Using Spatial Autocorrelation Techniques and Multi-temporal Satellite Data for Analyzing Urban Sprawl

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Abstract. Satellite time series offer great potential for a quantitative assessment of urban expansion, urban sprawl and for monitoring of land use changes and soil consumption. This study deals with the spatial characterization of expansion of urban areas by using spatial autocorrelation techniques applied to multi-date Thematic Mapper (TM) satellite images. The investigation focused on several very small towns close to Bari. Urban areas were extracted from NASA Landsat images acquired in 1976, 1999 and 2009, respectively. To cope with the fact that small changes have to be captured and extracted from TM multi-temporal data sets, we adopted the use of spectral indices to emphasize occurring changes, and spatial autocorrelation techniques to reveal spatial patterns. Urban areas were analyzed using both global and local autocorrelation indexes. This approach enables the characterization of pattern features of urban area expansion and it improves land use change estimation. The obtained results showed a significant urban expansion coupled with an increase of irregularity degree of border modifications from 1976 to 2009.

Keywords: Urban morphology, Remote sensing, Autocorrelation, Change Detection.

1 Introduction

Urbanization and industrialization are the key factors for social and economical development and represent specific response to economic, demographic and environmental conditions. In many European regions abandonment of agricultural land has induced a high concentration of people in densely populated urban areas during the last few decades. This phenomenon has been observed throughout the world. In 1950,

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only 30% of the world's population lived in urban areas. By 2000 that proportion rose up to 47%, and by 2030 the estimated number will be around 60% [25].

Such a rapid industrialization and expansion of urban areas has caused strong and sharp land cover changes and significant landscape transformations, which significantly impact local and regional environmental conditions. Nowadays, the increase of concentration of people in densely populated urban areas is considered as a pressing issue in developing countries. For example, following land reform initiated in 1987, vast areas of China have been involved in a rapid urban expansion and new urban settlements [4], so that in a few years, several cities rapidly have become big centres or regional nodes.

The analysis of city size distribution deals with different disciplines such as geography, economy, demography, ecology, physics, statistics, etc., because the evolution of a city is a dynamic process involving a number of different factors. An issue of great importance in modelling urban growth includes spatial and temporal dynamics, scale dynamics, man-induced land use changes. 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. To face such drawbacks, a continuous monitoring of urban growth evolution in terms of type and extent of changes over time is essential for supporting planners and decision makers in future urban planning.

Many recent researches have also explored ways of measuring dynamics of urban morphology. Shen [22], among others, compared the morphology of 20 urban areas in USA obtaining a wide range of results, due to the different size and character of each case study. Also, Frankhauser [6] used fractal dimension in the examination of outskirt areas in European cities, trying to obtain a typology of urban agglomerations. Finally, Benguigui et al. [2] examined the built-up settlement of Tel Aviv and concluded that fractal dimension tends to increase through time.

A critical point for understanding and monitoring 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 for obtaining useful data that 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 along with spatial analysis 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 [23] [14]

[18] [12] [21] and diverse methodological approaches to extract information on land cover and land use changes.

This study analyzes urban expansion over time in several towns of southern Italy, using satellite images. Sample towns are located south of Bari, one of the most important cities in southern Italy. Analyzes were carried out using Landsat images acquired in 1976, 1999 and 2009. The obtained results showed a significant urban expansion and an increase of irregularity degree in the fabric of the city. Such a variation is related to economic factors, industrial expansion and population growth.

2 Materials and Methods

2.1 Change Detection

Over the years, different techniques and algorithms were developed for change detection from the simplest approach based on (i) a visual interpretation and/or manual digitization of change [11] [15] to the computation and filtering such as (ii) image algebra change detection [9], image regression, image rationing [10] and vegetation index differencing [20] [11] [15].

The effectiveness of change detection algorithms is strongly dependent on surface characteristics of the study area, on spectral and spatial resolution of available historical data sets, and on decision makers needs. All these critical aspects make it difficult to develop a general methods effective and reliable for all applications in different regions.

