadsheet in order to define the minimum clearance between the skyline and the terrain profile and to calculate support and anchor forces.

**LiDAR for Geomorphology**

Information about topography is one of the most critical issues in geomorphology. Several
applications use surface morphology as the basis for earth surface processes analysis and modelling [Tarolli et al., 2009]. Some features that can be recognized may reflect erosion/deposition activity due to climate (rainfall) and/or geology (tectonic). Such analyses are accurate as much as accurate and detailed is the information that can be derived from topographic data.

The availability of high-resolution topography given by laser scanners offers now the opportunity to better characterize and differentiate the landslide morphology and for the determination of the location and distribution of landslide activity [McKean and Roering, 2004; Ardizzone et al., 2007; Tarolli et al., 2010], for the numerical modelling of shallow landslides [Tarolli and Tarboton, 2006], for geomorphological mapping of glacial landforms [Smith et al. 2006], for recognition of depositional features on alluvial fans [Frankel and Dolan, 2007], for the characterization of channel bed morphology [Cavalli et al. 2008], and for the the analysis of the hillslope-to-valley transition morphology and of the topographic signature of valley incision by debris flows and landslides [Tarolli and Dalla Fontana, 2009]. In the last few years, some researchers started to use high-resolution topography and landform curvature for channel head identification [Tarolli and Dalla Fontana, 2009], and channel network extraction [Passalacqua et al., 2010; Pirotti and Tarolli, 2010; Sofia et al., 2011]. These works reconsidered the classical procedures for channel network extraction introducing new methodologies, and reaching more detailed results than those obtained in the past.

Figure 7 shows the curvature map, calculated from 1 m DTM, and the related channel network extracted using the objective methodology proposed by Tarolli and Dalla Fontana [2009] and based on the threshold range identified as being n-times the standard deviation of landform curvature. In the same figure is also shown the reference network for a comparison with the extracted one.

Looking at Figure 7a, one can easily feel how topographic signatures from high resolution LiDAR data better discriminate channel network (blue colour) from hillslope elements. These new methodologies for channel network extraction based on high resolution topography really represent an advance for automatic feature extraction, and so a future challenge for understanding earth surface processes.
Figure 7 - Curvature map (a), channel network extracted (b), and reference channel network surveyed and mapped in the field by DGPS (c). Colour themes of curvature map is classified on the basis of multiples of standard deviation.

Figure 8 shows another example on the effectiveness of high resolution LiDAR derived topography in the recognition of earth surface features. In the analysis were considered some geomorphic features (surveyed in the field by DGPS) related to landslide crowns and bank erosion (Fig. 8c).

Figure 8 - Maximum curvature map (a), extracted features under the best performance of the methodology proposed by Tarolli et al. (2010) (b), reference features surveyed and mapped in the field by DGPS (c). The red arrows are related to shallow landslide crowns, and bank erosion correctly labeled.
Figure 8a shows the map of maximum curvature, according to Evans’ method [1979], obtained with kernel of 21 x 21 pixels, while Figure 8b shows the best extraction obtained with a threshold value of 1.5 IQR (Interquartile Range) of maximum curvature. If one compares the extracted features with those surveyed in the field (Fig. 8c), it is possible to observe how the main features were rightly detected. Obviously this is not a perfect extraction since a noise is present in the upper part of the study area. The methodology tends to recognize features where convex slope breaks are not related to instability [Tarolli et al., 2010]. Nevertheless, this methodology should be considered as a first and relatively fast approach to slope instability mapping when using high-resolution topography and it can be used to interactively assist the interpreter/user on the task of shallow landslide and bank erosion hazard mapping [Tarolli et al., 2010].

Conclusions
The topic of LiDAR applications for forestry and environmental purposes is very broad. This paper’s objective was to tie together recent developments over this field of research. It can be seen that the effort in further investigation is increasing and that LiDAR technology is still to be fully exploited, especially from a practical point of view. Many aspects of forestry and environmental analysis have included LiDAR data as part of the surveying protocols for various applications. Just to name a few: forest inventory, hydro-geological risk analysis, flood modelling, biomass and bioenergy quality and quantity assessment, ecological analysis, terrain modelling as a support to forest operations.
To describe the main pivot-points of what has been reported and propose a focus for future research, we can state that the following facts can be considered important:
- LiDAR technology is still improving, thus it is important to exploit new possibilities becoming feasible with new features (e.g. multi-return TLS, full-waveform analysis, LiDAR satellite ICESat2 with increased point density etc.).
- Protocols still have to be tested, especially in some countries, for importing LiDAR into existing workflows (e.g. in forest inventory).
- LiDAR surveys are costly and provide massive amounts of data, thus it is important to determine optimal characteristics (i.e. point density, necessity of multispectral information, to use full-waveform or not, etc.) for certain applications in order to achieve maximum efficiency both economically and from the point of view of processing methods. These considerations bring to the conclusion that a multi-disciplinary approach is essential when considering LiDAR as a way to gather the necessary data for analysis.

Acknowledgements
The authors wish to thank CIRGEO (Interdepartmental Research Center in Cartography, Photogrammetry, Remote Sensing and G.I.S.) of the University of Padova for image material. Part of this work is relative to a project financially supported by the University of Padova (Progetto di Ricerca di Ateneo 2009 – CPDA097420) and to a research contract with the Forest Service of Trento Province, that provided the DCM and the aerial photo used in Figure 5.

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j.geomorph. 2009.07.005.

Received 12/02/2011, accepted 6/07/2011
Estimating forest timber volume  
by means of “low-cost” LiDAR data

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Abstract  
The main purpose of the present research is to verify whether medium resolution LiDAR  
data, not forest-specific, can be used to carry out statistical models for estimating timber  
volume.  
LiDAR data with different characteristics, and taken in different seasons (winter and  
summer) on the same forest area (Foresta di Paneveggio, Trentino, Italy), were processed,  
and an estimation model using winter low-resolution data was performed. Such model was  
then applied to a different territory, having similar forest characteristics. Moreover, LiDAR  
and ground data, surveyed during the management plan inventory, were integrated.  
The final model allows to obtain good volume estimates with fair precision if applied at  
forest compartments level, and can produce detailed timber volume maps, very useful when  
planning forestry operations.  
Keywords: LiDAR, Airborne Laser scanning, Forest inventory, Forest planning, Timber  
volume.

Introduction  
Trentino province (North-East of Italy) has recently changed its forest management  
inventory procedures for growing stock estimates, moving from total callipering, currently  
performed on a small part of the forested areas because of cost reasons, to statistical sampling  
methods, in particular a stratified aligned systematic network of angle count samples (ACS).  
Stratified sampling was chosen in order to increase the precision of inventory estimates.  
Thus the strata (forest aggregations similar for species composition and structure) are  
defined by a preliminary activity carried out mainly by photo-interpretation and ground  
exploring. The sample point density on each stratum is initially calculated according to  
basic Bitterlich dimensioning principles [Bitterlich, 1984], and then modified according to  
the main features tought more likely affecting the strata internal variability. Such a sampling  
scheme allows to obtain reliable estimates of the investigated attributes in terms of the main  
statistical parameters (total, mean, standard error), but nothing is known inside the strata.  
Yet, foresters want to know something more about attributes distribution within two other  
spatial elements which are currently referred to in daily forest management operations,  
the forest compartment (marked on the ground, 15 ha wide on average in Trentino) and  
the stand, an highly homogeneous part of the forest compartment, 3 ha wide on average in
Trentino, accurately described under site / ecological / forest features [Scrinzi et al., 2008; Wolynski et al., 2008]. Continuous maps of a given attribute over the spatial domain of the inventory can be obtained by a proper coupling of data remotely sensed over the whole region of interest and ground data collected at inventory locations only [Corona, 2010]. In this light, LiDAR (Light Detection And Ranging) technique can provide a significant contribution both in the three-dimensional modelling of forest stands and in estimating main structural and biometric parameters of forests, such as basal area, timber volume and biomass [Dubayah and Drake, 2000; Renslow et al., 2000; Naesset, 2004; Barilotti et al., 2005; Packalén and Maltamo, 2006; Abramo et al., 2007; Corona and Fattorini, 2008]. Almost all the studies carried out in forest research have so far used LiDAR data with optimum technical requirements (high resolution, wide and well georeferenced ground calibration areas), the cost of which is often not compatible with the resources available in forest monitoring and management. Therefore, the aim of this study was to verify whether lower quality LiDAR data (i.e. data available over large areas) can be still adequate for timber volume estimation models, especially when applied at forest stand or forest compartment level. To this end, the ground calibration was also performed using data derived from ordinary context, such as forest management surveys by relascopic samples, collected with low-precision GPS georeferencing (approximately from 2 to 10 m of uncertainty). In addition to the statistical performance of the models, particular attention was given to ensuring their simplicity and to the possibility of carrying out all the processing phase within current GIS applications, avoiding the use of highly specialized software packages. The methods and results of a number of practical tests that have been carried out with reference to these issues in the Trentino province, in forest areas for which high quality and lower quality LiDAR data was available, are outlined here.

**Materials and methods**

**Characteristics of LiDAR data**

During the 2006-2007 winter seasons, the Province of Trento acquired LiDAR data over most part of its territory in order to produce a Digital Terrain Model (DTM) having 1 m of spatial resolution, 1 m of horizontal accuracy (2-σ) and 60 cm of vertical accuracy (2-σ). As a secondary product of these data, a Canopy Height Model (CHM) was calculated for all forest areas of the province, as well. In addition, the Forest Service of Trentino Province acquired other LiDAR data surveyed in summer 2008, specifically targeted to forest monitoring, on four most representative forest districts of the province, and produced a CHM too. In both cases small-footprint and discrete return processing were used. Data filtering and classification were performed by the vendor using Terrascan software (Terrasolid inc.) and the Axelsson algorithm [Axelsson, 2000; Vosselmann, 2003]. The native point cloud density was 1.3 pp×m⁻¹ (winter flight) and 5 pp×m⁻¹ (summer flight), respectively. The main metadata of the two flight campaigns are reported in Table 1.

**Study Areas**

Out of the four areas for which both LiDAR flights were available, the Foresta Demaniale di Paneveggio (Valle di Fiemme, Eastern Trentino) was chosen as the sample area (Fig. 1). On this area a timber volume estimation model, based on summer 2008 LiDAR shot and data
Table 1 – Main metadata of winter and summer LiDAR flight campaigns.

<table>
<thead>
<tr>
<th></th>
<th>WINTER survey</th>
<th>SUMMER survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laser scanner</td>
<td>Optech ALTM 3033</td>
<td>Optech ALTM 3100C</td>
</tr>
<tr>
<td>Airborne</td>
<td>PARTENAVIA P68</td>
<td>Helicopter ECUREUIL AS 350 B2</td>
</tr>
<tr>
<td>Height of flight</td>
<td>1500-1800 m agl</td>
<td>1000 mt agl</td>
</tr>
<tr>
<td>Impulse frequency</td>
<td>33 kHz</td>
<td>70 kHz</td>
</tr>
<tr>
<td>Point density</td>
<td>1.3 pp/m²</td>
<td>about 5 pp/m²</td>
</tr>
<tr>
<td>Footprint diameter</td>
<td>25-30 cm</td>
<td>25-30 cm</td>
</tr>
<tr>
<td>Altimetric accuracy</td>
<td>15-30 cm (1 σ)</td>
<td>15 cm (1 σ)</td>
</tr>
<tr>
<td>Number of returns</td>
<td>2 (first and last)</td>
<td>4</td>
</tr>
</tbody>
</table>

surveyed on ground plots, was already available [Floris et al., 2010]. This forest (about 370 ha in size) is a typical sub-alpine Norway Spruce forest, located between 1500 and 2100 m m.s.l. of altitude. The dominant species is Norway spruce (*Picea abies* (L.) Karsten), sometimes mixed with Swiss stone pine (*Pinus cembra* L.) and Larch (*Larix decidua* Mill.).

A second study area was located in the Foresta demaniale di Cadino (Valle di Fiemme), which has forest characteristics similar to Paneveggio forest: a subalpine Norway Spruce forest, located at altitudes comprised between 1400 to 1800 m m.s.l. For this area (about 900 ha in size, Fig. 1) only the winter LiDAR data was available (Fig. 2); moreover, its Forest Management Plan was undergoing a ten year revision in 2008-2009, and so recent ground data from the sampling inventory was available as well. For these reasons the Cadino forest was a particularly interesting area on which to apply and test the models.

**Ground data collection and processing**

In the Foresta Demaniale di Paneveggio, 39 circular ground plots, with a fixed radius of 20 m (lower stem density) or 13 m (higher stem density) were surveyed and the following attributes were collected for each tree: species, dbh_{130}, total height. From this data, basal area and timber volume (individual and per hectare) were calculated. More details about data collection and processing can be found in Floris et al. [2010].
A summary of measured and calculated parameters is reported in Table 2. In the Foresta di Cadino ground data from the management plan was used: it consisted in 365 angle count samples, chosen by a stratified aligned systematic sampling design, where basal area per hectare was measured using relascopic technique [Bitterlich, 1984], and then the volume per hectare was calculated by means of the local volume models ("tariffs") recently updated in Trentino [Scrinzi et al., 2010]. A summary of measured and calculated parameters is reported in Table 3.

Table 2 – Main dendrometric parameters collected on 39 ground sample fixed-radius plots in Paneveggio forest.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All trees</th>
<th>Trees above 17.5 cm dbh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean dbh diameter of the trees (cm)</td>
<td>28.0</td>
<td>38.0</td>
</tr>
<tr>
<td>Max dbh diameter of the trees (cm)</td>
<td>109.0</td>
<td>109.0</td>
</tr>
<tr>
<td>Min dbh diameter of the trees (cm)</td>
<td>3.0</td>
<td>17.5</td>
</tr>
<tr>
<td>Mean height of the trees (m)</td>
<td>18.2</td>
<td>26.1</td>
</tr>
<tr>
<td>Max height of the trees (m)</td>
<td>45.7</td>
<td>45.7</td>
</tr>
<tr>
<td>Min height of the trees (m)</td>
<td>1.6</td>
<td>7.8</td>
</tr>
<tr>
<td>Mean basal area (m² ha⁻¹)</td>
<td></td>
<td>51.6</td>
</tr>
<tr>
<td>Max basal area (m² ha⁻¹)</td>
<td></td>
<td>78.7</td>
</tr>
<tr>
<td>Min basal area (m² ha⁻¹)</td>
<td></td>
<td>16.6</td>
</tr>
<tr>
<td>Mean timber volume (m³ ha⁻¹)</td>
<td>615.8</td>
<td>596.7</td>
</tr>
<tr>
<td>Max timber volume (m³ ha⁻¹)</td>
<td>1016.7</td>
<td>1016.7</td>
</tr>
<tr>
<td>Min timber volume (m³ ha⁻¹)</td>
<td>136.1</td>
<td>118.3</td>
</tr>
</tbody>
</table>
Table 3 – Main dendrometric parameters collected on 365 angle count samples (ACS) in Cadino forest (trees with dbh > 17.5 cm).

