

Applying Spatial Autocorrelation Techniques to Multi-Temporal Satellite Data for Measuring Urban Sprawl

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Abstract- In last decades the spreading of new buildings, road infrastructures and a scattered proliferation of houses in zones outside urban areas, produced countryside urbanization with no rules, consuming soils and impoverishing the landscape. Such a phenomenon generated a huge environmental impact, diseconomies and a decrease in life quality. Although urban growth is perceived as necessary for a sustainable economy, uncontrolled or sprawling urban growth can cause various problems, such as loss of open space, landscape alteration, environmental pollution, traffic congestion, infrastructure pressure, and other social and economical issues. This study analyzes processes concerning land use change, paying particular attention to urban sprawl phenomenon. The application is based on the integration of Geographic Information Systems and Remote Sensing adopting open source technologies. The objective is to understand size distribution and dynamic expansion of urban areas in order to define a methodology useful to both identify and monitor the phenomenon. The application has been developed in a heavily anthropized area in southern Italy, Apulia region, using free spatial data and free multispectral and multitemporal satellite data (Apulia region was one of the first regions in Italy to adopt open data policies). An integration of free software (Linux Ubuntu, GRASS GIS and Quantum GIS, R) and data (Landsat) has been proposed in order to quantify phenomenon evolution. In order to produce more reliable data, autocorrelation techniques have been implemented in open source software.

Keywords- Urban Sprawl; Remote Sensing; Spatial Autocorrelation; Change Detection; Open Source Software; Open Data

I. INTRODUCTION

At the beginning of the last century Patrick Geddes, one of the fathers of planning theorized an important approach to planning based on the sequence: survey – analysis – plan [1]. The main difference between the first two steps is rooted in the distinction between mapping a phenomenon and its interpretation. This approach undoubtedly produced better plans, but lacked in the support of automated combination of sectoral analyses. The first attempt in combining sectoral analyses has been represented by the metaphor of “layer cake” developed by Ian McHarg [2] which represents the fundamental of overlay mapping. This approach represents a sort of bridge between simple descriptions and analysis interpretation.

In the same period of McHarg’s experience a lot of planners considered the systemic approach based on von Bertalanffy’s theories [3] focused on systems as realities more complex than the simple collection of their parts and characterized by interactions of a lot of sectoral domains.

An important qualitative leap is represented by the adoption of spatial simulation models which can improve the decision-making process predicting future scenarios [23, 25, 28].

An important application domain in predicting phenomena evolution can be undoubtedly represented by urban sprawl analysis [22, 24, 27].

Urbanization growth represents one of the main environmental threats of last decades. Several approaches have been adopted in analyzing this phenomenon, mainly related to different study domains. Urban sprawl, soil consumption, settlement risk, and even the attempt to reach a distinction between urban, peri-urban, exurban, rur-urban and rural areas are different sides of the same coin which examine the huge amount of negative aspects generated by urban expansion summarized in soil sealing, loss of productive agricultural lands and forest’s cover, habitat destruction and fragmentation, waste of energy, pollution, landscape degradation. Consequently, urban growth generates environmental impacts at local, regional and global scales.

Considering sustainability with a systemic approach, urban sprawl represents the typical case where economic, social and environmental systems have always to be considered [31]. The concept of sustainable development is a synthesis and a balance of three factors: social justice, economic utility and environmental integrity [4].

More particularly the concept of urban sprawl can be considered unsustainable under three points of view [5, 30]:

1. **environmental:** urban sprawl is one of the hugest environmental threats [26];
2. **social:** urban sprawl obliges people to travel many hours per day, leading to a total absence of social and neighbourhood relationships;

3. **economical:** urban sprawl produces agglomeration disadvantage in localizing services and activities and in realizing interventions and infrastructures [6, 7, 29].

A critical point to understand and monitor urban expansion processes is the availability of both (i) time-series data set and (ii) updated information relating to current urban spatial structure to define and to locate evolution trends. In such a context, an effective contribution can be offered by satellite remote sensing technologies, which are able to provide both an historical data archive and up-to-date imagery. Satellite technologies represent a cost-effective mean to obtain useful data which can be easily and systematically updated worldwide. Nowadays, medium resolution satellite images, such as Landsat TM or ASTER can be downloaded free of charge from NASA web site.

