Urban Versus Rural:
The Decrease of Agricultural Areas and the Development of Urban Zones Analyzed with Spatial Statistics

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ABSTRACT

Until a few decades ago it was very easy to distinguish between city and country: in most cases the edge was defined by defensive barriers. In recent times, the relationships between urban and rural areas completely changed, placing the country in a subordinate position. Consequently, many terms have been coined in order to describe the new phenomena taking place between city and country. The term adopted, "periurban area", despite its large use, does not have a clear and unambiguous definition. Such various approaches are due to the complexity of the phenomenon to be analyzed and to the huge variety of territorial contexts in which it may reveal. The phenomenon is characterized by urban growth with soil consumption generating loss of competitiveness for agricultural activities. This paper defines more precise rules in order to describe the periurban phenomenon, using techniques of spatial statistic and point pattern analysis. This approach has been tested in the case of study of Potenza municipality. Interest in this area comes after the earthquake of 1980, when a large migration of inhabitants began towards the countryside around Potenza.

Keywords: *Autocorrelation, Land Use Planning, Periurban Areas, Soil Consumption, Spatial Statistics, Urban Sprawl*

1. INTRODUCTION

Analyzing the main historical urban functions, Salsano (1998) considered town walls and the market as the first basic elements of the city. First the defensive functions, then the advantages of agglomeration principles and industrial development have led to a long migration process from rural areas to cities. In this period it was very easy to distinguish between city and country.

With the passing of time urban and rural concepts have undergone great changes. Land renting and the expulsion of several typical urban functions outside the city increased pressure on rural areas. The city organized the countryside influencing socio-cultural, economical and functional aspects. Consequently demographic relationships between city and countryside have been changed, generating a reversal trend. New concepts are emerging:

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urban exodus, new conurbations, "rurbanization", periurban countryside (Charrier, 1994). Therefore, it is not easy to define in a clear and unambiguous way which is the sharp boundary between urban and rural areas (Murgante & Las Casas, 2004; Murgante et al., 2008). Ahlqvist and Ban (2007) developed an ontology considering the degree of urbanization going from rural through exurban, from suburban to urban.

In planning literature, the periurban phenomenon has been defined in different ways. Le Jeannic (1997) describes the population displacement as the need to escape from the dense city in order to have more space and a better environment. Also, growth of periurban belt is due to high costs of flats, the need of individual dwellings and land rents (Guerois & Pumain, 2001). Since 1980s it has been less and less possible to distinguish town from country, denying the concept of two separate entities which was for many years one of the cornerstones of spatial planning (Hidding et al., 2000; Van Den Berg & Wintjes, 2000). Rural areas are more urbanized and an uncontrolled growth of periurban belts has increased the number of inhabitants. At the same time, urban areas have lost resident population gaining population in transit (Alberti et al., 1994), because of the activities concentration in urban areas. All these situations produce a huge commuting phenomenon (Cavailhès et al., 2004). The main feature of this trend is a low density of urbanization which spreads in all directions (Camagni et al., 1998). Growth of these areas is strictly related to urban sprawl, generating negative repercussions on agricultural activities. A great amount of roads have been built to improve dwelling accessibility and car is the only means of transport (Camagni et al., 2002). This is an opposite trend compared to the period after the Second World War, when urban planners used statistical methods to give a dimension of the migratory flows towards towns. This tendency, strictly related to Urban Sprawl, is so complex to analyze, that classical statistics are not enough for a complete understanding of the phenomenon. Settlement location in zones surrounding urban areas takes into account environmental features, accessibility, agricultural losses of productivity. In order to achieve a more complete analysis it is important to analyze each phenomenon according to its spatial location, so that it is possible to consider the concentration of some events in some areas and their possible interactions. Geostatistics can be useful in order to study this problem with an innovative approach compared to the classic socio-economic techniques. This method allows an analysis which may determine the actual trend in one region. This technique has been applied in Potenza Municipality, where a migratory phenomenon began from urban to rural areas after a strong earthquake occurred in 1980. All the informative layers have been combined with a land suitability procedure in order to define a periurban fringe with a certain precision.