This study deals with the spatial characterization of expansion of urban areas in southern Italy, by using geospatial analysis applied to multi-date Thematic Mapper (TM) satellite images.

Over the years, satellite time series data sets, such as Landsat MSS and TM images have been used to assess urban growth, mainly for big cities [16] [26] [27]. The investigation herein presented focused on assessment of the expansion of several very small towns very close to Bari (one of the biggest cities in southern Italy). To cope with the fact that small changes have to be captured and extracted from TM multi-temporal data sets, we adopted the use of spectral indices to emphasize occurring changes, and geospatial data analysis for revealing spatial patterns.

Analyses have been carried out using global and local spatial autocorrelation applied to multi-date NASA Landsat images acquired in 1976, 1999 and 2009. The results we obtained show a significant urban expansion coupled with an increase of the irregularity degree of urban pattern in 1976, 1999 and 2009. This variation is also connected with urban expansion and population growth.

Since 1972, the Landsat satellites have provided repetitive, synoptic, global coverage of high-resolution multispectral imagery. The characteristics of TM bands were selected to maximize each band's capabilities for detecting and monitoring different types of land surface cover characteristics.

LANDSAT TM multispectral data have been acquired from a nominal altitude of 705 kilometers (438 miles) in a near-circular, sun-synchronous orbit at an inclination of 98.2 degrees, imaging the same 185-km (115-mile) swath of Earth's surface, every 16 days. All TM spectral bands (1 to 5 and 7) are listed in Table 1. All of remote sensed data have been georeferenced according to UTM projection.

Table 1. TM spectral bands

Thematic Mapper (TM)		
Landsat 4-5	**Wavelength (micrometers)**	**Resolution (meters)**
Band 1	0.45-0.52	30
Band 2	0.52-0.60	30
Band 3	0.63-0.69	30
Band 4	0.76-0.90	30
Band 5	1.55-1.75	30
Band 6	10.40-12.50	120
Band 7	2.08-2.35	30

The availability of a long time series of TM data systematically acquired, stored and now free available from NASA website for the whole globe makes the TM time series an invaluable data source for change detection. Moreover, geometric stability and high positional accuracy of TM data enable a reliable co-registration of multiple images, whereas radiometric consistency allows us to adjust scenes to spectrally match. Such characteristics make TM data valuable and reliable low cost technologies useful not only for assessing large-scale changes, such as land-use and land-cover, but also for assessing variations occurring at smaller scales, such as urban expansion with new houses and roads.

Satellite images acquired in different years (1976, 1999 e 2009) have been used in this work. Table 2 shows a comparison between Landsat Terra Aster sensors.

Table 2. Comparison among several Landsat and Terra Aster sensors

	Landsat MSS	**Landsat TM**	**Landsat ETM+**	**Terra ASTER**
Resolution	80 m	30 m	30 m	15 m (VNIR)
Green	1 (0,5-0,6 µm)	2 (0,52-0,6 µm)	2 (0,52-0,6 µm)	1 (0,52-0,6 µm)
Red	2 (0,6-0,7 µm)	3 (0,63-0,69 µm)	3 (0,63-0,69 µm)	2 (0,63-0,69 µm
Near infrared	3 + 4 (0,7-1,1 µm)	4 (0,76-0,9 µm)	4 (0,76-0,9 µm)	4 (0,78-0,86 µm)

2.1.1 Spectral Band Analysis

Observing satellite spectral bands in RGB (Red, Green, Blue), the growth of a city is characterized by the transition from natural vegetation colours to lighter and brighter colours, generally due to high reflection of buildings and soils where vegetation has been removed.

In order to obtain an image in RGB, it is necessary to combine 3, 2, 1 bands. Using GRASS open source GIS software (www.grass.itc.it), it is possible to adequately combine the bands, through the module called i.landsat.rgb. This module performs a self-balancing action and increases the colour channels of a Landsat RGB image, obtaining a mixture of more natural colours. Original data remain intact and only colour table of each band is changed. The module operates computing a histogram for each colour channel and removing a controlled amount of outliers before colour scale recalibration with an appropriate module (r.colors). The i.landsat.rgb tool works with any set of RGB images and the script can be easily modified to work with other datasets and bands. In the present paper three TM images, acquired in 1976, 1999 and 2009, have been used. Two of TM images are shown in Figure 1 (1976 and 2009, respectively) using RGB composition to emphasize areas of concern; light spots are related to urban areas.