The use of satellite imagery coupled with autocorrelation techniques can be used for monitoring and planning purposes, as these enable the reporting of ongoing trends of urban growth at a detailed level. Nevertheless, exploitation of satellite Earth Observation in the field of urban growth monitoring is a relatively new tool, although during the last three decades great efforts have been addressed to the application of remote sensing in detecting land use and land cover changes. A number of investigations were carried out using different sets of remotely sensed data [8-12] and diverse methodological approaches to extract information on land cover and land use changes.

This study analyzes urban expansion over time in several southern Italian towns, using satellite images. Sample towns are located in south of Bari, one of the most important cities in southern Italy. Analyses were carried out using Landsat images acquired 2 August 1999 and 2 July 2009. The obtained results showed a significant urban expansion and an increase of irregularity degree in city fabric. In order to carry out such analyses, Landsat TM data have been adopted to compute Normalized Difference of Vegetation Index (NDVI). Results have been adopted as input data to test autocorrelation indexes in remote sensing.

II. SPATIAL AUTOCORRELATION TECHNIQUES AND REMOTELY SENSED DATA

The concept of spatial autocorrelation is rooted on Waldo Tobler [13] first law of geography: “*everything is related to everything else, but near things are more related than distant things*”. Spatial autocorrelation can be considered positive if similar values of a variable tend to produce clusters; in the same way spatial autocorrelation can be classified as negative when similar values of a variable tend to be scattered throughout the space [14].

Spatial autocorrelation takes into account spatial attributes of geographical objects under investigation; it evaluates and describes their relationships and spatial patterns, also including the possibility to infer such patterns at different times for the study area. Spatial patterns are defined by the arrangement of individual entities in space and by spatial relationships among them. Spatial autocorrelations measure the extent to which the occurrence of one object/feature is influenced by similar objects/features in adjacent areas. As such, statistics of spatial autocorrelation provide (i) indicators of spatial patterns and (ii) key information to understand spatial processes underlying the distribution of an object/feature and/or a given phenomenon under observation. Geographical observations can be arranged in spatial and temporal order, by latitude and longitude, and over given time periods. In this context time series data, such as aerial and satellite images, can provide useful data sets to examine changes in homogeneity over time, as well as to measure the strength of the relationship between values of the same variables over a given time window. Spatial autocorrelation statistics are considered very useful tools in analysing satellite images, since they consider not only pixel value (reflectance, temperature, spectral index) under investigation, but also the relationship between that same pixel and its surrounding pixels in a given window size.

In absence of spatial autocorrelation the complete spatial randomness hypothesis is valid: the probability to have an event in one point with defined (x, y) coordinates is independent of the probability to have another event belonging to the same variable. The presence of spatial autocorrelation modifies that probability. After fixing a neighborhood for each event, it is possible to understand how much it is modified by the presence of other elements inside that neighborhood. The presence of autocorrelation in a spatial distribution is caused by two effects, which can be clearly defined, but not separately studied in the practice:

1. first order effects: they depend on region of study properties and measure how the expected value (mean of the quantitative value associated to each spatial event) varies in the space by Equation 1:

$$\hat{\lambda}_{\tau}(s) = \lim_{ds \rightarrow 0} \left\{ \frac{E(Y(ds))}{ds} \right\} \quad (1)$$

where ds is the neighbourhood around s, E() is the expected mean and Y(ds) is events number in the neighbourhood;

2. second order effects: they express local interactions between events in a fixed neighbourhood, that tends to the distance between i and j events. These effects are measured with covariance variations expressed by the limit in Formula 2:

$$\gamma^{(s_i, s_j)} = \lim_{ds_i, ds_j \rightarrow 0} \left\{ \frac{E(Y(ds_i)Y(ds_j))}{ds_i ds_j} \right\} \quad (2)$$

Characterization of spatial autocorrelation requires detailed knowledge on:

- a) the quantitative nature of dataset, also called intensity of the spatial process, that is how strong a variable happens in the space [15, 16], with the aim to understand if events are similar or dissimilar;
- b) the geometric nature of dataset: this needs the conceptualization of spatial relationships, usually done with the use of matrixes: (i) a distance matrix is defined to consider at which distance events influence each other (distance band); (ii) a contiguity matrix is useful to know if events influence each other; (iii) a matrix of spatial weights expresses how strong this influence is.