2. AN OVERVIEW OF SPATIAL STATISTICS TECHNIQUES

The main aim of spatial analysis is a better understanding of spatial phenomena aggregations and their spatial relationship. Spatial statistical analyses are techniques which use statistical methods in order to determine if data show the same behaviour of the statistical model. Data are treated as random variables. The *events* are spatial occurrences of the considered phenomenon, while *points* are each other arbitrary locations. Each event has a set of attributes describing the nature of the event. *Intensity* and *weight* are the most important attributes; the first is a measure identifying the event strength, the second is defined by the analyst who assigns a parameter in order to define if an event is more or less important according to some criteria. Spatial statistics techniques can be grouped in three main categories: *Point Pattern Analysis*, *Spatially Continuous Data Analysis* and *Area Data Analysis* (Bailey & Gatrell, 1995).

The first group, *Point Pattern Analysis,* considers the distribution of point data in the space. They can follow three different criteria:

- Random distribution: the position of each point is independent of the others points;
- Regular distribution: points have an uniform spatial distribution;
- Clustered distribution: points are concentrated in some building clusters.

The second group, *Spatially Continuous Data Analysis,* takes into account the spatial location and the attributes associated to points, which represent discrete measures of a continuous phenomenon.

The third group, *Area Data Analysis,* analyzes aggregated data which can vary continuously through space and can be represented as point locations.

Spatial analysis aims to identify quantitative and spatial relationships among variables, studying the presence of *spatial autocorrelation.* If some clusters are found in some regions and a positive spatial autocorrelation is verified during the analysis, it can describe an attraction among points. The case of negative spatial autocorrelation happens when deep differences exist in their properties, despite the closeness among events. If it is impossible to define clusters of the same property in some areas, a sort of repulsion occurs. Null autocorrelation arises when no effects are surveyed in locations and properties. Null autocorrelation can be defined as the case in which events have a random distribution over the study area (O'Sullivan & Unwin, 2002). Essentially, the autocorrelation concept is complementary to independence: events of a distribution can be independent if any kind of spatial relationship exists among them.

Spatial distribution can be affected by two factors (Gatrell et al., 1996):

- First order effect, when it depends on the number of events located in one region;
- Second order effect, when it depends on the interaction among events.

If these two definitions seem clearer, it isn't as clear as the recognition of these effects over the space.

2.1. Kernel Density

Kernel density is one of the point pattern analysis techniques, where input data are point themes and outputs are grids. While simple density computes the number of events included in a cell grid considering intensity as an attribute, kernel density takes into account a mobile three-dimensional surface which visits each point. The output grid classifies the Si event according to its distance from the point S and the number of events found inside the three-dimensional surface (Bailey & Gatrell, 1995). The influence function de-fines the influence of a point on its neighbourhood. The sum of the influence functions of each point can be calculated by means of the density function, defined by:

$$\lambda(L) = \sum_{i=1}^{n} \frac{1}{\tau^2} k\left(\frac{L - L_i}{\tau}\right) \qquad (1)$$

where:

- λ is the distribution intensity of points, measured in L;
- L_i is the event i;
- K is the kernel function;
- τ is the bandwidth.

L_i, K and τ are the different factors that influence Kernel Density Estimation. L_i is the intensity of point pattern. It could be represented not only by the numerousness of events, but also in terms of strength of a single point.

Another important factor is kernel, characterized by unimodality, regularity, symmetry, finite moments of the first, second, etc. order (Breiman et al., 1977) and it is always not negative. Principal kernel types are uniform kernel, gaussian kernel (Burt & Burber, 1996), quartic kernel (Bailey & Gatrell, 1995), and Epanechnicov kernel (Epanechnikov, 1969). However, according to Silverman (1989) the choice of this parameter is less important than the bandwidth choice.

So the factor which more influences density values is bandwidth: if τ is too big the value of λ is closer to simple density; if τ is too small the surface does not capture the phenomenon (Jones et al., 1996). Approaches used to choose the bandwidth are two: the first one uses one fixed τ for the whole distribution; the second uses instead a variable value. Different methods used in literature are reviewed from Jones et al. (1996).

Finally, like in every grid analysis, a factor influencing density values is cell size. For cell choice, it is known that if the size is less than the bandwidth value divided by a factor between 2 and 5 times the bandwidth, this causes little effects on density estimation (O'Sullivan & Wong, 2007).

2.2. Straight Line Distance

Straight line distance is a function coming from map algebra techniques. It allows to measure the distance between each cell and the nearer source, where the distance calculation is based on the concept of Euclidean Distance (Tomlin, 1990; De Mers, 2002). The source can be in vector or grid format. In the case of grid format some cells will contain information about the source and some others will not, while in the case of a vector theme it will be necessary a previous transformation in grid before determining the distance.

The output of straight line distance is in grid format and the distance is measured between cells barycentre. Also, in this case it is important to estimate some factors such as the maximum distance within which one has to assess measures and sizes of cells.