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Basal area (m² ha⁻¹)</th>
<th>Volume (m³ ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>42.74</td>
<td>599.70</td>
</tr>
<tr>
<td>Max</td>
<td>104</td>
<td>1177.76</td>
</tr>
<tr>
<td>Min</td>
<td>4</td>
<td>21.65</td>
</tr>
<tr>
<td>St. dev.</td>
<td>17.81</td>
<td>223.97</td>
</tr>
</tbody>
</table>

The relation between winter CHM and summer CHM

For Paneveggio forest, a linear regression model to estimate timber volume per hectare (\(V\)), based on LiDAR data collected with a summer flight campaign, had been already
performed [Floris et al., 2010]. Such model used only the mean canopy height as predictive variable (HMEAN), calculated within a local matrix of given size. The main statistics of that model are summarized in Table 4 and Figure 3. In Paneveggio, both summer and winter LiDAR data being available, it was possible to study the existing relation between the two LiDAR-derived CHMs, in order to be legitimated to use the winter CHM to perform a volume estimation model. Firstly, a Map Algebra focal algorithm was applied to each CHM: the average value of canopy height within a local square matrix of 31 m side was assigned to the central pixel of the matrix itself. The size of the matrix was chosen having in mind the area probably explored, on average, by an angle count sample with BAF (Basal Area Factor) value of 4. The derived layers were called HMEAN_smr (summer flight) and HMEAN_wnt (winter flight). By averaging heights within the local square matrix it was reduced, at the same time, the effect of the unsystematic spatial displacement (of some meters) between omolougous pixels of the different campaigns, that some checks on known coordinate points had shown.

Table 4 – Main statistic parameters of the volume estimation linear regression model performed in Paneveggio forest [from Floris et al., 2010].

<table>
<thead>
<tr>
<th>Statistic parameter</th>
<th>Kind of model</th>
<th>$V$ (total volume)</th>
<th>$V_p$ (management volume)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure unit</td>
<td>$m^3 \times ha^{-1}$</td>
<td>$m^3 \times ha^{-1}$</td>
<td></td>
</tr>
<tr>
<td>Model equation</td>
<td>$V = \beta_0 + \beta_1 \times HMEAN_{smr}$</td>
<td>$V_p = \beta_0 + \beta_1 \times HMEAN_{smr}$</td>
<td></td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>32.24754</td>
<td>-19.8870</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>36.61670</td>
<td>38.6869</td>
<td></td>
</tr>
<tr>
<td>$\beta_0$ significance</td>
<td>no</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$ significance</td>
<td>&gt; 99%</td>
<td>&gt; 99%</td>
<td></td>
</tr>
<tr>
<td>$\beta_0$ lower confidence limit</td>
<td>-45.0325</td>
<td>-99.8954</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$ upper confidence limit</td>
<td>109.5276</td>
<td>60.12142</td>
<td></td>
</tr>
<tr>
<td>$\beta_0$ lower confidence limit</td>
<td>32.0886</td>
<td>33.9990</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$ upper confidence limit</td>
<td>41.1448</td>
<td>43.37487</td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>0.937483</td>
<td>0.939750</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.878874</td>
<td>0.883130</td>
<td></td>
</tr>
<tr>
<td>adjusted $R^2$</td>
<td>0.875600</td>
<td>0.879972</td>
<td></td>
</tr>
<tr>
<td>RMSE ($m^3$)</td>
<td>85.01</td>
<td>88.27</td>
<td></td>
</tr>
<tr>
<td>% SEE</td>
<td>13.8</td>
<td>14.8</td>
<td></td>
</tr>
</tbody>
</table>

Hollaus et al. [2009] adopted similar processing procedures, investigating also the influence of different matrix sizes on model performance. Then, the comparison between the HMEAN values of the two layers was performed on a sample of 5000 pixels randomly chosen out of all pixels (more than three million). The model obtained, shown in Figure 4, expresses the very high correlation ($R=0.988$) between HMEAN_smr and HMEAN_wnt, which suggests the possibility to use HMEAN_wnt as predictive variable in a regression model to estimate timber volume.
Besides, a derived summer CHM with more “realistic” tree height values, obtained processing winter data by the equation [1], can play a useful role in photo-intepretation and structure classification processes.

\[ HMEAN_{smr} = -0.0124 \left( HMEAN_{wnt} \right)^2 + 1.5062 \left( HMEAN_{wnt} \right) \]  

Figure 3 – The linear regression model of volume against \( HMEAN_{smr} \) (Paneveggio forest). \( V \) is the total volume (dbh > 2.5 cm), \( Vp \) is the “management” volume (dbh > 17.5 cm).

Figure 4 – The regression model between \( HMEAN_{wnt} \) and \( HMEAN_{smr} \) in Paneveggio forest.
The Volume estimation model

A $H_{\text{MEAN}}_{wnt}$ raster layer was produced for the Cadino forest, with the same processing procedure already adopted in Paneveggio forest. The value of $H_{\text{MEAN}}_{wnt}$ was then extracted for each pixel corresponding to the centre of a ACS, the data of which (basal area per hectare, volume per hectare) had been collected and calculated during the forest management plan inventory.

A set of 365 observations was obtained; the relation between the two observed variables $H_{\text{MEAN}}_{wnt}$ (m) and $V$ (m$^3$ ha$^{-1}$) is shown in Figure 5. The shape of the point distribution suggested the adoption of a linear regression model or, as an alternative, of a polynomial model. This latter model (degree 2) had not statistical performance much better than the linear one. According to Hollaus et al. [2009], regarding the simplicity of the estimation models to be adopted, the linear regression model was finally chosen, excluding from the regression 18 2-σ outliers.

![Graph showing the final regression model](image)

**Figure 5 – The final regression model to estimate $V$ in function of $H_{\text{MEAN}}_{wnt}$. 365 observations on ACS in Cadino forest, 18 of which considered as outliers.**

The final linear model is the following:

$$V = 137.93 + 25.177 H_{\text{MEAN}}_{wnt} \quad [2]$$

with a determination coefficient ($R^2$) of 0.5799

The analysis of residuals does not indicate any anormality in their distribution, as can be seen in Figure 6 (overall distribution) and in Figure 7 (standardised residuals vs. estimated $V$). RMSE is 136.34 m$^3$×ha$^{-1}$ and SEE% is 26.87%.

Statistical analysis continued with a k-fold cross validation [Witten and Frank, 2005], for
assessing how the results of the model could be generalized to an independent data set. A value of k=10 was used. The results of this test are reported in Table 5.

Figure 6 – Overall distribution chart of the residuals of the volume estimation model in Cadino Forest.

Figure 7 – Standardised residuals of the volume estimation model in Cadino Forest.
Table 5 – Results of the k-fold cross validation (linear regression model, Cadino forest).

<table>
<thead>
<tr>
<th>FOLD</th>
<th>mean_e (m$^3$)</th>
<th>RMSE (m$^3$)</th>
<th>det. coeff. (R$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.034950884</td>
<td>148.8427365</td>
<td>0.5813</td>
</tr>
<tr>
<td>2</td>
<td>-17.66338616</td>
<td>137.4821039</td>
<td>0.5686</td>
</tr>
<tr>
<td>3</td>
<td>35.23227086</td>
<td>132.1553506</td>
<td>0.5838</td>
</tr>
<tr>
<td>4</td>
<td>1.914282359</td>
<td>148.6105401</td>
<td>0.5938</td>
</tr>
<tr>
<td>5</td>
<td>-1.933042467</td>
<td>133.3358009</td>
<td>0.5809</td>
</tr>
<tr>
<td>6</td>
<td>-21.0673682</td>
<td>147.3479424</td>
<td>0.5782</td>
</tr>
<tr>
<td>7</td>
<td>-7.699249368</td>
<td>122.0107258</td>
<td>0.5791</td>
</tr>
<tr>
<td>8</td>
<td>-16.25263893</td>
<td>138.9103425</td>
<td>0.5767</td>
</tr>
<tr>
<td>9</td>
<td>10.04356018</td>
<td>123.7201474</td>
<td>0.5622</td>
</tr>
<tr>
<td>10</td>
<td>15.69128804</td>
<td>131.8444711</td>
<td>0.5944</td>
</tr>
<tr>
<td>MEAN</td>
<td>-0.069933281</td>
<td>136.4260161</td>
<td>0.5799</td>
</tr>
<tr>
<td>MIN</td>
<td>-21.0673682</td>
<td>122.0107258</td>
<td>0.5622</td>
</tr>
<tr>
<td>MAX</td>
<td>35.23227086</td>
<td>148.8427365</td>
<td>0.5944</td>
</tr>
<tr>
<td>ST. DEV.</td>
<td>17.24361977</td>
<td>9.702413832</td>
<td>0.00987</td>
</tr>
</tbody>
</table>

This kind of analysis accounts for model's accuracy at plot level (approx. 800 m$^2$). In general, it could be interesting to know how accurate is the model when applied at forest compartment level or at inventory strata level, as well. To answer this question, estimated volume was summarized by means of GIS procedures for each forest compartment and each inventory stratum, and the values of total volume were compared to those estimated by the ground sampling. The total $V_k$ per stratum is directly supplied by the sampling inventory design; the total $V_k$ per forest compartment has to be calculated as following:

$$V_k = \sum_j (\overline{V}_j \times a_{jk}) \quad [3]$$

where $\overline{V}_j$ is the average volume per hectare (m$^3$) of the $j$th stratum, estimated by ground inventory, $a_{jk}$ is the area of the portion of the $j$th stratum within the $k$th forest compartment.

Integration between LiDAR and ground-based data: the $k_{\text{LiDAR}}$ parameter

The average data per stratum does not allow to spatialise the volume on smaller territorial unit maintaining a sufficient statistical accuracy. Therefore, in the absence of LiDAR data it is only possible to assign to each forest compartment the average volume of the different strata which overlay it, weighted by their relevant area, as seen in [3], and by ignoring the variability of these average values which, in case of articulated strata, can be very high.

To overcome this obstacle, the $k_{\text{LiDAR}}$ index was defined for each pixel, as follows:

$$k_{\text{LiDAR}} = \frac{HMEAN_{ij}}{\overline{HMEAN}_j} \quad [4]$$

where $HMEAN_{ij}$ is the HMEAN of the $i$th pixel belonging to the $j$th stratum, and $\overline{HMEAN}_j$ is...
the average HMEAN of the jth stratum; in this way, the local value of HMEAN replaces the average value valid for the whole stratum. Thus:

\[ V_j = \overline{V}_j \times k_{LIDAR} \]  

[5]

where \( V_j \) is the volume (m\(^3\)) of the ith pixel in the jth stratum.

**Results and discussion**

Firstly, it seems opportune to remark that the correlation of the mean canopy heights in winter/lower-resolution and in summer/higher-resolution LiDAR surveys resulted particularly high in evergreen conifer forests, but further research in deciduous and in mixed forests is needed.

The model reported in Figure 5 and in equation [4] has been applied to 53 forest compartments in Cadino forest, which have an average total volume of 6811 m\(^3\).

As for the volume estimation model performed for Cadino forest (Fig. 4), its not high statistical performance at single plot level might be due to the uncertainty which affects the dependent variable itself (V/ha from ACS), that is in turn a result of an estimation performed applying tariffs models.

Nevertheless, the comparison between the volume estimated by HMEAN\(_{er}^{\text{smr}}\) and that estimated by the ground sampling shows fair results (Fig. 8) with a bias of -469 m\(^3\) (-6.9\%) and an average absolute difference of 757 m\(^3\) (11\%).

The k-fold cross validation analysis (Tab. 5) seems to indicate that the overall model is not overfitted and that the sample was well representative (low values of RMSE and \( R^2 \) standard deviation).

The integration between LiDAR data and inventory estimates by means of the k_LiDAR index can supply volume values \( V_{fc} \) at forest compartment level:

\[ V_{fc} = \sum V_j \forall i \in fc \]  

[6]

where \( fc \) is the forest compartment, and \( V_j \) has the same meaning than in [5].

Differences between the two volume values calculated by [3] and by [6] are reported in Figure 9 (bias of -7.1 m\(^3\) corresponding to -0.1\%, and av. abs. diff. of 11.4\%).

k_LiDAR index is targeted to the ground sample data spatialization compatible with the overall statistical estimates obtained by that sample: actually, the total volume obtained for the whole Cadino forest is the same estimated by the ground sampling (361000 m\(^3\)), unless the calculus approximation. It noteworthy stressing that \( V_j \) is a statistical estimator, being the product of the estimator \( \overline{V}_j \) (stratum mean volume) by the k_LiDAR parameter referred to each pixel: this fact, together with the implicit assumption that the ratios \( HMEAN_j / HMEAN_j \) and \( \overline{V}_j \) are linearly correlated, leads to the potential of further investigations on its statistical properties (e.g. similarly to what Corona and Fattorini [2008], and Barbati et al. [2009], have proposed).

k_LiDAR allows at the same time the production of volume maps for the desired spatial element: not only the forest compartment (Fig. 10), but the stratum and the forest stand, as well (Fig. 11).
Since the adopted ground sampling design did not supplied an adequate sample size at forest compartment level, so far it was not possible to compare directly the outcomes of the proposed method with those of alternative processing procedures, e.g. the model-assisted estimation procedure proposed by Corona [2010]. Such comparison could be of interest in further studies, adopting a stratification procedure on per-compartment basis.

**Figure 8** – Correlation between Volume from $HMEAN_w$ (LiDAR) and Volume from ground sample. Values are referred to total volume in forest compartments. 53 observations in Cadino forest.

**Figure 9** – Comparison between ground inventory and $k_{LiDAR}$ calibrated Volume. Values are referred to total volume in forest compartments. 53 observations in Cadino forest.
Conclusions
A regression model to estimate timber volume by means of non forest-specific LiDAR data, calibrated with ground data becoming from ordinary operational context, has been proposed in this paper.

The results of the experimentation here described indicate that the “poor” characteristics of a LiDAR survey (i.e. lower spatial resolution, low number of echoes and unsuitable season of shot) does not seem to be a major obstacle to the estimation of dendrometric parameters, at forest compartment level, by means of area based methods.

Winter flight campaigns, peculiar to the projects aimed at producing DTMs, can be fruitfully used in forestry for pure or nearly pure forest of evergreen conifers, which in some Italian
regions represent a significant proportion of forest land. The influence of the LiDAR mission season might be much more significant is in deciduous forests, for which it should correspond to that of the maximum vegetative growth [Corona et al., 2008]. Although several studies highlight the usefulness of approaches based on extraction of a number of height distributional parameters, like percentiles and others [Means et al., 2000; Gobakken and Naesset, 2005; van Aardt et al., 2006; Hollaus et al., 2007], the mean value of heights calculated on CHM remains the LiDAR variable which alone supplies the main contribution to volume estimations [Ioki et al., 2010, Tonolli et al., 2011]. The adoption of simple estimation models, like that discussed in this paper, makes the data processing easier and faster. Finally, the proper integration of LiDAR data and dendrometric ground data allows the statistical reliability of the ground sampling to be combined with the high spatial resolution of LiDAR data. Volume maps resulting from this integration can be extremely useful in planning silvicultural operations.