Concerning distance matrix, a method should be established to calculate distances in module and direction. For this concern, the module, namely Euclidean distance (3), is the most adopted.

$$d_E(s_i, s_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (3)$$

A. Global Indicators of Spatial Association

Several indexes have been developed in order to measure spatial autocorrelation discovering the presence and intensity of clusters in the distribution. The two main indicators are Moran I [17] and Geary C Ratio [18] indexes.

Moran I index is defined by the following equation:

$$I = \frac{N \sum_i \sum_j w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j w_{ij}) \sum_i (X_i - \bar{X})^2} \quad (4)$$

where:

- N is the number of events;
- X_i and X_j are intensity values at points i and j (with $i \neq j$), respectively;
- \bar{X} is the average of variables;
- $\sum_i \sum_j w_{ij} (X_i - \bar{X})(X_j - \bar{X})$ is the covariance multiplied by an element of weight matrix. If X_i and X_j are both upper or lower than the mean, this term will be positive, if the two terms are in opposite positions compared to the mean the product will be negative;
- w_{ij} is an element of weight matrix which depends on contiguity of events. This matrix is strictly connected to adjacency matrix.

Moran index shows a trend similar to the correlation coefficient, consequently it can have values included between -1 and 1.

Geary C Ratio is quite similar to *Moran I index* and it is defined by the following equation:

$$c = \frac{(N - 1) (\sum_i \sum_j w_{ij} (X_i - X_j)^2)}{2 (\sum_i \sum_j w_{ij}) \sum_i (X_i - \bar{X})^2} \quad (5)$$

Parameters are very similar to Equation 4: the main difference is represented by the cross-product term in the numerator, which in *Moran* is calculated using deviations from the mean, while in *Geary* is directly computed. The square root is provided to remove all negative values of the formula, consequently *Geary C Ratio* ranges between 0 and 2. Values between 0 and 1 define positive autocorrelation, while values greater than 1 and smaller than 2 indicate negative autocorrelation. Value 0 represents a perfect positive autocorrelation, the same of neighbouring values with cross-product equal to 0. Value 2 defines a perfect negative spatial autocorrelation.

B. Local Indicators of Spatial Association

Luc Anselin [19] defines as a local indicator of spatial association, any statistic that satisfies the following two requirements:

- the index for a single observation produces a spatial result of the extent of clustering of similar values around that observation;
- the sum of all observations indexes is proportional to the global indicator of spatial association.

Local versions of spatial autocorrelation are used to measure the magnitude of spatial autocorrelation within the immediate neighbourhood. Values indicating magnitude of spatial association can be derived for each areal unit and they can be located.

The local version of statistics employs distance information to identify local clusters and relies on the distance information captured in Distance matrix.

The *Local Indicator of Spatial Association (LISA)* [19] represents the local version of *Moran index I* and it is defined by the relation:

$$I_i = \frac{(X_i - \bar{X})}{S_x^2} \sum_{j=1}^N (w_{ij} (X_j - \bar{X})) \quad (6)$$

where \bar{X} is the intensity mean of all events, X_i is the intensity of event "i", X_j is the intensity of event "j" (with $j \neq i$), S_x^2 is the variance of all events and w_{ij} is the weight matrix. Considering z-score:

$$z_i = \frac{(X_i - \bar{X})}{S_x}$$

LISA index can be expressed in the following synthetic form:

$$I_i = z_i \sum_{j=1}^N w_{ij} z_j \quad (7)$$

The function by *Getis & Ord* [20] is represented by the following equation:

$$G_i(d) = \frac{\sum_{i=1}^n w_i(d) x_i - x_i \sum_{i=1}^n w_i(d)}{S(i) \sqrt{\left[(N-1) \sum_{i=1}^n w_i(d) - \left(\sum_{i=1}^n w_i(d) \right)^2 \right] / (N-2)}} \quad (8)$$

which is very similar to Moran index, except for $w_{ij}(d)$ which, in this case, represents a weight which varies according to distance. Such statistics allow us to locate clustered pixels, by measuring how much features inside a fixed neighbourhood are homogeneous. Nevertheless, the interpretation of Getis and Ord's G_i meaning is not immediate, but it needs a preliminary classification that should be done comparing G_i with intensity values.