2.3. Moran Index

Moran index I (Moran, 1948) is a global measure of spatial autocorrelation. This index takes into account the number of events occurring in a certain zone and their intensity. It is a measure of the first order property and can be defined by the following equation:

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

where:

- where: N is the number of events;
- X_i and X_j are intensity values in the 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 the weight matrix. If Xi and Xj are both upper or lower relative to 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 the weight matrix which depends on the contiguity of events. This matrix is strictly connected to the adjacency matrix.

There are two methods to determine w_{ij},: the "Inverse Distance" and the "Fixed Distance Band". In the first method, weights vary in inverse relation to the distance among events:

$$w_{ij} = d_{ij}^{x}$$

where z is a number smaller then 0.

The second method defines a critical distance beyond which two events will never be adjacent. If the areas to which i and j belong are contiguous, w_{ij} will be equal to 1, otherwise w_{ij} will be equal to 0. *Moran index* I can have values included between -1 and 1.

If the term is high, autocorrelation is positive, otherwise it is negative. Moran index vanishes in very rare cases, but usually the convergence is towards the theoretical mean value E(I), where each value is independent from the others.

$$E(I) = -\frac{1}{N-1}$$

If I < E(I), the autocorrelation is negative, if I > E(I) the autocorrelation is positive.

The significance of Moran index can be evaluated by means of a standardized variable z (I) defined as:

$$z(I) = -\frac{I - E(I)}{S_{E(I)}}$$

where $S_{E(I)}$ is the standards deviation from the theoretical mean value E(I).

2.4. Local Indicator of Spatial Association and the G Function by Getis and Ord

The Local Indicator of Spatial Association by Anselin (1995) and the G function by Getis and Ord (1992) are indicators at the local scale. Both LISA and G function take into account disaggregated measures of autocorrelation, considering the similitude or the difference of some zones. These indexes measure the number of events with homogenous features included within a distance *d*, located for each distribution event. This distance represents the extension within which clusters are produced for particularly high or low intensity values.

The Local Indicator of Spatial Association (Anselin, 1995) is defined as:

$$I_i = \frac{(X_i - \bar{X})}{S_X^{\ 2}} \sum_{j=1}^{N} (w_{ij}(X_j - \bar{X})) \qquad (3)$$

where symbols are the same used in Moran's I, except for $S_X^{\ 2}$ which is the variance.

The function by Getis and Ord (1992) is represented by the following equation:

$$G_i(d) = \frac{\sum_{i=1}^{n} w_i(d)\ x_i - \bar{x}_i \sum_{i=1}^{n} w_i(d)}{S(i)\sqrt{\left[\left(N-1\right)\sum_{i=1}^{n} w_i(d) - \left(\sum_{i=1}^{n} w_i(d)\right)^2\right] \Big/ N-2}} \qquad (4)$$

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

The use of the local indicator is not immediate, because there is the need to make explicit the dataset spatial structure, by defining: *1*) contiguity and distance rules and weight matrix; *2*) homogeneous classes of intensity.

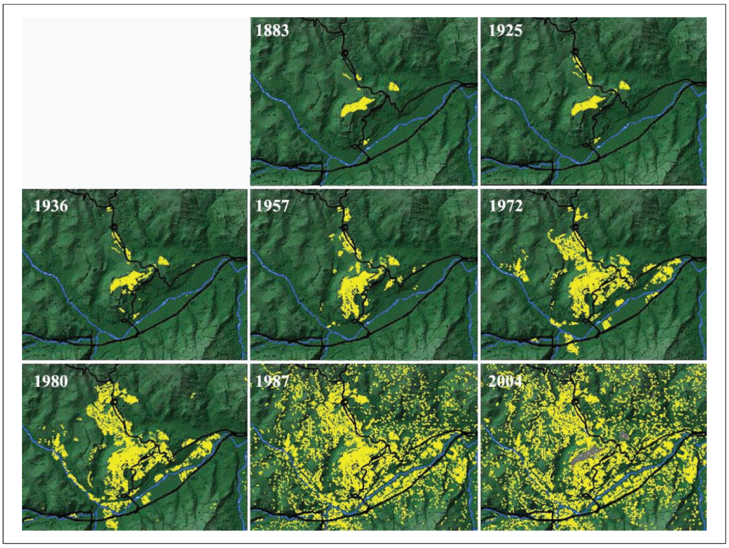
With this aim we left data speak by themselves using a method that integrates the global and the local indicators of spatial association together. More in detail, Moran's I was iteratively used with different values of distance band, with the aim of finding the value maximizing I, that is the degree of cluster level in the distribution. This distance is then used in local indicators.