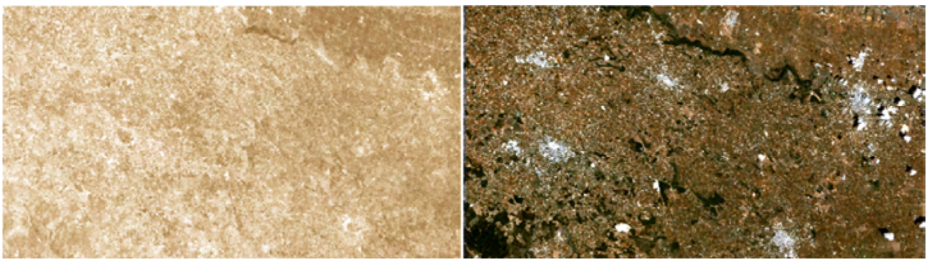

Fig. 1. Comparison of RGB Landsat images at 1976 e 2009 south of Bari municipality

The phenomenon of urban growth can be analyzed at different scales depending on the context of settlements to be examined. These slow dynamics can be analyzed with images of the same area at different times, with a not particularly high spatial resolution. In any case, urban areas can be identified by investigating spectral responses both in visible and infrared bands. The figure below highlights that buildings have higher values in the infrared than in the visible band.

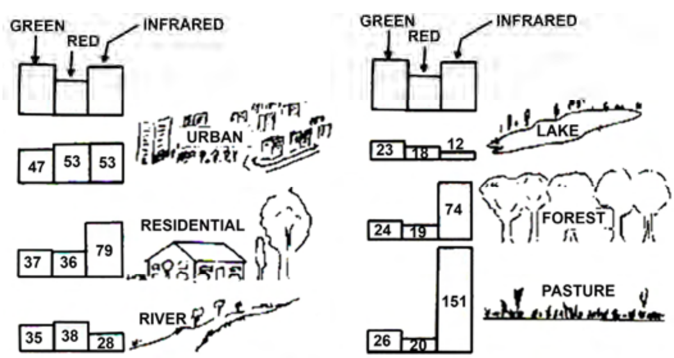

Fig. 2. Signal intensity in visible and infrared

A possible way to highlight changes, considering only three images at a time, is the composition in false colour. Another possibility is to combine bands in a different way. As for multispectral images, scenes with different acquisition dates, rather than bands with different spectral range, are combined. A colour image should be obtained where unchanged areas appear in gray scale, while zones where changes have occurred show brighter colours. In the following image (Fig. 3) the three 2 bands at 1976, 1999, 2009 have been combined.

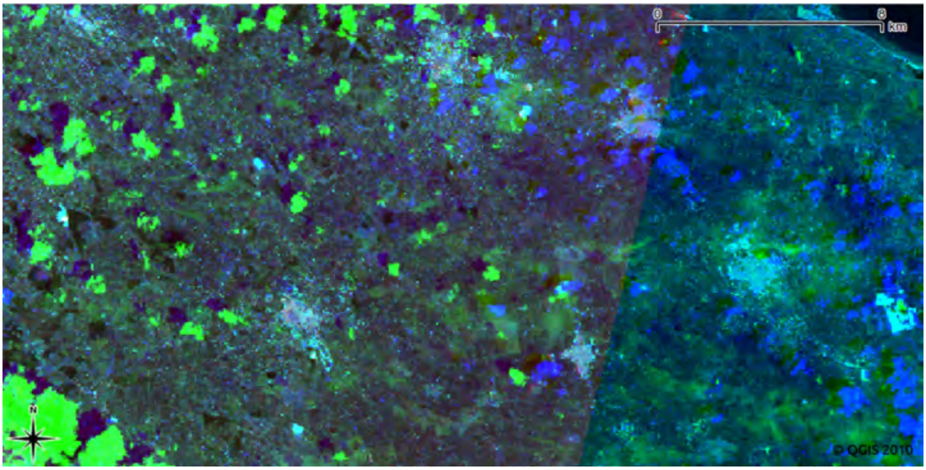

Fig. 3. False Colour composition

The most evident colours show variations occurred from 1976 to nowadays. Unfortunately, in the image there are clouds indicating pixel erroneous changes; but in other cases (indicated by light colour), the increase of urbanized area over the years is evident.