The local version of *Geary Ratio C* is defined as:

$$c_i = \sum_{j=1}^N w_{ij} (z_i - z_j)^2 \quad (9)$$

Local indicators of spatial association can be considered as local functions of statistical analysis and can be represented through georeferenced maps, representing very important tools for exploratory analysis of spatial structures especially with large databases.

C. Applying Spatial Autocorrelation to Satellite Images

In order to study spatial autocorrelation in satellite data, it is important to define which are the spatial events, their quantitative nature (intensity) and the conceptualization of geometric relationships. A spatial event is clearly the pixel. Spatial autocorrelation statistics are usually calculated considering geographical coordinates of its centroid. Concerning the intensity, it should be chosen strictly considering the empirical nature of the case study.

The conceptualization of geometric relationships in the case of image processing is very easy, because distance between events is always equal to or is a multiple of pixel size. In image processing, contiguity distance is called lag distance.

In image processing, Global measures of spatial autocorrelation provide a single value that indicates the level of spatial autocorrelation within the variable distribution, namely the homogeneity of a given value within the image under investigation.

Local measures of spatial autocorrelation provide a value for each location within the variable distribution and, therefore, are able to identify discrete spatial patterns that may not otherwise be apparent [21]. Statistics output is an image for each calculated index, which contains a measure of autocorrelation around that pixel. To apply spatial autocorrelation statistics, remotely sensed images allow us to obtain a new raster which contains in each pixel a number that expresses how much it is autocorrelated with other pixels. Both global and local statistics can be calculated using spectral channels, spectral combinations and/or multi-temporal combinations, as intensity.

III. THE CASE STUDY

This study deals with satellite based investigations on urban area expansion in some test areas of southern Italy, using change detection techniques and spatial statistics to capture the spatial characterization of feature variations.

The investigation herein presented was focused on the assessment of the expansion of several very small towns, Conversano, Rutigliano, Turi and Polignano a Mare, close to Bari (in southern Italy). The area of concern is characterized by an active and dynamic local economy, mainly based on small and medium enterprises, operative in commerce, industry and services. Bari has become one of the top commercial and industrial leaders in Italy, so it is known as ‘California of South’, to indicate the significant growth and leadership much higher than other southern areas. Industrial activities are quite numerous and dynamic (chemicals, machinery, printed materials, petroleum and textiles production), but also agriculture is quite notable in Bari surroundings, with intensive production of cherries, tomatoes, artichokes, grapes and wine. Bari has also a long history since the Middle-Ages, when it was one of the main ports from which pilgrims sailed to the Holy Land.



Fig. 1 Study area location

A. Analyzing Urban Sprawl with Normalized Difference of Vegetation Index (NDVI)

In order to identify areas of urban expansion, we looked for a change in spatial structure between two image dates. The main aim of our investigation was to evaluate the possibility to enhance spatial patterns of urban development of years 1999 and 2009 in the area of concern. The expansion of urban areas has been assessed by using change detection techniques.

Change detection is the assessment of variations between multitemporal, or time series data sets, or, in the case of remotely sensed data, between two or more scenes covering the same geographic area and acquired in different periods.

To cope with the fact that small changes have to be captured and extracted from TM multitemporal data sets, it is important that an adequate processing chain must be implemented. Indeed, multitemporal imagery data analysis requires a more accurate pre-processing than single date analysis. This includes calibration to radiance or at-satellite reflectance, inter-calibration among multitemporal images, atmospheric correction or normalization, image registration, geometric correction, and masking (e.g., for clouds, water, irrelevant features). These procedures improve the capability in discriminating real changes from artifacts introduced by differences in sensor calibration, atmosphere, and/or sun angle. Some radiometric rectification techniques are based on the use of areas of the scene under investigation whose reflectance is nearly constant over time.