Figure 11 - Timber volume map (m$^3$ ha$^{-1}$) of forest units (stands) in the Northern part of Cadino forest (detail).

Acknowledgements
The study, realized within the research programme RESIA2, has been partially financed by the Forest Service of Provincia Autonoma di Trento. Authors are grateful to dr. Alessandro Wolynski and his colleagues at Forest Management Office, for supplying LiDAR and ground-based data. Many thanks also to our colleague mr. Giuseppe Cappalonga and to ms. Jane Bevan for their precious help in revising the English text of the paper. Finally, we wish to thank the Referee who revised carefully the manuscript and contributed to improve it.
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Received 11/02/2011, accepted 11/06/2011
Rock face surveys using a LiDAR MMS

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Abstract
The analysis and prevention of natural hazards is one of the aims of the scientific community and those who are involved in managing the environment and territory. Terrestrial LiDAR and photogrammetric techniques are effective methods of acquiring environmental data and of integrating them in digital products. These techniques have shown remarkable effectiveness when the area of interest is limited. In this paper, the authors have attempted to resolve this problem by presenting an experimental vehicle that allows the extensive use of these techniques to survey rock faces. These procedures were then applied during a measurement campaign, which was conducted along a major international roadway (the Simplon Pass) near the Divedro Valley.

Keywords: Rock face monitoring, LiDAR, Mobile Mapping, low cost.

Introduction
In recent years, many natural disasters have occurred in Italy and most of them have been caused by an intensive use of the land, poor prevention activities and a lack of interest of the institutions in charge. At the same time, the scientific community that is working on environment management has dedicated particular attention to the forecasting and prevention of natural phenomena. Geomatics can play an important role in the prevention of natural disasters, in particular pertaining to hydro-geological risks. A historical analysis of natural disaster damage has highlighted how the number of incidents involving urbanized areas, viability infrastructures or other human constructions is increasing [Guha-Sapir et al., 2011]. LiDAR and photogrammetry techniques can be opportunely integrated in order to acquire and collect raw data which can be used to realize innovative digital products (solid image, solid true orthophotos), as shown in Bornaz et al. [2003]. These techniques have proved to be effective in some important and relevant case studies. The definition of a method devoted to evaluating the stability of a cracked rock face and the related risks, when strategic main roads are involved, requires a detailed analysis based on a dense geometric and photogrammetric dataset [Bornaz et al., 2002]. As shown in Campus et al. [2008], the terrestrial LiDAR-photogrammetry approach has already proved to be remarkably effective in many tests or when the area of interest is limited [Janeras et al., 2004; Jaboyedoff et al., 2010; Abellán et al., 2011]. Mobile Mapping Vehicles (MMVs) have been used since 1990 to georeference data acquired by different sensors along roads and the surrounding areas [Schwarz et al., 2004]. Today’s MMVs are designed to acquire data at an operating speed of about 50–80 km/h and
with a sub-metrical accuracy; data georeferencing is achieved with an on-board Position and Orientation System (POS), which is usually made up of an Inertial Navigation System (INS), one or more Global Navigation Satellite System (GNSS) receivers and, in most cases, a Distance Measuring Instrument (DMI). These MMVs are able to provide the position of the body system with respect to a reference mapping system and its orientation with respect to a local level system at high frequency (100–200 Hz). One of the main application areas is data collection, for example, for road cadastre databases or urban GIS. In this case, geometric and attribute data are collected about the road infrastructure, but also about its surroundings area. These systems allow a high productivity and accuracy to be obtained, but they suffer from the following disadvantages:

a) high costs (> 200 k€);

b) laser scanners have a limited range (< 100 m) and they only operate along a section if the vehicle is not in movement;

c) low point density on the rock face (about 20-40 pts./m$^2$ in dynamic applications);

d) the range measure is only available for the first laser echo;

e) low resolution of the image data.

In order to be able to use the Mobile Mapping System in more extensive areas and to overcome the limits of terrestrial LiDAR techniques, the authors have proposed an integrated prototype of mobile mapping system to directly georeference high density LiDAR data and the related high resolution digital images. In this way, it is possible to acquire and process LiDAR data of a rock face in a rapid and accurate way while driving along the main roads: the proposed techniques can be used both in static mode (“stop & go”), in which a high resolution acquisition is available, or in dynamic mode, in which fewer dense point clouds are available, but a faster survey can be obtained. The mobile mapping system has been applied to a case study conducted on a major route for international communication (the Simplon Pass) between Italy and Switzerland. During these tests, the “stop & go” mode was used to ensure a higher accuracy in GNSS/INS positioning. GNSS signal was partially
jammed by the Divedro Valley mountains.
A part of the “del Sempione” route E62 was selected, in particular from the town of Trasquera (VB, Italy) to the old Italian-Swiss border (about 6 km, Fig. 1). Twenty-four scan positions were set up along this road. The distance between each scan position was more or less equal to 250 m.

The MMV acquisition system
The LIDAR survey was conducted using the Riegl VZ400 Terrestrial Laser Scanner (TLS): the technical specifications are given in Table 1.

<table>
<thead>
<tr>
<th>Table 1 - Riegl VZ400 technical specifications.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Long range settings</strong></td>
</tr>
<tr>
<td>Laser PRR (peak)</td>
</tr>
<tr>
<td>Measurement rate</td>
</tr>
<tr>
<td>Max distance (90% - 20%)</td>
</tr>
<tr>
<td>Accuracy</td>
</tr>
<tr>
<td>Precision</td>
</tr>
</tbody>
</table>

This TLS allows several echoes to be collected for each laser direction by means of a ranging based on echo digitalization and online waveform processing.
A Nikon D700 digital camera with a NIKKOR (f=14mm) lens mounted on the LiDAR sensor was used to acquire the high resolution photographic data.
A special metallic platform was installed on the roof of the vehicle (a commercial city car – FIAT Doblò) to house all the used sensors. This support was made in aluminum by the Geomatics group at the Politecnico di Torino and it was designed on the basis of a previous mobile mapping experience [Piras et al., 2008]. This platform allows several sensors to be installed (Fig. 2):

- a) 3 multi-frequency GNSS receivers (Leica Geosystems GX1230+GNSS);
- b) 1 low cost single-frequency GNSS receiver (u-blox LEA 5T);
- c) 1 tactical-grade IMU (Crossbow IMU 700CA);
- d) 1 low cost IMU platform (XSens MTi);
- e) 1 webcam (Logitech Quickcam Pro 9000);
- f) 1 TLS Riegl VZ 400 + Nikon D700.

The low cost inertial platforms involved in this survey are based on two different technologies: Crossbow IMU 700CA (Fig. 3a) is a system in which FOGs (Fiber Optical Gyros) are embedded, XSens MTi (Fig. 3b) instead uses a MEMS (Micro Electro-Mechanical Systems) technology.

These platforms are able to estimate the attitude angle (roll, pitch and yaw) with a precision of 0.01 gon, if they are coupled with GNSS data (see § “Post-processing and first results” for more details). These values guarantee the level of accuracy necessary to conduct the geo-mechanical analysis dealt with in this study. In this analysis, a decimeter level of accuracy was required to estimate the dip and dip direction of the main planar discontinuities [Forlani et al., 2005].

The number of sensors was surely redundant for the survey campaign, but it was necessary
for this test which had the purpose of verifying, controlling and calibrating the system. The three multi-frequency GNSS receivers and the tactical-grade IMU platform were used to compute the positions and the attitudes of the vehicles during the survey, while the low-cost sensors were used to increase the redundancy of the system.

![Image of the complete acquisition system](image1.jpg)

**Figure 2 – The complete acquisition system.**

![Image of IMU sensors](image2.jpg)

**Figure 3 – IMU sensors used in the test.**

**Calibration of the system**
Each sensor (GNSS, IMU, TLS) works in its own coordinate system and is collocated on a well-known position on the platform. The entire system is made of several coordinate...
systems (camera, scanner and platform) which work in an absolute mapping coordinate system, as described in Figure 4.

It was necessary to define the relationship between each coordinate system before starting the survey. A dedicated calibration field (Fig. 5) was prepared to calibrate the instrumented vehicle in order to define a unique coordinate system that is joined to the platform (body coordinate system, Bcs).

In order to define the relationship between the coordinate systems of the various sensors, the following practical operations were carried out:

- a) each “level arm” between each sensor was measured in the laboratory, in order to define each sensor position in the Bcs;
- b) a calibration field (Fig. 5a) was realized using reflecting markers and some prisms located on both a tripod and on the ground. This field was measured using a total station, considering a local coordinate system (Total Station coordinate system, TScs);
- c) the positions of the GNSS antennas were defined in the same coordinate system, in order to establish a relationship between the Bcs and TScs;
- d) a detailed LiDAR acquisition was conducted (400 gon) to estimate the marker position in the scanner coordinate system (Scs), in order to define its position and attitude with respect to the TScs and Bsc. Furthermore, the position and attitude of the digital camera were defined with respect to the Scs.

Survey and positioning
The data acquisition was carried out along the “del Sempione” route E62, using the “stop & go” technique, which involved stopping the vehicle at each pre-fixed point (24) for about
15 minutes. This time was sufficient for both a 400 gon LiDAR acquisition and to take all the necessary pictures, and it also allowed the ambiguity carried phase of the master-vehicle baseline to be fixed. The laser scans were realized with an angular step of 0.45 gon, which means a point density of between 16–400 pts/m² for a variable distance of 50 m to 400 m. The average density on the rock face was 100 pts/m².

A dedicated GNSS master station (VAR) was positioned in the town centre of Varzo (VB, Italy), with the purpose of having a short baseline (about 10 km) in order to fix the ambiguity more easily and to have fewer outages due to the presence of the sides of the valley. The coordinates of this master station were estimated in the IGS05 reference system using two GNSS permanent stations that were located close to the test field. A single independent baseline was estimated and the network was adjusted. The GNSS data were all processed using the commercial Leica Geo Office (LGO) package. The position and attitude of the vehicle (Bcs) were defined considering both the GNSS and the IMU data.

**Post-processing and the first results**

**Position and attitude estimation**

The position and attitude of the vehicle were defined considering the estimated GNSS position, and integrating the solution with an IMU solution that was estimated as follows. The positions of the three GNSS antennas and u-blox receiver were estimated for each scan using a relative positioning where VAR was considered as the master station. The u-blox solution was considered when the geodetic antenna positioning was not available due to the
characteristics of the topography of the site. Because of the low cost of the IMU (less than 10000 €), the long length of the survey and the large number of epochs without any GNSS signal, the attitude of the vehicle was not computed using traditional GNSS/INS integration algorithms (loosely-coupled and tightly-coupled, [Cina et al., 2009]). The heading angle, in particular, was calculated from the angular rates measured by the gyros of the IMU, using a Runge-Kutta numerical integrator [Press et al., 1992]. This solution allows a better attitude angle solution to be obtained than the one that can be achieved using mechanization equations in a Kalman filter. A dedicated software tool, devoted to such an integration, was implemented in MATLAB language. The computed angle shows a time-variable drift, due to the integration of the gyro angular rate drift. These drifts were clearly visible during the “stop & go” periods, in which the vehicle was stopped in order to acquire LiDAR data. It is possible to calculate the gyro drift of each static period and then compensate the heading angle (Fig. 6).

The heading angle was then referred to the geographic North by linking it to a bearing angle calculated using the multi-antenna GNSS system, in an open-sky environment without obstacles. The bearing angle of the vehicle was then computed for each epoch as the median value of the angular measurements during each period in a stationary position. Other bearing angles were measured during the survey, using the GNSS multi-antenna system. These angles were used as control angles for the inertial solution. The calculated discrepancies between the two systems were always lower than the standard deviation of the bearing angles, and always lower than 0.01 gon, as shown in Fig. 7. Due to the vibrations of the vehicle during motion, it was not possible to compute the roll
and pitch angles using the same integration technique used before. For this reason, these angles were calculated from accelerometer measurements, using the formulas:

\[
\omega = \sin\left(\frac{a_y}{g}\right) \quad \varphi = \sin\left(\frac{a_x}{g}\right) \quad [I]
\]

where:
\(\omega\) is the roll angle
\(\varphi\) is the pitch angle
\(a_x, a_y\) are the accelerations along the x and y axes, respectively
\(g\) is the gravitational acceleration.

Again in this case, some angles were measured with the multi-antenna GNSS system, and they were used as a control of the goodness of the inertial solution. In this case, the link to the GNSS angle solution was not necessary, since the accelerometer measurements allowed an attitude angle that had already been referred to a geographical reference system to be obtained (Fig. 7).

Before producing solid images and other final products for a geomorphologic analysis, a coordinate system transformation was necessary to transform the data from the local system to a mapping coordinate system.
The ellipsoidal heights were converted into orthometric heights using a national geoid model called ITALGEO 2005.

**Final results**

Using the navigation information (position and attitude of the vehicle) and the calibration parameters, it was possible to georeference the 24 scans and generate the related solid images. The effectiveness of the solid image for geomorphological analysis has been demonstrated in Biasion et al. [2005] and Campus et al. [2008], and for this reason it is not be discussed in this paper.

About half part of the natural obstacles (i.e. trees, leaves, bushes) were filtered through the multi-echo technique offered by the used TLS. The authors suggest conducting this kind of survey in early Spring or late Autumn, in order to reduce the lack of data.

Some examples of geo-referenced point clouds obtained in this test are reported in Figure 8. Two adjacent scans can be matched with a discrepancy equal to 10-15 cm of standard deviation. The precision of the proposed technique was evaluated using the ICP (Iterative Closest Point) method [Besl and McKay, 1992] on an overlapped area between adjacent scans. The value of obtained discrepancies was on average equal to 0.06 m ± 0.11 m.

The individual three-dimensional models were loaded into SIRIO software to create solid images (Fig. 9a), to carry out some geomorphic measurements [Bornaz et al., 2003; Campus et al., 2008], to identify protection works and to assess their state of maintenance, etc. These measurements are only visible on a 3D point cloud model (Fig. 9b).

![Figure 8](image1.png)

*Figure 8 – Two examples of scans: (a) pos. 2 (b) pos. 24.*

![Figure 9](image2.png)

*Figure 9 – Solid image example (scan 24, a) and 3D point cloud model and measurements (b).*
Conclusions
The obtained results demonstrate that fast and extensive applications of LiDAR techniques using mobile mapping vehicles can be done in a short time (a day of surveying for 6 km of road) to obtain a set of geospatial information to effectively describe roads and their surroundings (buildings, rock faces, etc.).
The use of several low cost sensors allows to acquire a large number of observations (positions, attitudes, etc.). Combining these measurements, the required accuracy can be achieved.
LiDAR data can be georeferenced directly, showing the presence of several useful three-dimensional data regarding rock faces.
The acquisition of areas hidden by vegetation or similar obstacles should be implemented in future applications of the proposed methodology.

Acknowledgments
This research was funded by ARPA Piemonte as a part of the INTERREG project “ADAPITALP - Adaptation to Climate Change in the Alpine Space” approved by the Alpine Space II Committees.