2.2 Spatial Autocorrelation Techniques

In addition to RGB images composition and band classification at different periods, in this study Landsat images acquired in 1999 and 2009 have been examined using spatial autocorrelation techniques.

The concept of spatial autocorrelation is rooted on Waldo Tobler [24] 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 (Boots and Getis, 1988).

Spatial autocorrelation takes into account the spatial attributes of geographical objects under investigation, evaluates and describes their relationship and spatial patterns, also including the possibility to infer such patterns at different times for the study area. The spatial patterns are defined by the arrangement of individual entities in space and 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 for understanding 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. Fixed a neighbourhood for each event, it is possible to understand how much it is modified by the presence of other elements inside that neighbourhood. The presence of autocorrelation in a spatial distribution is caused by two effects, that could be clearly defined, but not separately studied in the practice:

(i) 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:

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

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

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

$$\gamma(s_i s_j) = \lim_{ds_i ds_j \to 0} \left\{ \frac{E(Y(ds_i)Y(ds_j))}{ds_i ds_j} \right\} \tag{2}$$

The 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 [5] [19], 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.

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

2.2.1 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* [7] indexes.

Moran I index is defined by the following equation:

$$I = \frac{N\Sigma_i\Sigma_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{(\Sigma_i\Sigma_j w_{ij})\Sigma_i(X_i - \bar{X})^2} \tag{4}$$

where:

- N is the number of events;
- X_i and X_j are intensity values at points i and j (with i≠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:

$$c = \frac{(N-1)(\Sigma_i\Sigma_j w_{ij}(X_i - X_j)^2)}{2(\Sigma_i\Sigma_j w_{ij})\Sigma_i(X_i - \bar{X})^2} \tag{5}$$

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 provides 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.

2.2.2 Local Indicators of Spatial Association

Luc Anselin [1] 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 the 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)* [1] represents the local version of *Moran index I* and it is defined by the relation:

$$I_i = \frac{\left(X_i - \overline{X}\right)}{S_X{}^2} \sum_{j=1}^{N} \left(w_{ij} \left(X_j - \overline{X}\right)\right) \tag{6}$$

where $\overline{X}$ 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≠i), S_X^2 is the variance of all events and w_{ij} is the weight matrix. Considering z-score:

$$z_i = \frac{\left(X_i - \overline{X}\right)}{S_X}$$

LISA index can be expressed in the following synthetic form:

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

The function by *Getis & Ord* [8] is represented by the following equation:

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

which is very similar to Moran index, except for $w_{ij}(d)$ which, in this case, represents a weight which varies according to distance. These 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 Gi with intensity values.

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

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

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

3 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 and characterize the spatial characterization of feature variations.

The investigation herein presented was focused on the assessment of the expansion of several very small towns very close to Bari (in southern Italy), the second largest city of Southern Italy, located in Apulia (or Puglia) Region. It faces the Adriatic Sea and has one of the major seaports in Italy. Bari is the fifth largest province (more than 5,000 square kilometres) in Italy and also the most populated with around 1,600,000 inhabitants in 2007. The city has around 400,000 inhabitants. 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 table 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.

3.1 Change Detection

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 along with both global and local geospatial statistical analysis.

Change detection is the assessment of variations between multidate, 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, multidate 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 multidate 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 artefacts 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.

The images under investigations 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 for capturing 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 Index Vegetation (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:

$$\mathrm{NDVI} = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \tag{10}$$

This index was computed for both 1999 and 2009, to emphasize occurring changes and improve change detection analysis carried out as classification comparison from NDVI processed using geospatial data analysis.