In the study case, images under investigation were pre-processed, co-registered and inter-calibrated to reduce sources of false changes, such as those caused by clouds, cloud shadows, and atmospheric differences. Relating to change detection, we should consider that up to now, a number of change detection techniques have been devised and applied to capture variations of surface characteristics, atmospheric components, water quality and coastal zones. Some methods focused on the monitoring of urbanization, agricultural development, forest land management, and environmental management. These procedures generally are coupled with data transformation to vegetation indices, whose principal advantage over single-band radiometrics is their ability to strongly reduce data volume for processing and analysis, and also to reduce residual of atmospheric contamination. In our analyses, we adopted Normalized Difference of Vegetation Index (NDVI), which is the most widely used index for a number of different applications, ranging from vegetation monitoring to urban sprawl. The NDVI is computed using the following formula:

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \quad (10)$$

This index was computed for both 1999 and 2009, to emphasize occurring changes and improve change detection.

In particular, the comparison between multitemporal (1999 and 2009) NDVI maps emphasizes the expansion of urban areas,

which is easily recognizable by a visual inspection.

Figure 2 shows the difference between 1999 and 2009 maps. The increase in the extension of urban area was connected to economic and demographic factors.

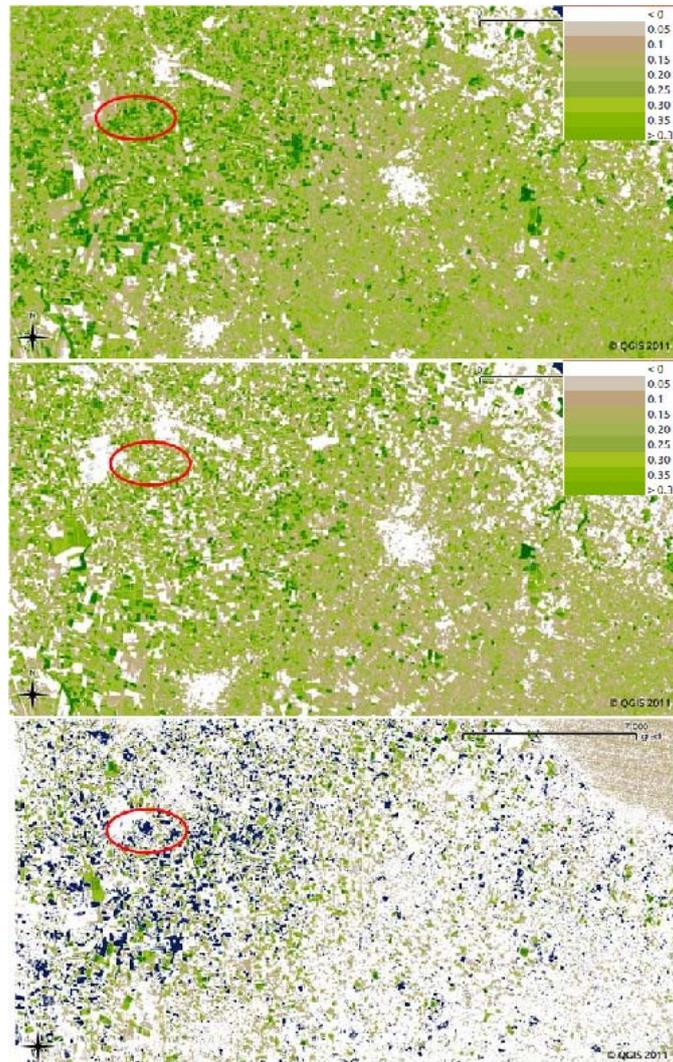


Fig. 2 NDVI map from the TM images acquired in 1999 (top) and 2009 (centre), note that light spots are urban areas NDVI difference map (bottom) from the TM images acquired in 1999 and 2009, note that white pixels are urban areas

In the first two images light colors (especially white) define poor (up to lacking of) vegetation areas, which can be associated to waterproof areas. In NDVI difference map, on the contrary, green and blue pixels indicate a “strong” variation in NDVI index. The red circle indicates a strong change in NDVI index where vegetation has been replaced by a urbanized area.

B. Testing Autocorrelation Indexes in Computing Urban Sprawl

Data obtained in previous analyses have been used as input data in applying autocorrelation techniques in image processing. Spatial dependency may be captured using Global spatial autocorrelation statistics, such as Moran I and Geary c.