References

**Received 09/02/2011, accepted 20/01/2012**
Rapid building damage assessment using EROS B data: the case study of L’Aquila earthquake

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Abstract
Recent events reveal that the use of very high resolution satellite images for “early damage assessment” after seismic events can be very useful and call for deeper investigation by the scientific community.
In the present study five monoscopic panchromatic images covering the historical city-center of L’Aquila, GCPs and DEMs from medium scale cartography were used because they are frequently utilized in emergency applications. The interest was to make a deeper investigation on geometric characteristics of those images, that were not fully investigated by the scientific community and to study the detection capabilities for the specific post seismic application, so several orientation and detection tests were executed.

Keywords: L’Aquila, earthquake, EROS B, orthorectification, orientation.

Introduction
When and if the satellite images are available in the immediate post seismic period, they constitute a tool to support the management of the emergency; in fact they can help to detect quickly the areas and the structures that suffered the worst damages. Recent application [Ajmar et al., 2010] demonstrated that also the simple manual vectorization by unskilled operators can be a valid tool to map the emergency quickly. If high resolution satellite images are available immediately after the seismic event they can allow to find out which buildings, roads and bridges have suffered more damage and collapsed; this information is strategic to plan the rescue operation properly.
In the present study the goals were two: the first was a deeper investigation of geometric characteristics of EROS-B imagery, testing different orthorectification strategies and the second was to assess the actual possibilities to detect damaged buildings from these specific images that are only available in panchromatic format. For the first goal several tests of orientation were performed using packages OrthoEngine 10.2 and ERDAS 2011 and using different sets of GCPs extracted by the same cartography, 1:5000 scale, realized before the seismic event by Regional administration of Abruzzo. GCPs from 1:5000 maps are not the best choice for a 0.7 meter resolution image but they were used because they are the commonly used in emergency applications when there is no time for a ground survey. For the second goal tests of detection of damaged buildings were executed by operators more or
less skilled (Tab. 1) to verify the actual and present possibilities of using the EROS B high
resolution images for these specific applications. In the first set of tests (“Double blind”
test) operators used only orthorectified images, in the second set of tests (“Not blind” test)
they used images and a map of damaged building together.

<table>
<thead>
<tr>
<th>Operator</th>
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</tr>
<tr>
<td>Beginner user</td>
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</tr>
<tr>
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<td>No</td>
</tr>
<tr>
<td>Skilled user 3</td>
<td>Yes</td>
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</tr>
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</table>

Methods and materials used
EROS-B satellite platform, probably one of the less studied among VHR (Very High
Resolution) images, releases panchromatic images with resolution up to 0.7 meters in
panchromatic modality, no multispectral sensor is reported for this platform. The orbital
period of the EROS satellites, for one revolution around the Earth, is 94-96 minutes. The
satellite, at an altitude of about 500 km, completes approximately 15 revolutions around the
Earth every 24 hours. Presently the only commercial SW supporting EROS B are: “ERDAS
IMAGINE LPS-9.2”, “Geomatica 10.1.1” and “SOCET SET 5.4.1” [http://www.imagesatintl.
com/ImageSat ]. The images are usually released in IA format that means only “radiometric
system correction” was applied without any geometric correction: this product is the most
suitable for photogrammetric use. EROS-B platform acquires in asynchronous mode, this
means that the attitude (mainly pitch) of the satellite changes deeply during acquisition and
consequently attitude angle and ground sample distance (GSD) declared for a single image
has to be considered as a mean value.

EROS-B images are available to the end user very quickly because there is a big number of
ground stations and also temporary stations can be installed if needed; furthermore the wait
between order and actual acquisition is usually shorter for EROS-B if compared with more
diffused competitor as Ikonos and Quickbird for example; obviously this is only a generic
consideration because, on a specific order, availability of the platform and priority of the
acquisition, can influence deeply delay for release of the single image. The shorter delay
can be obviously a fundamental advantage when managing emergency events.

For this experimentation five vector IA scenes (Tab.2) were oriented and orthorectified
using Orthoengine 10.2 (included in Geomatica package by PCI) and one of them was
oriented also using ERDAS IMAGINE 2011 photogrammetric models. They cover the
whole territory of the city-center of L’Aquila (Fig. 1) and were acquired on 17th and 24th
April 2009, few days after main seismic event (6th April 2009, 3:32 a.m., local time; Ml=5.8,
Mw= 6.2) of the seismic sequence that included hundreds of aftershocks (more than 30
of them 3.5<Ml<5.0) [INGV, 2009]. The rigorous model implemented in Orthoengine is
based on the photogrammetric approach developed by Dr. Thierry Toutin for synchronous
satellites and later adapted for the orientation of asynchronous platforms [Toutin, 2004].
Table 2 - Characteristics of acquired images as reported on metadata files (please note correspondence between name of the file and ID), $\gamma$-s and $\gamma$-e is for total angle of off-nadir at the beginning and at the end of the acquisition.

<table>
<thead>
<tr>
<th>ID</th>
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<th>$\gamma$-s</th>
<th>$\gamma$-e</th>
<th>GSD [m]</th>
<th>GSD (across) [m]</th>
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<td>0,83</td>
<td>1,20</td>
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<tr>
<td>im98</td>
<td>geo_MBT1-e2165298</td>
<td>38,4</td>
<td>39,2</td>
<td>0,87</td>
<td>1,40</td>
</tr>
</tbody>
</table>

In the ERDAS IMAGINE user’s handbook [ERDAS, 2011] the pushbroom model is described as: “A pushbroom model transformation is a 3D-to-2D transformation that is based on collinearity equations for pushbroom sensors”; this seems to be the only information for this model [Michalis and Dowman, 2004].

![Figure 1 - The five images used: foreground from W to E “geo_MBT1-e2166574” and “geo_MBT1-e2166575”, background from W to E “geo_MBT1-e2165298”, “geo_MBT1-e2165297” and “geo_MBT1-e2165296”.

\[ \text{Figure 1 - The five images used: foreground from W to E “geo_MBT1-e2166574” and “geo_MBT1-e2166575”, background from W to E “geo_MBT1-e2165298”, “geo_MBT1-e2165297” and “geo_MBT1-e2165296”}. \]
DEM and Ground Points - GPs (Ground Control Points - GCPs and Check Points - CPs) were extracted by 1:5000 scale digital cartography of Abruzzo Regional Administration: part of the maps used is updated to 2001-2002 the remaining part is updated to 2004-2005 [http://www.regione.abruzzo.it/xcartografie/]. In Italy 1:5000 scale maps are expected to have a graphical planimetric error of 1 meter and 1.8 meters for height error, so DEMs obtained by this map are accurate enough [Toutin, 2003] to obtain the maximum accuracy on the final orthorectified map. GCPs obtained from these maps are, in spite, not enough accurate to obtain the best accuracy on the final orthorectified image [Baiocchi et al., 2005] but we will evaluate anyway the final accuracy obtained because, for this specific application, the maximum accuracy is not needed. Unfortunately a ground survey with differential GPS/Gnss receivers is not always possible immediately after a seismic event; for this specific event a big part of the city-center is still not easily accessible after almost 2 years from the main event.

Utilized DEM

The first DEMs obtained by vectorial cartography showed unrealistic morphology, mainly in the urbanized areas where contour line and spot height aren’t represented, for this reason we tested if the modeling of ground could improve using also the point features of the digital maps that represent the base level of the buildings. In previous papers [Baiocchi et al., 2011] it was also tested how the results could change using the two different interpolation algorithm available in PCI: “Natural Neighbor” and “Finite difference”. Comparing the obtained DEMs combining the different options, we found that the best result is obtained using also the base level of the buildings and a “Finite difference” algorithm (Fig. 2 left). On this DEM some unnatural morphologies were noticed on NW part of the DEM itself, superimposing the vectorial maps it was noticed that incongruent morphologies match the path of the flyover of the highway this means that some height spots do not represent the real morphology of the ground. Similar errors can be avoided with a more detailed structure of the geodatabase where heights of the ground and heights of structure that are over the ground are not memorized as the same feature; for this experimentation the correct DEM (Fig. 2 right) was obtained through a manual editing of the features. The DEM extracted covers the whole territory of the historic city-center: the area that suffered the worst damages, it has a 2 meters grid and spans from 359100 to 376410 east and from 468400 to 4695500 north in UTM33N-WGS84-ETRF89 projection.

Orientation experimentation

Very little bibliography is available on geometric modeling of EROS-B satellite mainly with “Socet Set” and “ERDAS” packages, using GCPs from GPS survey [Ástrand et al., 2008] and from cartography [Lo Brutto and Pennacchio, 2009]. A system upgrade was implemented in April 2008 in order to allow correct telemetry in time for start/end of scene, the acquisition of image starts half a second earlier and finishes half a second later [Ástrand et al., 2009] so all images we used were acquired with this new method. On all five images at least 45 points were collimated (Fig. 3), trying to use the same points on overlapping images, but it wasn’t always possible because the different acquisition direction causes different apparent inclination of buildings, hiding some features visible on other images.
Figure 2 - DEM extracted from digital cartography (on the left with spot point on highway, on the right without) North direction is up, resolution is 2 m, NW corner (364824; 4692643) m, SE corner (370827; 4688355) m, UTM WGS84 33N. See height anomaly in detail.

Figure 3 - Distribution of GPs over the five images.
It is also to be underlined that all images present cloud cover (from 20 to 30%) on different areas so again details collimable on a specific image often aren’t visible on another image. GPs are concentrated over the northern part of the images and, for “geo_MBT1-e2165296”, also on the west part of the image, this is due to the mountainous morphology of the areas surrounding the city that are almost desert and so there are no surely recognizable “natural points”; anyway this reflects situations present also during the real emergency management.

![Figure 4 - GCPs and CPs RMSE trends varying number of used GCPs using PCI Orthoengine, from left to right and from top to bottom, 4a, 4b, 4c, 4d, 4e and 4f.](image)

All the GPs sets were used to test the precision of the Orthoengine model and the obtainable accuracy of the images, varying the number of GCPs from a minimum of 10 to a maximum of 45 and observing the consequent variation of RMSE on GCP residuals for precision and on CP residuals for accuracy during image orientation. It has been observed an unusual instability of the Orthoengine orientation model when little number of GCPs is used with residuals up
to some kilometers; anyway these effects disappear suddenly introducing further points. The observed trends match the expected behavior with RMSE of GCP residuals increasing until a stabilization; for the analyzed images with the GPs from cartography the stabilization is reached after the introduction of at least 15-20 GCPs. The trend of RMSE of CP residuals shows a specular behavior, with RMSE decreasing until a stabilization: this value represents the accuracy obtainable from these images oriented with GCPs from cartography.

It can be observed that stabilization starts after 15 GCPs and is completely reached after about 20 GCPs that has to be considered the number of GCPs needed to be sure to achieve the best results. For model precision we can affirm that, with these GCPs, a precision of 1.5 to 2.3 meters along East direction (Fig. 4a) and 1.0 to 1.5 meters along North (Fig. 4c) can easily be reached, image accuracy spans from 1.7 to 2.4 along East (Fig. 4b) and from 1.4 to 2.1 for North (Fig. 4d), these last results were obtained without considering the unusual trend of image “geo_MBT1-e2166574”. In figure 4d and 4e global RMSE is reported that can be an useful information from the emergency response point of view. It has to be noticed that RMSE in East direction seems to be always higher than in North direction; this behavior is exactly the opposite of what reported in literature for all other satellite images including EROS-A [Baiocchi et al., 2005] that is a very similar satellite, managed by the same company and has the same asynchronous modality of acquisition. For all the other satellites the best results on the East direction may be explained considering that pushbroom sensors have CCD array disposed along that direction so pixel geometry is more defined along that direction instead of North direction, along which different rows are acquired in different times and with different satellite attitudes.

Figure 5 - GCPs and CPs RMSE using different sets of 15 GCPs each.
A possible cause of this particular characteristic of EROS-B may be that still some problems of telemetry exist also after the satellite update of April 2008. To exclude the effects of some outlier, for each image three different sets of 15 GCPs were repeated using the remaining 30 points as CPs (Fig. 5): a suspect outlier was only detected in the third set of image “geo_MBT1-e2165297”, but nothing of strange was observed for image “geo_MBT1-e2166574” so its particular trend for accuracy in North direction probably is not caused by an outlier in GPs coordinate, but may depends on some characteristics of the image itself.

Tests on image “geo_MBT1-e2166575” were repeated also in ERDAS IMAGE 2011 to compare the behavior of the two different models. The two software gave similar results especially for the image accuracy (Fig. 6) even if they present different behaviors with specific sets of GCPs (Fig. 7). These results has to be considered only as a tentative guideline for this specific situation and not a definitive evaluation of the accuracy obtainable from 0.7 meters resolution images for this and other applications, in fact the accuracy depends on different parameters like sun angle, cloud cover, off-nadir angle, radiometric resolution and so on.

**Detection of damaged building tests**

To assess the actual possibility to manually vectorize damaged buildings from EROS-B
imagery, “Double-blind” tests of detection were performed by four voluntary operators with different skills: three operators are used to work with remotely sensed images while the fourth is a beginner user like some of the volunteers that were employed during recent disasters. Some resampling techniques as Nearest Neighbor (Fig. 8a) show also little details that can be useful to detect a damaged building but some other algorithms as Cubic Convolution (Fig. 8b) are in some situations more easily interpretable so it can be useful to use sinoptically two images resampled with both techniques; anyway some effects of the earthquake are easily detectable on the images whatever resampling algorithm is used (Fig. 9).

![Figure 8 - Details of orthoimage resampled with Nearest Neighbor (a) and Cubic Convolution (b) algorithms.](image)

Test were performed on a limited area of the historic city-center for which the damage maps are freely available on the web site of the municipal administration [http://www.comune.laquila.it/documenti/terremoto/esiti.htm]. These maps were realized by “Protezione Civile” (National agency for civil protection) considering ground survey. So the area interested by the test is more than 2 Km$^2$ and contains more than 200 buildings the damage of which was classified on the maps in six classes from “Very serious or collapsed building” to “undamaged building”. During “double-blind” tests the operators couldn’t look at the damage maps during detection; only after completing the tests on both the images covering this area (“geo_MBT1-e2166574” and “geo_MBT1-e2165296”), they compared the results to observe how many detected collapsed buildings are actually damaged building according to “damage maps” (Fig. 10 and Tab. 3). From these results it seems that in a historic center it is not very easy to detect damaged or collapsed building from monoscopic panchromatic image with such resolution, in fact only a percentage between 36 and 70 % for image “geo_MBT1-e2166574” and from 50 to 72% for “geo_MBT1-e2165296” percent of detected building on the images are reported as “collapsed”, “serious damage” or “medium damage” on the maps, the remaining detections have to be considered almost surely as false detections. It seems that there is no big difference between the results of skilled and less skilled operators, what really makes the difference is a good knowledge of the site (Tab. 1) (Figs. 10 and 11). To check if such images can be, instead, usefully utilized to confirm expected collapsed buildings coming, for example, from a first ground survey, the same operators were allowed to compare again the images with maps of damaged building overlapped to verify suggested damage. In these second tests most part of damaged buildings were recognized (from 31 to 80 % for image “geo_MBT1-e2166574” and
from 23 to 73% for “geo_MBT1-e2165296”) but still not all of them (Fig. 11 and Tab. 4), so again from these first tests we did not observe a significant difference between skilled and not skilled operators.