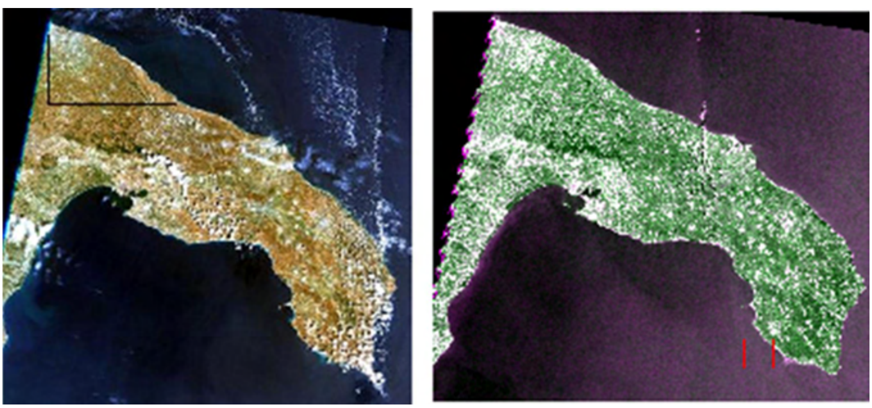

Fig. 4. RGB of TM images acquired in 1999 and 2009, note that light spots are urban areas. The black rectangle indicates the location of the study area.

Figure 4 show NDVI maps computed from TM images acquired in 1999 and 2009, respectively. A visual comparison between the figures clearly points out that the use of spectral combinations of red and NIR bands highlights light spots related to urban areas. In particular, the comparison between multidate (1999 and 2009) NDVI maps emphasises the expansion of urban areas, which are easily recognizable by a visual inspection.

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

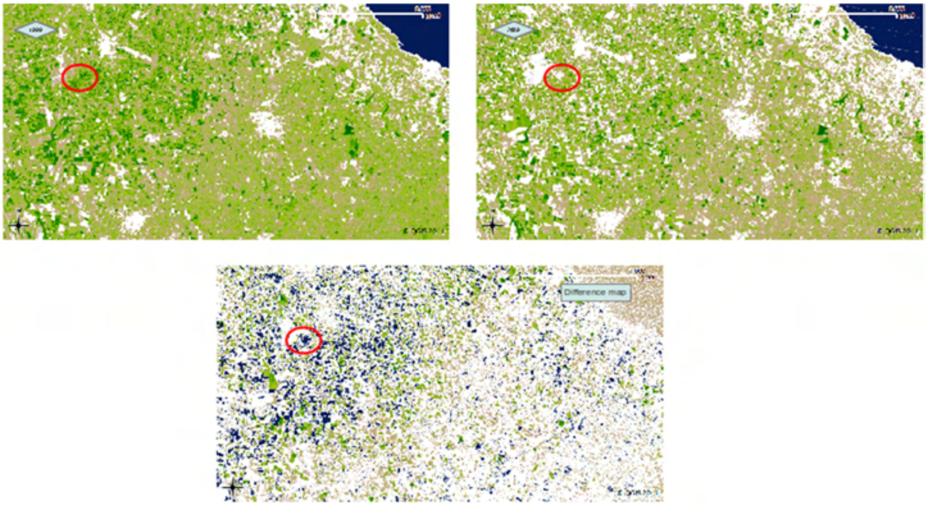

Fig. 5. NDVI map from the TM images acquired in 1999 and 2009, note that light spots are urban areas. NDVI difference map from the TM images acquired in 1999 and 2009, note that white pixels are urban areas. The red circle indicates a strong change in NDVI index where vegetation has been replaced by the urbanized area.

3.2 Spatial Autocorrelation

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.

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 [23]. Statistics output is an image for each calculated index, which contains a measure of autocorrelation around that pixel.

Both global and local statistics can be calculated using spectral channels, spectral combinations and/or multi-temporal combinations as intensity.