For a given pixel, switching from one date to another one will take into account changes in spatial structure within the range of spatial windows of that same pixel. Spatial differences, which are equal between two dates for a given co-registered pixel window, will not induce a change.

However, results from such analyses may be unrepresentative if nature and extent of spatial autocorrelation significantly vary throughout the area of interest. To cope with this issue, we considered: (i) local indicators of spatial association (Getis Gi, Local Geary c and LISA) and (ii) the hypothesis that a region with urban settlements will exhibit spatial homogeneity in spectral response, due to a lowly variable spatial and spectral structure of concrete and building materials.

In the current study, both global and local geospatial statistics were applied to 1999 and 2009 TM images, using spectral combinations of single bands to enhance variations occurring during the time window under investigation. The comparison was made using single date NDVI maps, computed for both 1999 and 2009, along with the map obtained as the difference be-

tween NDVI 1999 and 2009 images. Later on, the multirate data set was analyzed using a pixel-by-pixel comparison, followed by change region analysis and verification of results from the two successive temporal scenes (1999 and 2009).

Figure 3 (from top to bottom) shows local autocorrelation indexes presented as RGB Getis Gi, Local Geary c and LISA applied with lag 2. All panels clearly reveal the increase in urbanized area; RGB Getis, Geary's c and LISA of the map well show variations linked to concrete and building materials.

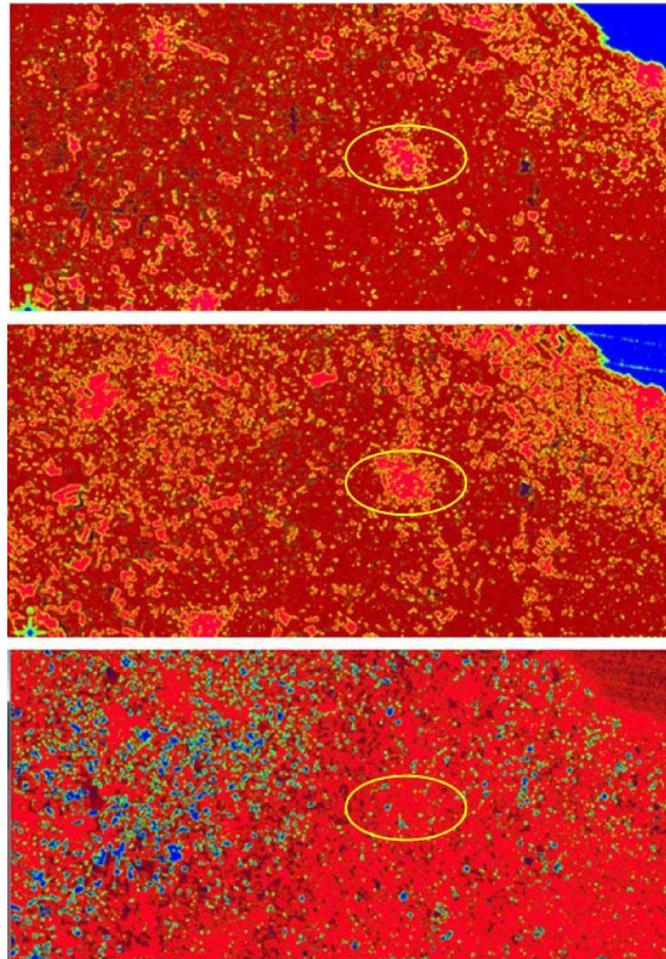


Fig. 3 (from top to bottom) show the local autocorrelation indexes presented as Getis Gi, Local Geary c and LISA applied with lag 2

Results are represented in Figure 3 and they can be compared with the aerial photo in Figure 4. In particular, in Figure 3 some urban areas are highlighted by an ellipse to better compare results. In this picture it is possible to see areas characterized by autocorrelation looking for pixels of the same color, which are at the same time aggregated: autocorrelated areas in light red represent searched urban areas, while dark red ones represent not urban areas.



Fig. 4 Aerial photo

Looking at the yellow ellipse in Figure 3 and comparing it to the urban area in the centre of Figure 4, among the three pictures, the first one, that contains Getis and Ord's Index, better captures this phenomenon. Instead, in Figure 3 second picture (representing Geary index), areas with light red pixels are too large and autocorrelated areas include not only urban areas, but also bare terrains. Finally the third picture in Figure 3, representing Lisa index, gives the worst result, because it generates a spread of pixels of several colors, so there is not a strong autocorrelation and urban areas are not captured by this analysis.