3. THE CASE STUDY

These techniques have been applied to Potenza municipality. This is located in the southern Apennines area of Italy and it is the chief town of Basilicata, which is a region with a very low residential density.

Its territory, about 18000 ha sized, lays on an area roughly 900 m a.s.l., characterized by a relevant presence of forests, by very steep slopes and by a large number of areas interested by landslides. Although the morphology of this area did not encourage the diffusion of isolated houses, existing houses in the extra urban territory increased by 25% during the 1980-1990 decade. The migration of people

Figure 1. Expansion of Potenza Municipality from 1883 to 2004



from urban to rural areas mainly happened after the earthquake in 1980 (Figure 1), when a huge number of buildings in the urban area were defined uninhabitable and the fear of new seismic events, mixed with the wish of running away from the most damaged places, induced citizens to choose new localizations for building new houses. These reasons coupled with social, economic and cultural aspects generated an inhabitant flow to the countryside around Potenza, so intense that it deeply altered the urban morphology and modified the traditional physical functional relationships between urban and rural areas.

This process caused a decrease of agricultural areas and a development of new settlements with a crown shape all around the town, with no respect for natural morphology and without considering the consequent resources consumption. This kind of uncontrolled expansion, for more than twenty years, generated the following phenomena:

- Diffuse territorial decline, with hydrogeologic phenomena due to anthropic uses (construction of small road infrastructures);
- Abandonment of agricultural soils related to expectations of real estate development, especially in areas close to the town;
- Diffusion of scattered settlements in rural areas, with inadequacy of facilities and infrastructures;
- Pauperization of environmental and landscape valuable components.

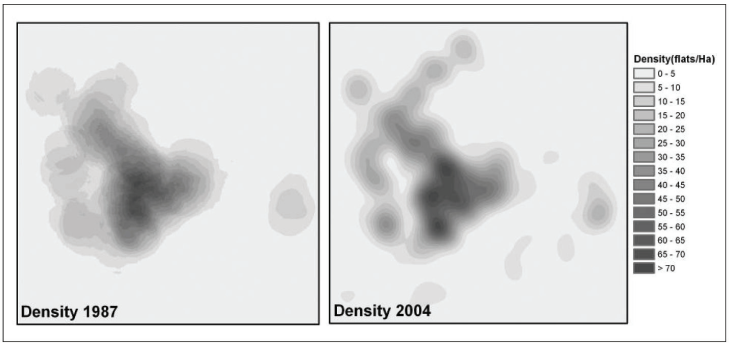
On this purpose, it can be useful to apply spatial statistic techniques to define criteria concerning suitability in locating new settlements, considering particular tendencies that some specific areas already manifest.

A first factor considered in this study is density. Periurban area is characterized by a spread of settlements with extensive features, compared to urban area, which has a greater density. Lower density is the first condition distinguishing periurban areas from urban ones.

Rural sites have a strong connection with agricultural activities and the relationship with the urban area is weak. It is also necessary to establish a lower threshold which can distinguish periurban areas from rural ones.

In order to calculate density, all the polygons representing buildings have been con-

Figure 2. Density of scattered settlements in 1987 and 2004 (flats/hectare)



verted in points which are the events to take into account in point pattern analysis. The ratio between the number of flats and the number of buildings has been calculated from census data; this value, considered as the intensity of events, has been calculated for each census unit and has been assigned to each building falling inside each unit. Figure 2 compares the density of scattered settlements between 1987 and 2004 and it shows the huge growth of urban sprawl. In the case study, a value of bandwidth of 400 m and a cell size of the grid of 10 m have been used. This bandwidth has been chosen considering a distance between periurban fringe and urban areas that can be travelled on by walking. Consequently the bandwidth becomes representative of accessibility to urban area.

A first rough analysis of periurban fringe takes into account zones with a low density expansion including areas with values of kernel density included between 1 and 18 flats/ha (Figure 3). Orography and accessibility define the second factor, which consists of the distance from infrastructures because urban growth is more concentrated along the main line of road network. In order to locate areas with a good accessibility, distance from infrastructures has been defined so that it represents the tendency. Straight Line Distance identified areas with a distance from the main infrastructures within 200 meters. The third factor is the spatial autocorrelation which has been analyzed considering Moran Index, G function as developed by Getis and Ord (1992) and Local Indicator of Spatial Association (LISA).