In order to identify areas of urban expansion, we looked for a change in spatial structure between two image dates.

Spatial dependency may be captured using spatial autocorrelation statistics such as join-counts, Moran's I and Geary's c. Therefore, we consider that the temporal change of geospatial statistic between image dates provides information on change in spatial structure of some unspecified nature between two image dates.

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

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

4 Results

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 difference between NDVI 1999 and 2009. Later on, the multidate 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 6 (from left to right) 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 Moran of the map well show variations linked to concrete and building materials.

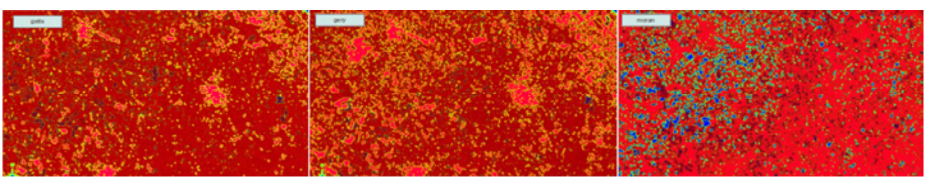

Fig. 6. (from left to right) show the local autocorrelation indexes presented as Getis G_i, Local Geary c and LISA applied with lag 2

Taking into account the obtained results, we can observe that the distribution of the built-up area was more homogeneous and less fragmented in 1999, without the presence of different urban centres. During the period up to 2009 changes led to an increase of density leading to an increase in urban areas expansion.

Another procedure in analyzing the evolution of urbanized areas is given by the combination of bands. In this way, more appropriate indices of remote sensing for the study of a given phenomenon can be built. One of the indices used for the study of urban phenomena is BAI Built-up Areas Index = (blue - ir)/ir + blue). The BAI is a very useful index for identifying impermeable surfaces like asphalt and concrete. Values generated using BAI index range from -1 to 1 and this also emerges from basic statistics (module r.stats GRASS) performed on raster data.

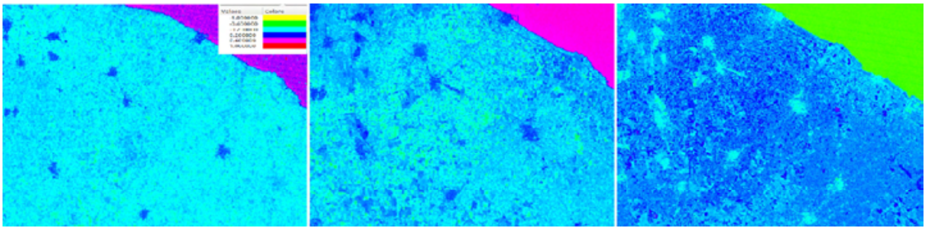

Fig. 7. Built-up Areas Index using Landsat images (1976-1999-2009)

5 Final Remarks

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

As regards 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) to assess if the variation of urban structure over time can be quantitatively determined using TM images, (ii) to investigate and describe the modification of urban shape and morphology over time.

Analysing and comparing different years, the process of urban intensification has been observed, and the increase of urbanized area was 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 analysing the urban structure and its transformation through time.

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

References

1. Anselin, L.: Local indicators of spatial association – LISA. Geographical Analysis 27, 93–115 (1995)
2. Benguigui, B., Chamanski, D., Marinov, M.: When and where is a city fractal? Environ. Planning B 27, 507–519 (2000)
3. Boots, B.N., Getis, A.: Point Pattern Analysis. Sage Publications, Newbury Park (1988)
4. Cheng, J., Masser, I.: Modelling urban growth patterns: a multiscale perspective (2002)

