# SATELLITE AND AIRBORNE REMOTE SENSING DATA FOR MONITORING DEGRADED AREAS

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Abstract – This study introduces two applications of remotely sensed data to detect degraded areas and to evaluate the relative pollution produced in the neighborhood areas. The first one regards the possible methodology to extract spatial information for dumps monitoring based on the discrimination ability of texture analysis. The second one analyses the spectral behaviour of an area stressed by an industrial settlement in Southern Italy. Both cases have been studied with the aid of high and very high resolution images. The general purpose is the development of models and automated procedures to identify environmental parameters associated to pollution and degradation by using satellite images.

Keywords: degraded areas, pollution, high resolution images.

# 1. INTRODUCTION

An important use of satellite imagery is to provide information on land surface properties for monitoring polluted areas. Low and medium resolution sensors can give an overview of the territory, putting in evidence large and strong pollution phenomena (Escadefal, 1994). Satellites with on board high resolution sensors, such as Ikonos and Quickbird, allow the detection of small degraded areas such as dumps if an appropriate approach is used. In this paper two different methodologies are illustrated. The first one is devoted to the characterization of dumps based on texture analysis. These metrics are used to analyze landscape structure for a variety of natural fields, looking for possible distinguishing features of degraded areas with respect to agricultural ones (Fig.1). The second application regards the spectral analysis of an industrial settlement and its effect on the environment. The study is carried out with both Ikonos and Landsat images, from which spectral signatures are extracted.

### 2. DUMPS MONITORING

# 2.1 Correlation between vegetation indices and orthophoto mean reflectance

The presence of dumps in a territory is very hard to be revealed due to their small sizes and to the fact that they are often covered with vegetation. In this analysis Landsat images in combination with orthophotos have been used. They were both acquired in spring period so that they shared similar vegetation cover. An empirical approach has been utilised to link the spectral characteristics of the Landsat image to the orthophoto reflectance (Simões et al., 2003). To our purposes, the orthophoto characteristics have been correlated to the NDVI of the Landsat images. In fact, the reflectance registered by the camera depends upon the composition, roughness, moisture and vegetation conditions. This correlation permits to transform the black and white orthophoto in a NDVI image without losing spatial resolution. Having a NDVI image with high resolution, it is easier to detect and analyse vegetation anomalies that may reveal the presence of a dump. Furthermore, the classification appears to be less fragmented (Schowengerd, 1997).

In order to determine the correlation, some training areas were selected on the orthophoto and on the TM NDVI. Subsequently, the linear relationship was verified on different test areas. In table A some characteristics of this analysis are listed.

	Training areas	Test areas
$\mathbf{R}^2$	0.74	0.81
relationship	NDVI = -0.0038*Mean + 0.837	

Table A. Characteristics of the Relationship between NDVI (Landsat) and Mean Reflectance (Orthophoto).



Figure 1. Some textural examples. First row: dumps. Second row, from left: agricultural fields and woodland, two different tree distributions.

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### 2.2 Spatial Metrics

Spatial or landscape metrics can be defined as quantitative indices to describe structures and patterns of a landscape (O'Neill et al., 1988). Their development is based on information theory measures and fractal geometry. In this study, landscape metrics were calculated using the public domain *Fragstats* program (McGarigal et al., 1994), where three general landscape metrics were selected: shape, connectivity and diversity metrics.

Within each of these groups a certain number of indices are calculated to quantify the spatial textures of the landscapes (McGarigal et al., 1994). The technique proposed to quantify the spatial pattern of agricultural fields from high-resolution optical remote sensing data is based on the following issues:

1. Multispectral optical remote sensing allows for a pure separation of different land cover types like built up areas, vegetation and water to derive accurate thematic land cover maps. However, within the category of vegetated fields, dumps or generally degraded lands cannot be discriminated by applying "per-pixel" analysis methods, as they are often vegetated and can be spectrally indistinguishable from other vegetation covers (Notarnicola et al., 2003).

2. The spatial and textural context is important information for field characterization. Landscape metrics, as measures of spatial structures used to describe agricultural area features, are proposed as quantitative analysis.

3. The analysis of the different field types requires high spatial sensor resolution that is quite recently available from satellite systems. However, for the development and the evaluation of this approach, aerial photographs with 1 m resolution, similar to current available data from space-borne systems (IKONOS, QuickBird) have been exploited.

Two orthophotos and two Landsat images were chosen on areas with dumps. After the derivation of a high resolution NDVI, as described in the previous paragraph, an unsupervised classification, ISODATA, was performed on the images. The classification identifies these land classes: city, bare soil, cultivated fields, cultivated fields with trees, bare fields with trees, woodland. In the classified images, the dump sites have both bare and vegetated characteristics. From each of these classes, excluding the city that can be easily identified, some test areas were chosen and used to derive spatial metrics indices. Among the available indices, the following ones were selected as most representative of the different area shapes:

- **Shannon's diversity index (SHDI):** it is an index for measuring diversity in a landscape. It is equal to 0 when the landscape contains only 1 patch (i.e., no diversity). SHDI increases as the number of different patch types increases and/or the proportional distribution of area among patch types becomes more equitable.

- **Connect:** it is defined on the number of functional joinings between patches of the same type, where each pair of patches is either connected or not based on a user-specified distance criterion. Connectance is reported as a percentage of the maximum possible connections given the number of patches. Connect = 0 when either the landscape consists of a single patch, or all classes consist of a single patch, or none of the patches in the landscape are "connected" and connect = 100 when every patch in the landscape is "connected."

- **Contiguity index:** it assesses the spatial contiguity of cells within a grid-cell patch to provide an index of patch boundary configuration and thus patch shape. The contiguity index

equals 0 for a one-pixel patch and increases to a limit of 1 as patch contiguity increases (McGarigal et al., 1994).