Figure 9 - Details of easy detectable damaged buildings.
Figure 10 - Distribution of buildings detected during “double-blind” tests compared with damage maps classes.

Table 3 - Distribution of buildings detected during “double-blind” tests compared with damage maps classes.

<table>
<thead>
<tr>
<th></th>
<th>Im96</th>
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<tbody>
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<td>17%</td>
<td>7%</td>
<td>26%</td>
<td>32%</td>
<td></td>
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<td>Serious d.</td>
<td>25%</td>
<td>21%</td>
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<td>22%</td>
<td></td>
</tr>
<tr>
<td>Medium d.</td>
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<td>64%</td>
<td>56%</td>
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Figure 11 - Percentage of correctly confirmed damaged buildings during “not-blind” tests.

Table 4 - Percentage of correctly confirmed damaged buildings during “not-blind” tests.

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<td>40%</td>
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<tr>
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<td>73%</td>
<td>60%</td>
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<td>58%</td>
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Conclusions and further developments
Images from EROS-B satellite can be easily oriented and orthorectified obtaining accuracy
of 2.5 meters or better using GCPs from 1:5000 scale maps and DEMs from the same cartography. This accuracy is completely compatible with emergency management needs and may be considered adequate to update medium scale map cartography, obviously only from a geometric point of view. Rigorous models implemented both in Orthoengine 10.2.1 and ERDAS IMAGINE 2001 reach stability after the introduction of 15-20 points. It was observed that precision and accuracy achievable along North direction is always better than along East direction: for all other VHR satellites it is just the contrary: this need deeper investigations. The accuracy achievable using GPS ground points must be investigated; our effort will be a search for the best distribution of GPS points to achieve the best internal reliability of the network.

The images so orthorectified allow to identify some of the damaged buildings but a percentage between 28 to 73 % are false detections, even if taken by a skilled operator. This may be caused by the particular urbanization of historic center like the one of L’Aquila. Best results can be obtained using images to confirm suspected collapsed buildings after a first ground survey, but also in this case not all the collapsed buildings can be confirmed. The possibility to extract a DSM from such images has to be investigated because it can reveal height variations very useful to detect entirely or partially collapsed building.

Acknowledgments
We would like to acknowledge “ipt s.r.l.” company for the kind availability of EROS_B images, Dott. Francesca Albanese of “Planetek” company for the kind availability of ERDAS IMAGINE 2011 and for her suggestions, Dott. Arch. Eride Tanga, Dott. Eng. Roberta Valerio and Dott. Eng. Filippo Del Guzzo for their suggestions regarding the damage maps and Dott. Elisabetta Ferrari, the “beginner” user, for her voluntary help.

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Received 12/02/2011, accepted 16/06/2011
Integration of satellite and rainfall data for the identification of flood events in developing countries

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Abstract
The aim of the study is to identify flood events by comparing and integrating two methodologies based on different principles: the first is based on the identification of precipitation anomalies by the means of the analysis of pluviometric data, the second is focused on the analysis on remote sensed data for the detection of ground effects of flood events. Precipitation data were analysed for identifying and classifying events. MODIS archive images were classified in order to derive flood extents. This study is a preliminary stage aimed at the production of scenarios for flood events, in order to provide information in real-time in support of WFP emergency activity.

Keywords: floods, precipitation, MODIS, remote sensing, Bangladesh, scenario.

Introduction
Hydrological disasters are the ones with the highest impact, in terms of damages, victims and occurrence [Vos et al., 2008]: the provision of tools for better manage this kind of disaster is thus a priority for the scientific community.

Present work is performed in the framework of the collaboration between UN World Food Programme (WFP) and ITHACA association. The WFP is the largest UN Agency and responds to more than 120 emergencies per year worldwide, with a particular focus on developing countries; the WFP Emergency Preparedness and Response Unit (OMEP), is responsible for enhancing the effectiveness and responsiveness of WFP operations at the global level, by providing normative guidance and technical support to field offices. The availability of reliable early-warning and real-time alerts is a critical element for triggering emergency operations in advance, to reduce the impact on lives and economies.

In order to meet the need of gathering real-time alerts for the management of flood events, present work aims at performing a preliminary analysis for producing flood extent scenarios; the methodology is based on the identification of the correlation between meteorological events characteristics and their consequences on the ground, through the analysis of an historical archive of meteorological and remotely sensed data.

Study area
Among developing countries, Bangladesh is one of the most flood prone areas in the world;
most of the country has an altitude less than 12 m above the sea level and the region is yearly subject to monsoons (from June to October), tropical storms (from March to November) and tidal bores along the coasts (http://www.hewsweb.org/_download/SHC7Dec2010.pdf).

In addition, the country presents a high vulnerability to floods being the 8th most populous (estimates from 150 to 164 million) and the 11th most densely populated country in the world.

**Materials and methods**

The methodology integrates at basin scale rainfall data from gauge stations network with satellite data derived from Moderate Resolution Imaging Spectroradiometer (MODIS). First part of this section is dedicated to the description of the methodology for watershed delineation; basins are functional units and therefore represent an ideal way to subdivide the study area for flood related analysis. Secondly, the methodology for the identification of precipitation anomalies starting from rainfall data is described. Thirdly, satellite images classification process for the identification of flooded areas is detailed. The integration of the two methodologies concludes present section.

**Watershed delineation**

As previously mentioned, drainage basins are the adopted reference unit for all analytical process performed in present work. The choice of aggregating data and results at basin level is natural while analysing the relationship between rainfall and floods; furthermore, basin are a fundamental landscape unit for development planning and management [Verdin and Verdin, 1999].

In order to correctly distribute precipitation values to basins, it is necessary to adequate basin size to the number and distribution of the gauge stations network and, consequently, a simple threshold on hierarchical order to obtain final basins cannot be applied uniformly on the whole country. That brought to the necessity of deriving a customized watershed delineation starting from an elevation dataset having adequate resolution and accuracy parameters; a subsequent manual aggregation/disaggregation process was adopted in order to adapt basins to actual distribution of rainfall stations (Fig. 1).

For the purposes of this study, the Shuttle Radar Topography Mission (SRTM) version 3 was chosen as base elevation dataset. SRTM provides elevation data on a near-global scale, covering about 80% of land areas, from 60°N to 54°S latitudes, with a resolution of 90 m at the equator [USGS, 2011].

STRM was pre-processed in order to create depressionless elevation model by removing sinks that cause an erroneous flow-direction raster [Hickey et al., 1994; Yuan et al., 2006]. Then, watershed delineation was obtained through the application of a series of hydrological analysis steps, including the computation of flow direction, flow accumulation and stream definition.

Basins were hierarchically organized by defining the hydrological dependencies, in order to consider downstream flood propagation; the final set is composed by 70 basins covering the whole Bangladesh.

Furthermore, in order to consider the variability of the effects on each basin of rainfall precipitation, basins were also classified according to two criteria: type (major river beds, minor river and coastal) and percentage of irrigated areas.
The first criterion should highlight cases with different main controlling factors for flood triggering, while the second will make possible to take into consideration false positives while classifying and identifying flooded areas on the basis of satellite images; in fact, particular agricultural practices (i.e. artificially flooded rice fields) may cause error of commission while classifying flooded areas on satellite images [Bouvet et al., 2009].

**Rainfall data analysis**

Rainfall data come from the Flood Forecasting and Warning Centre (FFWC) measurement network of Bangladesh, under the Bangladesh Water Development Board (BWDB). Among available 54 series of historical data, collected on a daily basis period, only those covering a common time period were selected, deriving a subset of 45 stations, from 1979 to 2008. These input data were used to calculate precipitation depths for the 70 hydrographical basins.
from 1979 to 2008, with the inverse–distance–squared weighting method [US Army Corps of Engineers, 2000]. This method computes the precipitation hyetograph for each basin using the four nearest gauges to it, selected by calculating their distances to each basin centroid (Fig. 2).

A basic statistical analysis of these data was performed in order to evaluate the main characteristics of rainfall. The results show that, at country level, the mean annual rainfall is about 2400 mm, varying from a minimum of about 1300 mm in the West (basin 35, Fig. 1) to a maximum of about 6000 mm in the East (basin 42). The total annual precipitation increases gradually from West to East, reflecting the elevation trend. All stations have a modal distribution with a maximum in July; the mean rainfall value in this month is about 500 mm, ranging from a minimum of 300 mm, again in the western part (basin 37) to a maximum of 1300 mm in the eastern part (basin 24).
**Extreme events identification**

In order to identify extreme rainfall events, it is necessary to know the relation between the duration of rainfall, the height of precipitation and the degree of rarity of the event, in order to be able to select the precipitations that exceed a certain threshold. This relationship is commonly represented by rainfall depth-duration-frequency (DDF) curves, that allow computing the expected rainfall depth ($h$) for a given duration of rainfall ($d$) and a given probability of occurrence ($P$). It is current practice to express the probability of occurrence of an event by specifying its return period or return interval ($T$), which is the average length of time separating the event itself from the closest one having equal or greater magnitude [Maidment, 1993]. It consists in the number of years in which, meanly, an event is occurring one time only; it is the inverse of the probability ($P$) that the event will be exceeded in any single year [1]:

$$T = \frac{1}{1 - P} \quad [1]$$

The DDF parametric curve is expressed by the formula [2]:

$$h = a \cdot d^n \quad [2]$$

Where $h =$ depth of precipitation;

$d =$ duration of precipitation (number of days);

$a, n =$ parameters function dependent on the return period $T$, that must be estimated.

First step for estimating the DDF curves is the computation of the rainfall quantiles for each basin and each precipitation duration, analyzing the annual maximum series, which means taking for any duration only one observation (the maximum value) per year, from 1979 to 2008 in this case. For that purpose, in hydrological literature, different probability distributions are proposed for the analysis of extreme values on hydrological series [Maidment, 1993; Maione and Moisello, 2003]. In this study, three different distributions were used:

1) Gumbel Extreme Value probability distribution, also known as extreme value type I distribution;

2) Generalized Extreme Value distribution (GEV);

3) Three Parameter Lognormal distribution.

Distribution parameters were estimated by applying the method of L-moments. The application of opportune statistical tests (Kolmogorov, Pearson and Anderson-Darling) allowed the identification of the best distribution, namely the one that better regularize each analyzed data series [Maione and Moisello, 2003; Laio, 2004], used for the creation of DDF curves.

The statistical distribution that best fits data is the Lognormal distribution for 62 basins, the Gumbel distribution for 5 basins and the GEV distribution for 3 basins.

Applying these distributions, the DDF curves were estimated, for the return period from 2 to 100 years and for the rainfall durations from 1 to 10 days (Fig. 3). The choice of the calculation of the curves up to 10 days is based on the fact that in Bangladesh 300 mm or...
more of rainfall in a 10 day period may cause floods [FFWC Flood Report, 2009]. For each basin, the entire historical series was processed comparing the cumulated values from 1 to 10 days to DDF curves; for each days of the historical series, the return period was calculated, selecting the maximum value among those obtained for different durations. In order to correlate the results of rainfall analysis with the results of the classification of satellite images (see next paragraph), extreme events were identified since year 2000 and grouped into ten days period. For this reason, for each ten days period the maximum return period occurred were determined and the associated characteristics (depth and duration of rainfall) were selected. In this way the return periods for each ten days period from year 2000 were obtained; starting form this list, the extreme events were identified, by means of selecting the rainfall having a return period higher than 2 years, in order to select larger events and exclude floods that occurred every years.

![Figure 3 – Depth-duration-frequency (DDF) curves.](image)

**Image classification**

In order to appreciate the effects on the ground of rainfall events, the authors needed a complete archive describing the evolution of water bodies with a time frequency that could allow to appreciate their effects. In this way, whenever a flood event is detected, it can be associate to effect on the ground.

To consider the needs of global availability, scale, time frequency and completeness of archive, MODIS (Moderate Resolution Imaging Spectroradiometer) derived data were selected as input dataset, in particular the authors used products MOD09GQ MYD09GQ - MODIS / Terra and Aqua Surface Reflectance [Vermote et al., 1999] which are daily global reflectivity data, corrected by the effects of the atmosphere, available from February 2000.
up to present at the spatial resolution of 250 m.

Two main issues were faced: the choice of an automatic classification procedure globally applicable and the solving of the issues due to clouds and cloud shadows.

Actually different techniques for the automatic classification of water bodies are available in literature, that use combinations of thresholds in IR bands and particular indices derived from the combination of bands different indices, such as NDVI [Brackenridge, 2006], Normalized Differential Water Index NDWI [Gao, 1996], Modified Normalized Differential Water Index MNDWI [Zhuowei, 2007; Hui et al., 2008; Fengming et al., 2008].

At the moment there is not a procedure that can be applied globally with suitable accuracy for the analysis of water bodies and a complete archive of classification outputs is not available everywhere. For this reasons authors needed to elaborate a methodology which could be applied globally and that minimizes computation times and hardware resources.

Different methodologies were tested by the authors in 3 areas: Bangladesh, Mozambique and Pakistan. Finally, a combination of those methodologies was chosen, providing the best compromise between output accuracy level and required computing and storage resources: the methodology combines NDVI indices and threshold in the IR band.

In order to reduce the influence of clouds and cloud shadows, a flexible compositing technique was used, based on the counting of the number of time an area is covered by water on a daily basis. In fact, the influence of cloud cover can be minimized if a time compositing period greater than the mean persistence of cloud cover in a specific area is used; this composition time can depend on the climatic characteristics of the considered areas and on the type of the event. In the case of Bangladesh it was highlighted that 10 days period is a best compromise [Disabato, 2008; Ajmar et al., 2010]. The result of this composition, is an image containing a classification in three classes representative of the situation on the ground during the time period considered: water bodies, soil, clouds (Fig. 4). The class cloud represents the pixels that for the whole 10 days period resulted to be covered by clouds.

The available archive of MODIS MOD09GQ ad MYD09GQ was classified using this methodology for the area of Bangladesh, thus producing a complete archive of water bodies was produced for the period of 2000-2010 with a frequency of 10 days.

Data integration

In order to develop a model that, with a given intensity of rain, will be able to provide scenarios of flooded areas, a first verification of the correlation between rainfall events and floods on the ground was performed on the ten days basis and at basin scale. For the analyzed period, from 2000 to 2008, the full set of records is constituted by a data referred to 324 ten days periods.

In order to better study, explain and characterize correlation results, several filtering criteria are proposed (Tab. 1):

a) correlations was verified both on the basin where the event occurred ($s_0$) and on its downstream basin ($s_1$), assuming that floods are normally propagated according with the hierarchical organization of the stream network;

b) ground effects were verified both in the same 10 days period of the event ($t_0$) and in the next period ($t_1$), for considering the effects of flood propagation and the fact that the event may have occurred toward the end of the considered 10 days period;
c) filters was also applied on return periods (T), creating two different classes of event magnitude (T higher than 2 and 5 years);

d) the percentage of basin surface covered by clouds, affecting the results of the classification of optical satellite images, where considered, selecting the cases where the percentage of the basin surface covered by clouds was less than 40%.