After calculating which index provides the best results, it is important to apply this index to both NDVI maps realizing a comparison between 1999 and 2009 maps.

In Figure 5 Getis and Ord's Index, which produced the best results in tests of Figure 3, has been applied to NDVI maps at 2009 and 1999. This index allows identifying the clustering of not vegetated pixels.

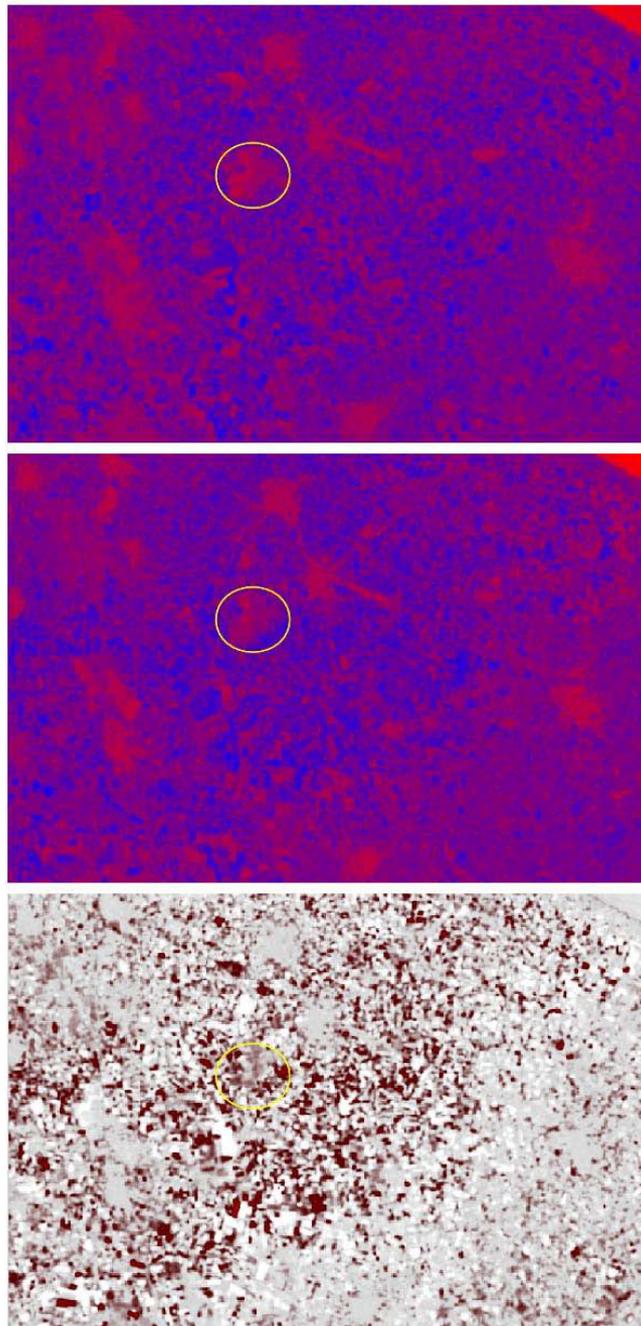


Fig. 5 Getis and Ord's Index applied to NDVI maps 2009 (top) and 1999 (centre), note that red spots are urban areas

The difference map (bottom), note that brown pixels represent the more transformed areas.

Analyzing results of Getis and Ord's Index at the most recent date, new settlement ramifications or new directions of development of urban areas are quite evident. Interesting considerations can also be made on soil consumption due to the build-

ing of new waterproof areas. This is clearly a quick assessment, because the analysis focused only on data produced by means of NDVI index. More in particular, in 10 years (1999-2009) a soil consumption of approximately 30 km² (more or less equal to 8.5%) has been estimated in the study area of approximately 350 km².