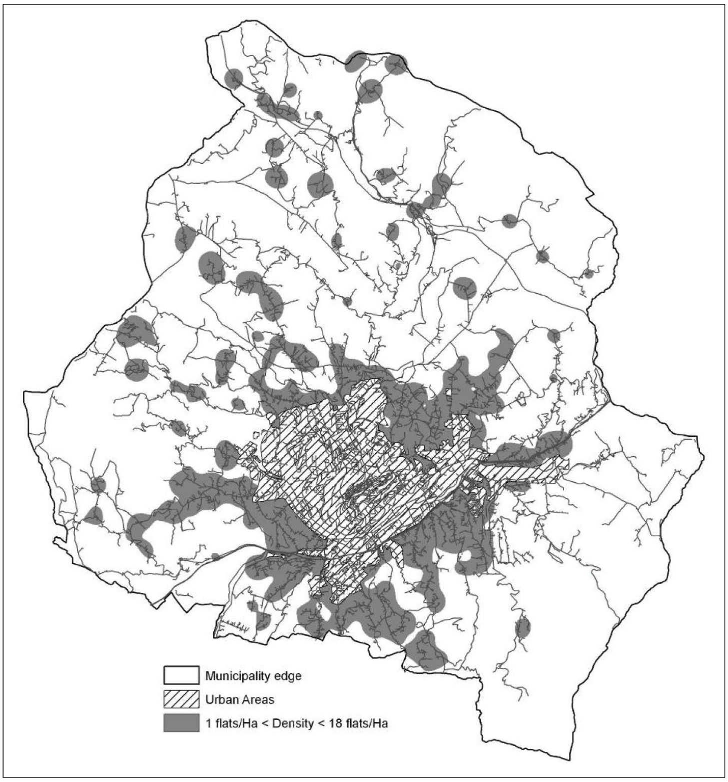
In this case intensity of events is obtained as the ratio between number of inhabitants and number of buildings in each census zone. Moran index is able to specify if an event is clustered, scattered or with a random distribution. It has been calculated by means of the inverse distance method considering data in two different periods, 1987 and 2004, to evaluate the variation of scattered rate of settlements. The following values have been achieved:

- Moran Index at 1987: $I_{1987} = 0.0698$;
- Moran Index at 2004: $I_{2004} = 0.0722$.

These two indexes show a low autocorrelation in both cases, and the second one is higher than the first one. These data can be interpreted as growth of settlements concentrated in some particular zones.

The next step of our study was to calculate the contiguity belt considered as the area where the phenomenon grows homogenously and where it will intensify in the future. Moran index depends from the distances among points; it is possible to calculate a distance value which produces an index I with the maximum level of correlation among events, by maximizing the deviation z. This value has been calculated in 1600 m and it has been used as an input parameter in LISA and then in Getis and Ord (1992)

Figure 3. Areas which have Kernel density included between 1 and 18 flats/hectare



function determining zones where events are autocorrelated.

A LISA positive value indicates a positive autocorrelation; obviously a negative autocorrelation corresponds to a negative value.

For the periurban fringe it is important to pay attention to the medium-low level of intensity, so the classes in Table 1 have been considered.

In Getis and Ord (1992) function, highest and lowest values of G mean highest and lowest values of phenomenon intensity.

The classes in Table 2 have been considered.

Figure 4 compares results, showing the similitude of areas with positive autocorrelation achieved with both indicators. In our study case Getis and Ord (1992) function fits the phenom-

Table 1. LISA classes

Class	Autocorrelation	LISA
no correlation	Negative autocorrelation	-106,9 ÷ 0
1 low	Positive autocorrelation among lower bounds	0 ÷ 14
2 low	Positive autocorrelation among low bounds	14 ÷ 28
3 low	Positive autocorrelation among medium-low bounds	28 ÷ 54
4 high	Positive autocorrelation among high bounds	54 ÷ 84.7

Table 2. Getis and Ord (1992) function classes

Class	Autocorrelation	Intensity value X_i (inhabitants/ buildings)	G'
no correlation	Negative autocorrelation	$X_i \leq 18$ $X_i \geq 18$	-1.3 ÷ - 2 -6.3 ÷ 1
1 low	Positive autocorrelation among lower bounds	$X_i \leq 18$	-1.3 ÷ - 2
2 low	Positive autocorrelation among low bounds	$X_i \leq 18$	-2 ÷ - 4
3 low	Positive autocorrelation among medium-low bounds	$X_i \leq 18$	-4 ÷ - 6.3
4 high	Positive autocorrelation among high bounds	$X_i \geq 18$	1 ÷ 11.9