Figure 4 – Decadal soil classification used for the analysis of events. Classes: white=clouds, blue=water, brown=soil.

For all the above mentioned cases the Pearson’s linear correlation coefficient was calculated, in order to evaluate the cases in which correlation between rain and effects on the ground is higher.

Additionally, for the cases of critical events (return time higher or equal than 2 years) and no filter on cloud cover, further analysis was performed in order to verify possible different behaviour in function of:

- basin type, differentiating between major river beds, minor river and coastal basins;
- percentage of irrigated surfaces, distinguishing between low (< 15% of the basin surface), moderately (15-30%) and highly (> 30%) irrigated basins.
Table 1 - Synthesis of filters applied.

<table>
<thead>
<tr>
<th>Basin</th>
<th>Ten days period</th>
<th>Return period</th>
<th>Cloud filter</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Where the event occurred</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(s₀)</td>
<td></td>
<td>&gt;&gt;&gt;2</td>
<td>no filter</td>
<td>s₀t₀^{2}</td>
</tr>
<tr>
<td>(t₀)</td>
<td></td>
<td>&gt;&gt;&gt;2</td>
<td>&lt;40%</td>
<td>s₀t₀^{2c}</td>
</tr>
<tr>
<td>(t₀)</td>
<td></td>
<td>&gt;=5</td>
<td>no filter</td>
<td>s₀t₀^{5}</td>
</tr>
<tr>
<td>(t₀)</td>
<td></td>
<td>&gt;=5</td>
<td>&lt;40%</td>
<td>s₀t₀^{5c}</td>
</tr>
<tr>
<td>Next to the event</td>
<td></td>
<td>&gt;=2</td>
<td>no filter</td>
<td>s₀t₁^{2}</td>
</tr>
<tr>
<td>(t₁)</td>
<td></td>
<td>&gt;=2</td>
<td>&lt;40%</td>
<td>s₀t₁^{2c}</td>
</tr>
<tr>
<td>(t₁)</td>
<td></td>
<td>&gt;=5</td>
<td>no filter</td>
<td>s₀t₁^{5}</td>
</tr>
<tr>
<td>(t₁)</td>
<td></td>
<td>&gt;=5</td>
<td>&lt;40%</td>
<td>s₀t₁^{5c}</td>
</tr>
<tr>
<td>Downstream of where the event occurred</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(s₁)</td>
<td></td>
<td>&gt;=2</td>
<td>no filter</td>
<td>s₁t₀^{2}</td>
</tr>
<tr>
<td>(t₀)</td>
<td></td>
<td>&gt;=2</td>
<td>&lt;40%</td>
<td>s₁t₀^{2c}</td>
</tr>
<tr>
<td>(t₀)</td>
<td></td>
<td>&gt;=5</td>
<td>no filter</td>
<td>s₁t₀^{5}</td>
</tr>
<tr>
<td>(t₀)</td>
<td></td>
<td>&gt;=5</td>
<td>&lt;40%</td>
<td>s₁t₀^{5c}</td>
</tr>
<tr>
<td>Next to the event</td>
<td></td>
<td>&gt;=2</td>
<td>no filter</td>
<td>s₁t₁^{2}</td>
</tr>
<tr>
<td>(t₁)</td>
<td></td>
<td>&gt;=2</td>
<td>&lt;40%</td>
<td>s₁t₁^{2c}</td>
</tr>
<tr>
<td>(t₁)</td>
<td></td>
<td>&gt;=5</td>
<td>no filter</td>
<td>s₁t₁^{5}</td>
</tr>
<tr>
<td>(t₁)</td>
<td></td>
<td>&gt;=5</td>
<td>&lt;40%</td>
<td>s₁t₁^{5c}</td>
</tr>
</tbody>
</table>

Results
Correlation results, grouped according the aggregation criteria explained in the previous chapter, are commented in the following paragraphs; correlation were calculated only in the case where the number of events selected for each filtering criterion is higher or equal to 3. For each criterion, Table 2 shows mean correlation values from 1 to 10 days cumulated rainfall and the total number of considered basins and events.

In cases (t₀), correlation values increase with longer period cumulated rainfall, with in most cases a breakline at 8 or 9 days value, possibly due to the flood propagation time factor. On the contrary, in cases (t₁), the same behaviour is not evident. That can be explained considering that, when observing the time frame corresponding with the event, an higher number of days is necessary to reach critical cumulated rainfall; while the following time frame includes the contribution of the previous 10 days and thus, even with a shorter cumulated period, higher correlations with consequences on the ground can be observed.

In cases t₀ it can also be derived that higher correlation values correspond to events with a return period (T) higher than 2 and filter on cloud coverage (0.38). In cases t₁, higher correlation values correspond to events with T higher than 5 and no filter on cloud coverage (0.36). That can be explained by the fact that, in order to obtain effect on the ground in the next 10 days period, a more intense rainfall event is necessary.

At equal conditions, the filter on cloud coverage influences significantly the results, but the influence is either positive or negative. That may be explained by the reduction and the lost of significance of the sample in the case of 5 years return period events, considering the relatively shortness of the common historical time frame (2000-2008).
Table 2 - Average of correlation values for different rainfall cumulated periods, from 1 (r1) to 10 (r10) days. Filter types highlighted in grey represent those with higher correlation values for each group.

<table>
<thead>
<tr>
<th>Filter type</th>
<th>r1</th>
<th>r2</th>
<th>r3</th>
<th>r4</th>
<th>r5</th>
<th>r6</th>
<th>r7</th>
<th>r8</th>
<th>r9</th>
<th>r10</th>
<th>N. of basins</th>
<th>N. of events</th>
</tr>
</thead>
<tbody>
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<td>s_0</td>
<td>2</td>
<td>-0.23</td>
<td>-0.19</td>
<td>-0.12</td>
<td>-0.10</td>
<td>-0.09</td>
<td>-0.05</td>
<td>-0.05</td>
<td>0.01</td>
<td>0.09</td>
<td>0.15</td>
<td>70</td>
</tr>
<tr>
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<td>-0.21</td>
<td>-0.12</td>
<td>-0.12</td>
<td>-0.10</td>
<td>0.00</td>
<td>0.08</td>
<td>0.19</td>
<td>0.32</td>
<td>0.38</td>
<td>66</td>
<td>488</td>
</tr>
<tr>
<td>5</td>
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<td>-0.20</td>
<td>-0.20</td>
<td>-0.24</td>
<td>-0.30</td>
<td>-0.26</td>
<td>-0.27</td>
<td>-0.23</td>
<td>-0.06</td>
<td>0.08</td>
<td>48</td>
<td>238</td>
</tr>
<tr>
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<td>-0.30</td>
<td>-0.33</td>
<td>-0.41</td>
<td>-0.36</td>
<td>-0.32</td>
<td>-0.19</td>
<td>0.21</td>
<td>0.26</td>
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<td>t_0</td>
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<td>0.15</td>
<td>0.21</td>
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<td>0.21</td>
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<td>0.18</td>
<td>0.18</td>
<td>0.23</td>
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<td>488</td>
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<td>0.37</td>
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<td>0.15</td>
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<td>0.25</td>
<td>0.23</td>
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<td>0.26</td>
<td>0.15</td>
<td>25</td>
<td>97</td>
</tr>
</tbody>
</table>

The shortness of the common historical time frame can be considered one of the causes of the low correlation values, as few anomalies may have an high influence on overall mean values.

In order to investigate the behaviour of basin according with basin types and irrigation practices, further analysis was performed for the cases having higher correlation values in each group (Tab. 2).

**Basin type**

Coastal basin (included only in the first two groups as they have not a downstream basin) present higher variability in correlation values (Tab. 3); the effects of tidal bores, preventing inland flood drainage, is not negligible; Bangladesh coast, in fact, is characterized by low elevation and subject to the possibly combined effect of tides and cyclonic surges and the combined effects of tidal surges and rainfall events makes the effects on the ground less predictable.

Major and minor basins seem to have similar behavior and then the identification of those two types is not relevant for the flood scenarios definition.

**Percentage of irrigated surfaces**

Only in the case s_0t_0 correlation values are higher for low irrigated basins (Tab. 4).

According to those results, possible commission errors while classifying flood water on MODIS images seems not to be a factor.
In most cases, moderately to high irrigated basins have a good correlation for shorter rainfall cumulated period in respect to low irrigated basins; this behavior may be explained by soil saturation process, causing a faster basin response. Nevertheless, it must be considered that the dataset used for estimating the percentage of irrigated surfaces, the FAO Occurrence of irrigated areas (FGGD) dataset (http://www.fao.org/geonetwork/srv/en/metadata.show?id=14070&currTab=simple), has a low geometrical resolution (5 arc-minutes, approximately 8.5 km at Bangladesh latitude).

Table 3 - Average of correlation values for different rainfall cumulated periods, from 1 (r1) to 10 (r10) days, according to basin types. Filter types with higher correlation values in Table 2 are represented.

<table>
<thead>
<tr>
<th>Filter type</th>
<th>Basin type</th>
<th>r1</th>
<th>r2</th>
<th>r3</th>
<th>r4</th>
<th>r5</th>
<th>r6</th>
<th>r7</th>
<th>r8</th>
<th>r9</th>
<th>r10</th>
<th>N. of basins</th>
<th>N. of events</th>
</tr>
</thead>
<tbody>
<tr>
<td>s_t_2c</td>
<td>Coastal</td>
<td>-0.30</td>
<td>-0.29</td>
<td>-0.23</td>
<td>-0.26</td>
<td>-0.21</td>
<td>-0.12</td>
<td>-0.04</td>
<td>0.08</td>
<td>0.25</td>
<td>0.49</td>
<td>10</td>
<td>72</td>
</tr>
<tr>
<td></td>
<td>Major</td>
<td>-0.40</td>
<td>-0.30</td>
<td>-0.18</td>
<td>-0.15</td>
<td>-0.14</td>
<td>0.03</td>
<td>0.11</td>
<td>0.25</td>
<td>0.32</td>
<td>0.36</td>
<td>12</td>
<td>98</td>
</tr>
<tr>
<td></td>
<td>Minor</td>
<td>-0.25</td>
<td>-0.16</td>
<td>-0.08</td>
<td>-0.07</td>
<td>-0.06</td>
<td>0.02</td>
<td>0.10</td>
<td>0.20</td>
<td>0.34</td>
<td>0.37</td>
<td>44</td>
<td>318</td>
</tr>
<tr>
<td>s_t_5</td>
<td>Coastal</td>
<td>0.19</td>
<td>0.13</td>
<td>0.18</td>
<td>-0.07</td>
<td>-0.10</td>
<td>-0.13</td>
<td>-0.14</td>
<td>0.03</td>
<td>0.17</td>
<td>0.22</td>
<td>8</td>
<td>44</td>
</tr>
<tr>
<td></td>
<td>Major</td>
<td>0.42</td>
<td>0.42</td>
<td>0.29</td>
<td>0.44</td>
<td>0.46</td>
<td>0.50</td>
<td>0.56</td>
<td>0.54</td>
<td>0.44</td>
<td>0.38</td>
<td>10</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>Minor</td>
<td>0.19</td>
<td>0.23</td>
<td>0.18</td>
<td>0.20</td>
<td>0.19</td>
<td>0.29</td>
<td>0.34</td>
<td>0.39</td>
<td>0.40</td>
<td>0.37</td>
<td>30</td>
<td>138</td>
</tr>
<tr>
<td>s_t_2c</td>
<td>Major</td>
<td>-0.48</td>
<td>-0.36</td>
<td>-0.28</td>
<td>-0.15</td>
<td>-0.13</td>
<td>0.02</td>
<td>0.13</td>
<td>0.29</td>
<td>0.43</td>
<td>0.45</td>
<td>12</td>
<td>92</td>
</tr>
<tr>
<td></td>
<td>Minor</td>
<td>-0.37</td>
<td>-0.33</td>
<td>-0.31</td>
<td>-0.28</td>
<td>-0.20</td>
<td>-0.08</td>
<td>-0.01</td>
<td>0.15</td>
<td>0.29</td>
<td>0.35</td>
<td>42</td>
<td>303</td>
</tr>
<tr>
<td>s_t_5</td>
<td>Major</td>
<td>0.43</td>
<td>0.47</td>
<td>0.38</td>
<td>0.49</td>
<td>0.51</td>
<td>0.53</td>
<td>0.59</td>
<td>0.56</td>
<td>0.39</td>
<td>0.35</td>
<td>9</td>
<td>52</td>
</tr>
<tr>
<td></td>
<td>Minor</td>
<td>0.25</td>
<td>0.24</td>
<td>0.17</td>
<td>0.27</td>
<td>0.27</td>
<td>0.32</td>
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<td>0.48</td>
<td>0.45</td>
<td>0.40</td>
<td>29</td>
<td>134</td>
</tr>
</tbody>
</table>

Table 4 - Average of correlation values for different rainfall cumulated periods, from 1 (r1) to 10 (r10) days, according to irrigation classes. Filter types with higher correlation values in Table 2 are represented.