In Fig. 2, the values of these indices are reported for different land classes as indicated on the abscissa axis. The SHDI increases as the complexity of the landscape increases. This is evident for the cultivated fields with trees (indicated as fieldstrees) with respect to the cultivated fields without trees. It does not allow a clear distinction between fields-trees and dumps. Instead, the connect index is low and with a limited variability (values ranging 0.4-0.8) for both fields-trees and cultivated fields. For dumps, the connect index is higher and variable (values ranging 1.1-3.3). In fact, in the case of cultivated fields the landscape mainly consists of a single patch, while in the case of trees, the patches that represent trees are not connected each other (Fig.1). Thus, this index makes a distinction between areas with regular shapes (fields and fields-trees) and those with patch irregularity (dumps). The contiguity index is close to 1 for cultivated fields as the patch contiguity is high. For dumps, it is stable around 0.5 - 0.6 while for tree it is variable between 0.3 and 0.7.

# **3. EFFECT OF AN INDUSTRIAL SETTLEMENT**

#### 3.1 Area description

The ILVA iron settlement located in Taranto is the largest European integrated steel industry about the production of pig iron and steel. It extends on 1500 hectares and has about 12000 employees.

The end products facturing is represented by the following main stages:

• transferring and stockage of raw materials (sands and gravels containing iron ores, coking coals, limestones);

• winnowing, grinding and mixing of raw materials;

• distillation of coking coals, production of metallurgical coke and transferring to the blast furnace silos;

• homogenization of iron ores and transferring to the blast furnace silos;

• agglomeration of same middling products;

• loading of blast furnace for pig iron production from which, after furnace refining, the steel is obtained;

• rolling of semifinished products pointed to the end products making (tapes, sheets, coils, tubes, etc).

This study is referred to a surveying analysis focused on the environmental exposure evaluation derived from the industrial settlement of ILVA (Cifelli et al., 2003).

### **3.2 Spectral Analysis**

For this analysis, data are extracted from an IKONOS image (multispectral with 4 m resolution) acquired on the area on 8 June 2004. The analysis is divided in two main steps; firstly spectral signatures from main classes present in the area are obtained, then, a probability map, to state which area shares the same spectral characteristics of the industrial area, is calculated. In Fig. 3, the IKONOS image is shown, where the following classes are considered: 1. and 2. Cultivated fields; 3. Harbour; 4. Sea; 5. Area A close to oil stockage area Punta Rondinella; 6. Area B close to oil stockage area Punta Rondinella; 7. Area C close to ILVA; 8. ILVA, the industrial settlement; 9. Quarries; 10. Bare soils; 11. Clouds; 12. City of Taranto.

A further analysis has been carried out within the stockage area:



Figure 2. Results of the textural indices for different types of land cover (bare fields, fields, fields-tree, dumps, woodland).

1-Pr 1: interior of an oil tank; 2 - Pr 2: area surrounding oil tanks; 3 - Pr 3: shining roof of an oil tank; 4 - Pr 4: dark roof of an oil tank.

From the analysis of the spectral signatures illustrated in fig.5 and 6, these considerations emerge:

- the industrial area has distinguishing features from the surroundings due to its very low reflectance values in all the Ikonos bands (Langrebe, 2003);
- the areas which exhibit similar features, higher values of reflectance, are: the quarry, the cloud and the white roof of some oil tanks in Punta Rondinella;
- the area denominated Pr1 has low reflectance values due to the presence of dark material inside, it is clearly visible also from the Ikonos image;
- the C area near ILVA reveals a spectral behaviour similar to cultivated fields 1 and 2 even though the reflectance values in each band are lower than those of the cultivated fields. In particular the reflectance in the red band is higher for C area than for fields 2 and the reflectance in the near infrared band is lower for C area than for fields 2. The reduced difference between the red and near infrared band is a symptom of stressed vegetation (Schowengerd, 1997).

- Pr3 and Pr4 have similar spectral trend, even though Pr4 has lower reflectance values than Pr3. The ratio between the respective band values ranges from 1.4 to 2.0.

These low reflectance values suggest a criterion to map the area in terms of such similar spectral characteristics that represent a certain case of pollution. To this purpose, a region of interest has been extracted from the industrial settlement and starting from the band histograms, a probability density function (pdf) has been built.

The probability has been modelled using a normal function (Nezry, 1997) and the mean and the standard deviation have been calculated with Maximum Likelihood algorithm.

A chi-squared test has been used to verify the goodness-of-fit of the calculated pdfs. Using these pdfs, the whole area has been mapped in each of the four bands, and then the four maps have been averaged to obtain a final probability map (fig.7). The meaning of the map is that clear areas indicate high probability to have spectral characteristics similar to polluted areas (in this case the sea should not be considered).



Figure 3. Ikonos image, the numbers indicate the main classes of the area.

# 4. CONCLUSION

High resolution remotely sensed images have been exploited for two case studies. One is related to the analysis of spatial metrics to detect degraded lands such as dumps. Three indices, SHDI, Connect and Contiguity lead to a discrimination of dumps from other categories such as cultivated fields, fields with trees and bare fields.

The second application is referred to a surveying analysis focused on the environmental pollution derived from the industrial settlement of ILVA. Starting with the spectral signatures of the industrial area, it is possible to create a map that indicates the areas that have similar spectral characteristics and then could be heavily polluted.

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Figure 4. Ikonos subimage, the numbers indicate the studied areas in the stockage area of Punta Rondinella.



Figure 5. Spectral signature extracted from Ikonos image in the area surrounding the ILVA settlement.

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Figure 6. Spectral signatures extracted from studied areas within the stockage area of Punta Rondinella.



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