5. Danese, M., Lazzari, M., Murgante, B.: Kernel Density Estimation Methods for a Geostatistical Approach in Seismic Risk Analysis: The Case Study of Potenza Hilltop Town (Southern Italy). In: Gervasi, O., Murgante, B., Laganà, A., Taniar, D., Mun, Y., Gavrilova, M.L. (eds.) ICCSA 2008, Part I. LNCS, vol. 5072, pp. 415–429. Springer, Heidelberg (2008), doi:10.1007/978-3-540-69839-5_31.
6. Frankhauser, P.: The Fractal Approach, a new tool for the spatial analysis of urban agglomerations, Population: An English Selection. New Methodological Approaches in the Social Sciences 10(1), 205–240 (1998)
7. Geary, R.: The contiguity ratio and statistical mapping. The Incorporated Statistician (5) (1954)
8. Getis, A., Ord, J.: The analysis of spatial association by distance statistics. Geographical Analysis 24, 189–206 (1992)
9. Green, K., Kempka, D., Lackey, L.: Using remote sensing to detect and monitor land cove and land use. Photogrammetric Engineering and Remote Sensing 60, 331–337 (1994)
10. Howarth, J.P., Wickware, G.M.: Procedure for change detection using Landsat digital data. International Journal of Remote Sensing 2, 277–291 (1981)
11. Lacy, R.: South Carolina finds economical way to update digital road data. GIS World 5(10), 58–60 (1992)
12. Lambin, E.F.: Change detection at multiple scales seasonal and annual variations in landscape variables. Photogrammetric Engineering and Remote Sensing 62, 931–938 (1996)
13. Lanorte, A., Danese, M., Lasaponara, R., Murgante, B.: Multiscale mapping of burn area and severity using multisensor satellite data and spatial autocorrelation analysis. International Journal of Applied Earth Observation and Geoinformation (2012), doi:10.1016/j.jag.2011.09.005
14. Lichtenegger, J.: ERS-I: land use mapping and crop monitoring: a first close look to SAR data. Earth Observation Quarterly, 37–38 (May-June 1992)
15. Light, D.: The national aerial photography program as a geographic information system resource. Photogrammetric Engineering and Remote Sensing 59, 61–65 (1993)
16. Masek, J.G., Lindsay, F.E., Goward, S.N.: Dynamics of urban growth in the Washington DC metropolitan area, 1973-1996, from Landsat observations. Int. J. Rem. Sensing 21, 3472–3486 (2000)
17. Moran, P.: The interpretation of statistical maps. Journal of the Royal Statistical Society (10) (1948)
18. Muchoney, D.M., Haack, B.N.: Change detection for monitoring forest defoliation. Photogrammetric Engineering and Remote Sensing 60, 1243–1314 (1994)
19. Murgante, B., Danese, M.: "Urban versus Rural: the decrease of agricultural areas and the development of urban zones analyzed with spatial statistics" Special Issue on Environmental and agricultural data processing for water and territory management. International Journal of Agricultural and Environmental Information Systems (IJAEIS) 2(2), 16–28 (2011) ISSN 1947-3192, doi:10.4018/jaeis.2011070102
20. Nelson, R.F.: Detecting forest canopy change due to insect activity using land sat MSS. Photogrammetric Engineering and Remote Sensing 49, 1303–1314 (1983)
21. Sailer, C.T., Eason, E.L.E., Brickey, J.L.: Operational multispectral information extraction: the DLPO image interpretation program. Photogrammetric Engineering and Remote Sensing 63, 129–136 (1997)
22. Shen, G.: Fractal dimension and fractal growth of urbanized areas. Int. J. Geogr. Inf. Sci. 16, 419–437 (2002)

23. Tateishi, R., Kajiwara, K.: Global Lands Cover Monitoring by NOAA NDVI Data. In: Proceeding of International Workshop of Environmental Monitoring from Space, Taejon, Korea, pp. 37–48 (1991)
24. Tobler, W.R.: A computer movie simulating urban growth in the Detroit region. Economic Geography 46(2), 234–240 (1970)
25. United Nations Population Division (2001) World Population Monitoring 2001: Population, environment and development (2001), http://www.un.org/esa/population/publications/wpm/wpm2001.pdf
26. Yang, X., Lo, C.P.: Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. Int. J. Rem. Sensing 23, 1775–1798 (2002)
27. Yuan, F., Sawaya, K., Loeffelholz, B.C., Bauer, M.E.: Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Rem. Sensing Environ. 98, 317–328 (2005)