<table>
<thead>
<tr>
<th>Filter type</th>
<th>Irrigation class</th>
<th>r1</th>
<th>r2</th>
<th>r3</th>
<th>r4</th>
<th>r5</th>
<th>r6</th>
<th>r7</th>
<th>r8</th>
<th>r9</th>
<th>r10</th>
<th>N. of basins</th>
<th>N. of events</th>
</tr>
</thead>
<tbody>
<tr>
<td>s_t_2c</td>
<td>Low</td>
<td>-0.31</td>
<td>-0.26</td>
<td>-0.17</td>
<td>-0.12</td>
<td>0.01</td>
<td>0.14</td>
<td>0.24</td>
<td>0.33</td>
<td>0.44</td>
<td>0.55</td>
<td>19</td>
<td>131</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>-0.23</td>
<td>-0.19</td>
<td>-0.04</td>
<td>-0.09</td>
<td>-0.11</td>
<td>0.01</td>
<td>0.08</td>
<td>0.12</td>
<td>0.20</td>
<td>0.27</td>
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<td>187</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>-0.32</td>
<td>-0.19</td>
<td>-0.17</td>
<td>-0.14</td>
<td>-0.16</td>
<td>-0.11</td>
<td>-0.03</td>
<td>0.17</td>
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<td>0.39</td>
<td>23</td>
<td>170</td>
</tr>
<tr>
<td>s_t_5</td>
<td>Low</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.08</td>
<td>0.26</td>
<td>0.32</td>
<td>0.30</td>
<td>0.36</td>
<td>0.41</td>
<td>11</td>
<td>58</td>
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<tr>
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<td>Moderate</td>
<td>0.23</td>
<td>0.21</td>
<td>0.18</td>
<td>0.12</td>
<td>0.12</td>
<td>0.17</td>
<td>0.18</td>
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<td>0.41</td>
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<td>19</td>
<td>85</td>
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<td>High</td>
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<td>0.44</td>
<td>0.33</td>
<td>0.38</td>
<td>0.35</td>
<td>0.35</td>
<td>0.42</td>
<td>0.47</td>
<td>0.32</td>
<td>0.25</td>
<td>18</td>
<td>95</td>
</tr>
<tr>
<td>s_t_2c</td>
<td>Low</td>
<td>-0.45</td>
<td>-0.44</td>
<td>-0.29</td>
<td>-0.21</td>
<td>-0.10</td>
<td>0.15</td>
<td>0.22</td>
<td>0.25</td>
<td>0.30</td>
<td>0.42</td>
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<td>91</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>-0.23</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.16</td>
<td>-0.06</td>
<td>0.03</td>
<td>0.07</td>
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<td>0.37</td>
<td>0.40</td>
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<td>153</td>
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<td>-0.38</td>
<td>-0.39</td>
<td>-0.34</td>
<td>-0.34</td>
<td>-0.27</td>
<td>-0.16</td>
<td>0.03</td>
<td>0.28</td>
<td>0.30</td>
<td>22</td>
<td>160</td>
</tr>
<tr>
<td>s_t_5</td>
<td>Low</td>
<td>0.16</td>
<td>-0.02</td>
<td>-0.17</td>
<td>-0.08</td>
<td>-0.05</td>
<td>0.00</td>
<td>0.17</td>
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<td>0.26</td>
<td>0.25</td>
<td>7</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>0.24</td>
<td>0.23</td>
<td>0.18</td>
<td>0.19</td>
<td>0.18</td>
<td>0.28</td>
<td>0.29</td>
<td>0.41</td>
<td>0.50</td>
<td>0.47</td>
<td>14</td>
<td>62</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>0.38</td>
<td>0.45</td>
<td>0.38</td>
<td>0.55</td>
<td>0.54</td>
<td>0.54</td>
<td>0.58</td>
<td>0.57</td>
<td>0.41</td>
<td>0.33</td>
<td>18</td>
<td>95</td>
</tr>
</tbody>
</table>
Conclusion
Current work highlights the benefits of integrating rainfall data analysis with remote sensing, in order to correlate major rain events with their consequences on the ground. This study is a propaedeutic investigation in order to define cases linkable to flood scenarios, and to understand which are the factors to be taken into consideration when trying to associate rainfall with effects on the ground. In particular, spatial and temporal parameters seems to be the key factors, as higher correlation values are detected for the downstream basin, for high rainfall cumulated period (higher than 8 days) and for the time frame next to the event; those conditions seems in favour to the possibility of the system to provide scenario with a predictive capacity suitable for early-warning.
In order to better consider rainfall events variability in terms of duration, a system for identifying and isolate each event and for cumulating rainfall values with a flexible time frame could improve the analysis. The subdivision in basin types brought to the consideration that coastal basin will be particularly critical for the definition of reliable scenarios. High irrigation patterns seems to have a positive effect in the correlation between rainfall and effects on the ground in the time frame next to the event.
The next phase of work is the definition for each basin of flood scenarios associated to different rainfall thresholds. An example is shown for one basin (Tab. 5): in this case two appropriate time intervals were identified (250-350 mm and 350-450 mm of cumulated rainfall in 10 days) and for both intervals two events are present in the historical dataset. For the first interval, both cases produced a similar number of flooded pixel (respectively 9884 for the events occurred on the 2nd decade of September 2004 and 9366 on the 3rd decade of October 2005) and similar scenarios.
Also for the second interval considered, the two events (2nd decade of July 2005 and 2nd decade of June 2007) produced similar number of water pixels (respectively 11570 and 10817). In case of more than one image is associated with the same interval of rainfall, reduced cloud cover and greater flooded area can be used as selection criteria, in order to present the worst case scenario. In this example, the interval 250-350 mm (of cumulated rainfall in 10 days) is associated to the image of 2nd decade of September 2004; the interval 350-450 mm is associated to the images of 2nd decade of July 2005, where the clouds do not cover the considered basin.
After having associated flood scenarios to rainfall values of the historical series, the purpose of forecasting floods could be achieved comparing the real-time rainfall values to these thresholds and selecting the flood scenario associated with the same characteristic of rainfall.
This work is continuing on the creation of flood scenarios using the illustrated methodology for each basin of Bangladesh and automating and generalizing the methodology for its extension to other developing countries, with a priority to those of interest of WFP.

Acknowledgements
The authors thank Dr. John McHarris (WFP) for providing the rain gauge data of Bangladesh.
MODIS data are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (lpdaac.usgs.gov).
Table 5 – Flood scenarios for basin 49.

<table>
<thead>
<tr>
<th>Rainfall 10 days</th>
<th>Events</th>
<th>N pixel flooded</th>
<th>Flood scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>250-350 mm</td>
<td>2nd decade September 2004</td>
<td>9884</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3rd decade October 2005</td>
<td>9366</td>
<td></td>
</tr>
<tr>
<td>350-450 mm</td>
<td>2nd decade July 2005</td>
<td>11570</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2nd decade June 2007</td>
<td>10817</td>
<td></td>
</tr>
</tbody>
</table>

References


Received 12/02/2011, accepted 16/08/2011
The ITHACA Early Warning System for drought monitoring: first prototype test for the 2010 Sahel crisis

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Abstract
The non-profit association ITHACA cooperates with the World Food Programme in order to define a global drought Early Warning System, mostly based on satellite data, with the scope of mapping critical areas that may be potentially subject to food crises. In 2010 the African regions of Sahel, especially Niger and Chad, faced a relevant food crisis due to strong deficits in agricultural and pastoral production, and the World Food Programme requested technical support to outline the areas most affected by drought. Testing the tools under development, ITHACA analyzed environmental conditions potentially related to the 2010 food crisis. The paper describes the studies performed and their contribution to the improvement of the ITHACA drought Early Warning System.

Keywords: drought, Early Warning System, precipitation, NDVI, phenology, Sahel, WFP.

Introduction
Drought is a natural condition of temporary significant reduction in rainfall and water availability with respect to the normal values for a significant period of time and over a wide region. The economic and social consequences are more severe the greater is the vulnerability of water supply systems, agricultural systems and socio-economic characteristics of society in the affected areas [VV.AA., 2006]. Prolonged periods of drought may lead significant environmental, economic and social consequences in developing countries and, in particular, where subsistence farming exists, drought events can be the cause of severe famine, death of livestock and displacement of the population because of lack of food resources. According to the World Food Programme (WFP), the largest operational agency of the United Nations that deals with the rapid distribution of goods for survival in case of emergencies, we are currently witnessing an increase in natural disasters such as floods, tropical storms and long periods of drought, with devastating consequences for food security in poor and developing countries (http://www.wfp.org/). Therefore, in this frame, it is necessary to define proper methodologies and tools in order to support drought planning and management policy. These methodologies and tools must primarily enable the early detection of events, their monitoring and characterization, and are necessary to define appropriate Early Warning Systems. However, their definition and implementation is strongly influenced by the availability of basic environmental data, primarily meteorological.
Satellite remote sensing techniques provide successful tools for studying and monitoring the various aspects related to the drought phenomena, due to the availability of several raw and thematic data with different spatial, temporal and spectral resolutions [Kogan, 1991; Walter, 1994]. Various Early Warning Systems have been developed by the international community focused on drought and food security, which involve the use of geospatial data collected both by satellite and ground sources, especially for the monitoring areas belonging to poor and developing countries. Some of them are global or cover different continents, such as US-AID FEWSNET (www.fews.net), EU MARS FOOD-SEC (http://mars.jrc.it/mars/About-us/FOODSEC), FAO GIEWS (www.fao.org/giews), EU ESA GMFS (www.gmfs.info), while others are designed for a specific area of interest, for example the African continent, as in the case of AU-EU AMESD (www.amesd.org) and EU-Geoland2 NARMA (www.geoland2.eu). In such a context, through its partnership with the WFP, ITHACA (Information Technology for Humanitarian Assistance, Cooperation and Action) is responsible for a project aimed at creating tools and procedures, based mostly on satellite data, for early detection of drought events on a global scale.

Realizing an Early Warning System which can deliver clear, easy to interpret and reliable information to decision makers is considered an important issue. Although it seems obvious, it is often hard to achieve a good level of mutual communication and understanding between Early Warning System providers and the final users [Wilhite, 2000]. ITHACA’s efforts are consequently oriented towards the development of a new automated system, fully customized in order to respond to the WFP’s specific requirements for an efficient, web accessible and downloadable product.

The system is still under development and its aim is to integrate different parameters in a simplified agricultural drought model which considers environmental data related to vegetation production and irregular precipitations. The model outputs that identify alerted areas will be updated every month and disseminated using web display applications and will be made available in form of maps for downloading.

To date, some preliminary procedures have been developed in the context of this project which are in the evaluation phase. The 2010 severe food crisis that hit the Sahel region and, specifically, the Niger and Chad areas was the first occasion to test the procedures developed. The WFP delivered considerable food aid and reported that over 7 million people in Niger, 46% of the total population, were in a situation of moderate to high food insecurity, and over 2 million in Chad suffered acute malnutrition.

In February 2010, after the crisis had already started, ITHACA was involved in the production of maps showing the areas affected by a reduction in vegetation productivity, in order to provide value added information for food aid operations. At this stage, ITHACA procedures were exploited to test the methodologies on a real case and not to provide early warnings on drought events. A re-analysis of the 2009 data made it possible to verify the effectiveness of the produced outputs, and to plan future improvements in the system. The paper describes the main features of the drought Early Warning System being developed and the results of its first application to the case study in Sahel.

**Data and methodology**

Concerning the study of drought events, ITHACA’s main scope is to define an Early Warning System which monitors relevant environmental variables and indices on a
global scale, that enables the detection and the characterization of drought phenomena and provides suitable information for emergency preparedness and operational activities undertaken by the WFP. The need to pay attention to water scarcity and its impacts mainly on agriculture led to the decision to conduct a preliminary study of the two following key environmental variables: vegetation health, explained using Normalized Difference Vegetation Index (NDVI) data, and precipitation. In particular, the continuous monitoring of precipitation during a vegetation season under examination makes it possible rapidly detect any water stress conditions for the vegetation, while monitoring specific phenological parameters, extracted from NDVI data, is used in order to formulate an assessment of vegetation productivity at the end of the considered season.

In the context of drought events, which are slow-onset threats with a natural evolution of months, even monthly monitoring can be considered a near real-time operation. Thus the system, once operational, is supposed to provide alerts to Local Offices of the WFP on a monthly basis in the form of maps that synthesize all monitoring results and show the distribution of critical conditions. The timely detection of possible critical conditions in vegetation health and productivity, during a vegetative season and at its end, will allow WFP users to:

- identify agricultural areas with increased crop failure or food crisis risk, which subsequently require more specific and local monitoring activities;
- better organize and manage livestock displacement toward more productive pastures.

**Selected data**

In order to monitor vegetation dynamics and productivity over a long time scale and on a wide spatial scale, fundamental base data are represented by various vegetation indicators derived from satellite imagery [Hassan, 2004]. The NDVI is a satellite derived index of vegetation health and density, which uses the visible and near-infrared bands of the electromagnetic spectrum. This index has often been used for vegetation monitoring, crop yield assessment, and vegetation stress detection. Moreover, as reported by several authors, the relationship between the NDVI and vegetation productivity is well established [Prince, 1991; Bai, 2008; Fensholt et al., 2008; ]; the NDVI has been shown to be related to biophysical variables that control vegetation productivity, such as the leaf-area index (LAI), the fraction of photosynthetically-active radiation absorbed by vegetation (fAPAR), and net primary productivity (NPP) [Running et al., 2004; Pettorelli et al., 2005; Tagil, 2007; Bai, 2008]. Of course, some limits in the use of vegetation indices ought to be taken into consideration. The NDVI is affected by different deficiencies due to sensitivity to soil color, atmospheric effects, illumination and observation geometry. Nevertheless, it is the vegetation index most widely used by the research community. The reason behind this is that the development of different vegetation indices has not resulted in the creation of a consistent long-term time series of data [Herrmann, 2005].

Nowadays, several NDVI datasets derived from satellites are available, with different spatial and temporal resolutions, and different temporal coverage. For monitoring purposes, a global 15-day NDVI time-series at a 5.6 km spatial resolution was used, extracted from the MODIS MOD13C1 Terra CMG data for the 2000 - 2010 period.
All the MODIS vegetation products, available at different spatial and temporal resolutions, derive from MODIS atmospherically corrected data (MOD09 series) [Vermote et al., 2002] and are obtained using a constrained view angle - maximum value compositing (CV-MVC) methodology. Despite the smoothing effects of temporal compositing, residual atmospheric and bidirectional effects often still persist in NDVI time-series, particularly in regions of prevalent cloud cover or at higher latitudes due to wider sun and sensor view angles [Carreiras et al., 2003]. For this reason, further noise reduction procedures are usually carried out on composited NDVI time-series. Many noise smoothing techniques are available, usually based on function-fitting and filtering techniques. J. N. Hird [2009] performed accurate comparison tests of several common methods of noise reduction and demonstrated the general superiority of Asymmetric Gaussian (AG) and Double Logistic (DL) function-fitting techniques over a set of alternative filters. In particular, these procedures showed a balanced ability to reduce noise while maintaining relevant NDVI signal integrity. The TIMESAT analysis software, freely distributed to the scientific community [Jönsson and Eklundh, 2004; Jönsson and Eklundh, 2010], provides tools for applying the described techniques. This software was used in the proposed methodology both to correct residual noises of the base NDVI data, and to extract phenological metrics.

As previously mentioned, the second parameter chosen to detect drought conditions was precipitation.

In recent years there was significant development in the field of satellite rainfall estimation, particularly in estimation algorithms that can generate high-resolution rainfall products by merging infrared (IR) and microwave (MW) satellite observations [Vicente, 1994; Sorooshian et al., 2000; Huffman et al., 2001; Kuligowski, 2002; Joyce et al., 2004; Turk and Miller, 2005; Huffman et al., 2007]. One recent algorithm was developed at the National Aeronautics and Space Administration (NASA) Goddard Space Flight Center (GSFC): the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) [Huffman et al., 2007]. The TMPA consists of fields of 3-hourly rainfall rates over a 0.25°×0.25° grid within the global latitude belt ranging between 50° north and 50° south. The rainfall data selected and used comes from TMPA and consists in the daily accumulated rainfall product TRMM_3B42_daily, derived from the 3-hourly product with a temporal coverage from 1997-12-31 to present and released 10-15 days after each month. Contained parameter per file is precipitation rate (mm/day).

Lastly, additional data was used: hydrological basins derived from HYDRO1K dataset and land cover information from GlobCover 2009. The HYDRO1K dataset (http://gcmd.nasa.gov/records/GCMD_HYDRO1k.html) is a GIS watershed layer developed at the U.S. Geological Survey’s Centre for Earth Resources Observation and Sciences (EROS). The GlobCover 2009 products are based on ENVISAT Medium Resolution Imaging Spectrometer (MERIS) data with a spatial resolution of 300 meters and labeled according to the UN FAO Land Cover Classification System.