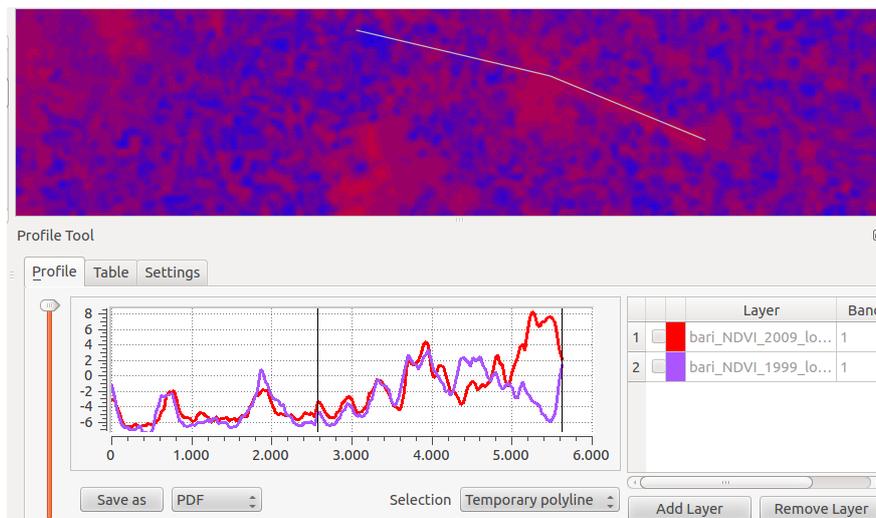


Fig. 6 Profile with Getis and Ord's Index values at 1999 (violet) and at 2009 (red)

Drawing a profile on the study area, it was possible to obtain the trend of Getis and Ord's Index at 1999 (violet) and at 2009 (red).

The final part of the profile highlighted two interesting trends that Getis and Ord's Index completely captures. At approximately 4500 meters, it can be noticed that Getis and Ord's Index is more elevated in 1999 than in 2009. This means that in this place urbanizations built between 1999 and 2009 are very fragmented and scattered, producing a decrease of G_i index. Considering the profile in a range of 5000-6000 meters, a significant decrease of G_i index in 1999 is evident, which corresponds to a sharp increase of G_i index in 2009. This trend translated in territorial terms can be interpreted as a very fragmented area in 1999 and has been very compacted and densified in the following decade 1999-2009.

IV. CONCLUSIONS

In the present paper, each step of the process has been carried out using free tools and data. Operating system (Linux Ubuntu), GIS software (GRASS GIS and Quantum GIS) and software for statistical analysis of data (R) are open source type, while Landsat data are downloadable and ready to use. This aspect is very important, since it puts no limits and allows everybody to carry spatial analyses on remote sensing data.

Concerning autocorrelation analysis, it was considered as a method for examining transformations taking place in urbanized areas located in southern Italy. The main objectives of the study were: (i) assessing if variation in urban structure over time can be quantitatively determined using TM images, (ii) investigating and describing modification of urban shape and morphology over time.

Analyzing and comparing different years, the process of urban intensification has been observed, and the increase of urbanized area has been revealed. This change shows the transformation that took place in the area under investigation and the transformation from quite regular to more fragmented peripheral settlements. The relevance of the technique herein used is that it provides a reliable way of analyzing urban structure and its transformation over time.

The methodology implemented allows obtaining synthesis maps useful to analyze land use change and to interpret urbanized areas, or more precisely complementary areas to vegetated surfaces.

In the first phase, change detection based on NDVI index, focusing attention on complementary pixels to vegetation allowed us to identify where a loss of green areas occurred over time.

In the second step, always based on NDVI index, autocorrelation allowed us to identify the clustering of not vegetated pixels and, comparing the results at different dates, to understand if a small settlement has become an important center after ten years. The planner can get support by reading such developments and trying to rectify trends and organizing new actions for the future development of the area.

In order to produce land use dynamics, data more connected to built up areas and to new waterproofing, due to urbanization, should be included in methodology of also supervised classification. In this way it could be possible to define appropriate land use classes as buildings, roads, etc. and assess how they are changed over time.

However, this study is a preliminary one and quite suggestive and its main objective was to present a way of applying autocorrelation analysis to the monitoring of urban areas evolution. The need of analyzing more time periods and a comparative analysis among many urban areas would be fruitful, and the application of geostatistical analysis applied to satellite time series represents a major challenge for further investigation.

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