**Vegetation monitoring using satellite remote sensing data**

Vegetation productivity monitoring procedures, developed in the context of the planned ITHACA drought Early Warning project, are based on extracting and elaborating phenological parameters from satellite derived datasets. The vegetation phenology concerns the study of annual green-up, or growth, and senescence cycles of plants. Seasonal changes observed in NDVI time-series have proven useful in tracking land
surface phenology and vegetation development stages, and for mapping vegetation dynamics [e.g. Justice et al., 1986; Townshend and Justice, 1986; Reed et al., 1994; Pettorelli et al., 2005].

As it can be seen in Figure 1, from the yearly NDVI function (the regular curve depicted in the figure) that best fits the original yearly NDVI time-series (the irregular one) the following phenological parameters or metrics can be extracted for each vegetation season under consideration [Jönsson and Eklundh, 2010] and used for analytical purposes:

- the time for the Start of the Season (A): time when the left edge of the NDVI fitted function has increased to a user defined level measured from the left minimum level. This is the time at which seasonal photosynthetic activity begins;
- the Length of the Season (G): time from the Start to the End of the Season (B, that is the time when the right edge has decreased to a user defined level measured from the right minimum level);
- the Seasonal Amplitude (F): difference between the NDVI Largest Data Value (E) for the fitted NDVI function during the season and the base level (given as the average of the left and right minimum values). This is a measure of seasonality;
- the Seasonal Small Integral (H): integral of the NDVI function describing the season from the season Start to the season End (area between the fitted function and the base level).

Among the existing phenological metrics which are derivable from NDVI time-series, only four are selected, considered able to describe synthetically and completely the trend of a vegetation season in different domains (only time domain: the Start of the Season, SOS, and Length of the Season, LS, parameters; only NDVI domain: the Seasonal Amplitude, SA, parameter; and integrated NDVI/time domain: the Seasonal Small Integral, SMI, parameter).

![Figure 1- Diagram of NDVI/time and derived phenological parameters.](image-url)
The basic idea is that these phenological parameters, for a given growing season, are related to the seasonal vegetation productivity, considering both agricultural production and biomass available in pastoral areas. Therefore comparing their values for a given growing season with the average, minimum and maximum ones computed using eleven years of NDVI data, helps to explain the performances of the considered vegetative season and to formulate an opinion on its expected productivity.

Three different indices are proposed in order to quantify, on a pixel basis, the deviation of the examined vegetation season conditions from the historical normal behaviour:

- the Condition Index (CI), given by Kogan [1990, 1995], which provides a measure of the proximity of the current value of the considered parameter to the minimum (at which CI=0) and maximum (C=1) ones. It is expressed as:

\[
CI = \frac{x - \min_x}{\max_x - \min_x} \times 100 \quad [1]
\]

where \(x\) is the value of the phenological parameter for the examined growing season and \(\min_x, \max_x\) are the minimum and maximum values of the parameter considered, extracted from the whole available historical time-series;

- the Deviation (D) and the Percent Deviation (PD) from the average value:

\[
D = x - \mu_x \quad [2]
\]

\[
PD = \frac{x - \mu_x}{\mu_x} \times 100 \quad [3]
\]

where \(\mu_x\) is the historical average value of the considered parameter, estimated using the whole available time-series.

Specific routines are implemented in IDL (*Interactive Data Language* programming tool) in order to manage an automatic work-flow that includes the following operations: the NDVI time-series preparation, the elaboration of binary outputs produced from the TIMESAT software, the extraction and reorganization of phenological historical and real-time values and lastly, the calculation of the proposed indexes of deviation for each phenological parameter under consideration.

Mapping the distribution of the proposed indexes on a pixel by pixel basis makes it possible to identify areas of potentially reduced vegetation productivity and to quantify its severity. This base information, completed by ancillary data, such as the distribution of cultivated areas and the type of prevailing cultivation, help to detect critical conditions in agricultural productivity for an examined vegetative season and to predict future crop failures and food crises.
Precipitation analysis using satellite rainfall data

For this study the rainfall temporal distribution is calculated on a monthly basis, according to methods most commonly used to analyze precipitation distribution (e.g. Climatological Data Annual Summaries published by NOAA National Data Center where normal rainfall is presented on annual and monthly basis), using an automatic procedure which extracts average monthly cumulative rainfall values on a pixel basis, starting from the available time series of 3B42 raw data (1998-2009).

In particular three rainfall parameters are calculated:
- cumulative rainfall (CR), which allows to identify significant spatial differences in the amount of rainfall and to identify rainfall regime over a particular area;
- number of rainy days (NRD), which, used in combination with cumulative rainfall, allows to identify the intensity of monthly rainfall;
- rainfall density (RDE, ratio between precipitation CR and number of rainy days NRD).

In order to study the effects of rainfall at different time scales, monthly data is aggregated in seasonal and annual intervals. Seasonal intervals are selected according to the specific pluviometric regime.

Average behaviour and deviations (D) of the considered rainfall parameters are lastly calculated for the 12 years of available data on selected time intervals.

Application of developed procedures during the 2010 drought crisis in Sahel

In February 2010, during the food crisis in Niger and Chad, the WFP requested Ithaca for spatial information useful to assess irregular precipitation patterns and areas of potentially reduced vegetation productivity in order to prioritize emergency interventions. Several cartographic products, derived from the procedures being developed, were then supplied to the WFP users involved in humanitarian operations on the field. As already mentioned, in this case ITHACA procedures were not used for an early warning alert, but only for assessment purposes, based on the detection of vegetation stress conditions during the previous 2009 vegetative season, which can be considered the cause of the 2010 crisis.

As previously described, the monitoring procedures are based on the comparison between the values of the chosen environmental variables for the current vegetative season and the historical minimum, maximum and average values, extracted from the whole available NDVI and precipitation time-series.

In order to describe drought intensity according to vegetation conditions and phenology during the 2009 vegetative season, the following maps were produced:
- maps showing the SoS deviations (day-shifts in advance or delay of the Start of the Season dates) in the considered areas for the 2009 vegetative season, obtained using the raw outputs of the analysis performed on a pixel basis (about 5 km spatial resolution). In addition, in order to provide a more effective display of the most affected areas, raw results were aggregated at a second level administrative boundary (Fig. 2), according to a higher frequency distribution rule;
- maps showing the Percent Deviation and Condition Index distribution of the Seasonal Length (SL), Amplitude (SA) and Small Integral (SMI) parameters in
the areas under consideration for the 2009 vegetative season. Their deviations made it possible to detect any reductions in vegetation productivity related to an increased risk of crop failure and a decrease in available resources.

Meteorological conditions over Niger and Chad and anomalies for the 2009 rainy season (June, July, August and September) were described by the following maps:
- rainfall regimes calculated considering 1998-2009 precipitation data: average monthly CR maps;
- average NRD and RDE maps calculated considering 1998-2009 precipitation data;
- maps of rainfall Deviations (D) from the average monthly cumulative rainfall (1998-2009) of the rainy months of the 2009; 
- maps of rainfall Deviations (D) from the average seasonal cumulative rainfall (1998-2009) for the rainy season of the 2009 (see Fig. 3).

Correlation analysis of vegetation and precipitation data

After the emergency phase, the dynamics of the considered drought variables (precipitation and vegetation) in the last years were investigated and further analyses were performed mainly aimed at verifying two different aspects: the existing linear correlation between the selected time-series, in order to choose the most suitable parameters for the Early Warning System, and their behaviour in the years when food crises were reported.

The correlation analysis between phenological parameters and precipitation data was carried out considering their values in the 2000-2009 interval, using the Pearson correlation coefficient.

In order to overcome evident spatial co-registration problems, the input variable values used for the analysis were obtained spatially aggregating base data with different geometric resolutions, over masks suitably produced according to the data type. The masks used were defined considering, for each country, hydrological basins from HYDRO1K data layer and vegetation coverage information extracted from GlobCover 2009 (selecting, in particular, croplands and pasture vegetation types). After a preliminary analysis of land cover distribution over the two areas of interest, the Chad region showed a high lack of homogeneity in vegetation classes, being characterized by a wide portion of sub-equatorial forest and shrub land classes that were not modeled. Therefore, the statistical analyses was performed only for Niger due to its greater homogeneity in vegetation classes, which are characterized for the major part by rainfed croplands and grasslands.

Using the proposed spatial aggregation approach, a correlation analysis was carried out considering, for precipitation and phenological metrics, sum and average of values calculated over proposed masks. In detail, in order to calculate the final phenological metrics, the analysis considered only the pixels of the original base data covered by a percentage of selected vegetation types greater than 50%, while, to define final precipitation, original pixels were accounted only if pertaining for the 50% of their area to basins afferent to the selected vegetation.

The phenological and rainfall metrics averaged over the abovementioned masks were: SoS, SL, SA parameters for the vegetation; monthly Cumulative Rainfall (in the following called MCR), annual Cumulative Rainfall (called ACR), seasonal Cumulative Rainfall (considering the most
rainy months of June, July, August and September; in the following called SCR) and rainfall Deviations (D). The SMI parameter represents an exception, since it was obtained as a sum of all pixels of the mask considered.

**Results**

According to results of the analysis aimed at mapping the SoS shifts (Fig. 2), the majority of departments both in Niger (24 departments out of 34) and Chad (46 departments out of 62) faced a considerable delay in the start of the vegetative season. As reported in other experiences, particularly for the Sahel region, the Start of the Season metric seems to be a fundamental parameter related to vegetation productivity (a recent example is reported in Bacci et al. [2010]).

Similarly, the 2009 vegetative season maps of the deviation indices of Seasonal Length, Amplitude and Small Integral parameters, show large areas where the considered parameter had negative Percent Deviations and reached values close or equal to the historical minimum.

The outcomes obtained resulted to be consistent with reports of serious damage to crops and pastures in several areas of the examined countries [UN OCHA and ReliefWeb, 2010] and with the 2010 food crisis severity assessment, also as regards the estimates of the total number of people affected [source: Emergency Events Database EM-DAT, http://www.emdat.be/].

The most rainy months turned out to be June, July, August and September which have rainfall values that vary spatially between 0 and 400 mm/months. As expected, rainfall is strongly variable according to latitude, from the northern desert regions to the sub-tropical southern regions. Deviation indexes were calculated for the above mentioned months and for the cumulative rainfall over the rainy season (June-September) for the year 2009. Results show that highest negative deviation from the average in the rainy season were in the southern and southwestern
part of Niger and in the southern and southwestern Chad (as depicted in Deviations (D) maps, an example is given in Fig. 3). All the produced maps are accessible in the map archive on ITHACA’s web site (http://www.ithacaweb.org/maps/niger/).

![Figure 3 – 2009 seasonal Rainfall Deviations (D) map. Reference average was calculated for the period 1998-2009.](image)

After the emergency and the delivery of the described maps, further considerations were derived plotting annual values of phenological (SMI, SoS, SL, SA) and precipitation (ACR and SCR) parameters for the years 2000-2009 (Fig. 4), in order to identify critical conditions in the vegetative seasons preceding the crises. Preliminary standardizations of the considered values were carried out using mean and standard deviation values in order to make them comparable. For the Niger country, as reported by several sources (e.g. Emergency Events Database EM-DAT, http://www.emdat.be/; humanitarian crises information extracted from ReliefWeb, http://reliefweb.int/countries), three major food crises can be identified in the years 2001, 2005 and 2010. In occasion of each of these crises, the major cause was considered a reduction in crop and pasture production for the year preceding the crisis. In compliance with this information, SMI and SL parameters show the lowest values in the observed time-series for the years 2000, 2004 and 2009, and the vegetative season starts late. Nevertheless, the corresponding cumulative rainfall values for the rainy season (in 2000, 2004 and 2009) are not sufficient to explain the different behaviour of the phenological parameters in the years of crisis (especially in 2009). This suggests that the temporal distribution of the monthly cumulative rainfall values (Fig. 5) ought to be taken into consideration. For example the year 2009 differs from 2000 and 2004, showing larger precipitation values in September and October. It
is remarkable that in the years with a good rainy season (see 2003 and 2005, months of March, April, May and June, in Fig. 5), the high precipitation values are accompanied by maximum values for the Small Integral, Amplitude and Length parameter and a very advanced Start of the vegetative Season.

Figure 4 – Trend of the standardized values of the vegetation parameters from 2000 to 2009 - Small Integral (SMI), Start of the season (SoS), Season Length (SL), Season Amplitude (SA) - compared with those of the annual (ACR) and seasonal cumulative rainfall (SCR, June - September).

Figure 5 - Rainfall regime calculated on a monthly temporal scale over Niger, and monthly cumulative rainfall for crisis years (2000, 2004, 2009) and years having good precipitations (2003, 2005).
Furthermore, the existing linear correlations between the drought parameters considered were investigated with the main scope of screening the most effective parameters to be considered in the final developments of ITHACA’s drought monitoring activities. The correlation analysis conducted showed significant values of the correlation coefficient (estimated using a t-test with a significance level of 5%) both among phenological parameters and between them and the seasonal cumulative rainfall values (Tab. 1). As expected, the SMI parameter is positively correlated with SA and SL parameters and with the cumulative rainfall in the rainy season. Moreover, according to correlation values, the SoS delays are influenced by the rain fallen in months immediately preceding the rainy season and lead to a reduction in the SMI and SL values. Additional linear interdependence exists between the SA parameter and the cumulative rainfall in the rainy season (SCR).

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<td>0.322</td>
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<td>0.427</td>
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<td>0.571</td>
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**Table 1 - Correlation matrix among the selected parameters for the Niger country (values in bold type are different from 0 with α=0.05).**

**Conclusions**

The procedures developed in the frame of ITHACA’s Early Warning System for drought were applied in order to support the World Food Programme in defining the priorities of intervention during the food crisis that hit Niger and Chad countries in 2010. Although the whole project was still work in progress, the preliminary analysis of time-series for the base data considered proved useful to encourage improvements in the procedures and produced maps that supported WFP operations during intervention activities. The different mapped parameters selected in order to describe the examined drought phenomenon were not easily interpretable by WFP final users. On this occasion, to help legibility and user-friendliness, descriptive documents explaining the meaning of the produced maps were provided, but in future developments of the ITHACA Early Warning System, the final outputs will be simplified in cartographic synthesis products. Quantifying vegetation productivity led to detecting potential food crisis conditions. The expected vegetation productivity assessment is related to vegetation stress conditions during the vegetative season. According to the results obtained in this study, and in
particular to the results of the correlation analysis, the double monitoring of studied parameters is proposed for the ITHACA drought Early Warning system. In particular, the near real-time monitoring of precipitation values during a vegetation season examined can contribute to the rapid detection of possible water stress conditions for vegetation, that are then verified at the end of the season by analyzing phenological parameters. Even though the analysis was based on short time-series, the incomplete linear dependence found in the dynamics of phenological parameters on the cumulative seasonal and annual rainfall values, suggested that further analysis is required, particularly to:

- define more significant pluviometric regime values using at least 30 year precipitation time-series;
- better investigate the spatial distribution of the examined relationship using a per-pixel approach and/or homogeneous classes of vegetation for masking base data;
- take into consideration also decadal and monthly rainfall distribution in the correlation analysis.

References


Received 12/02/2011, accepted 01/08/2011