Figure 4. Clusters location

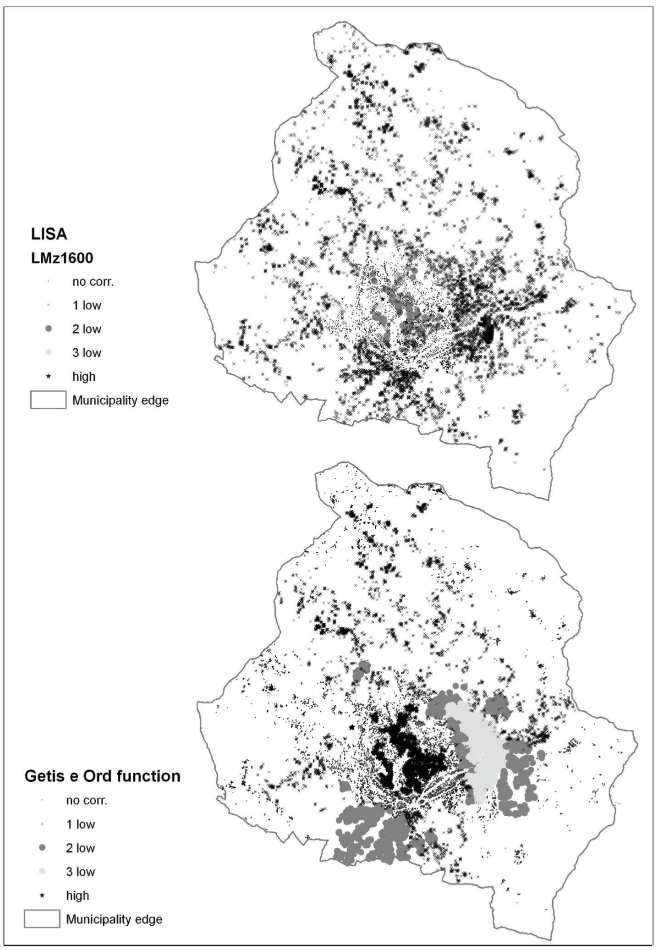
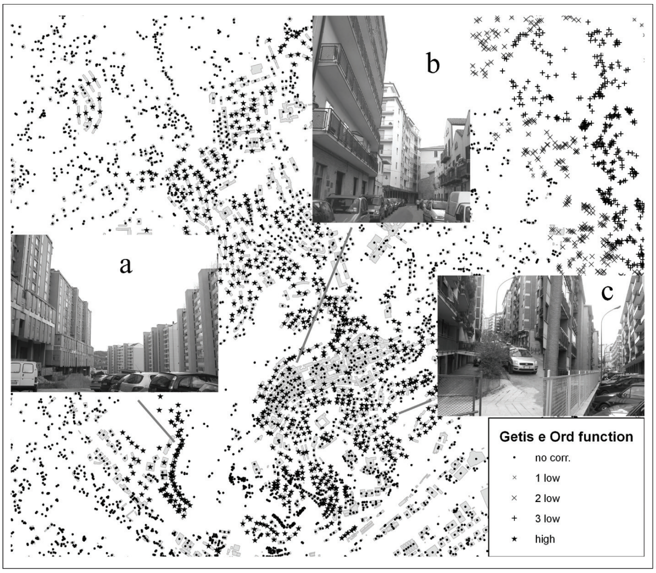


Figure 5. Detailed map with pictures which show autocorrelation difference



enon better because it is more sensible to intensity changes allowing more accurate classification.

Figure 5 shows in a more detailed map how deep are analyses produced with Getis and Ord (1992) function. Opposite values can occur in contiguous areas. Picture it shows how the highest values of autocorrelation correspond to the highest buildings of the town. Picture b highlights an abrupt transition, in a few metres, from no correlation to high correlation passing from ancient low buildings to high concrete buildings. Picture c shows how very elevated values of autocorrelation correspond to high buildings separate by narrow streets.

4. RESULTS AND FINAL DISCUSSION

Autocorrelation phenomena included in medium medium-low values have been interpolated thus generating polygons which represent the contiguity belt. These polygons represent the second level of suitability. It is composed by the inclusion rules considered in land suitability procedures reduced considering the global and local measures of autocorrelation. It is obvious that kernel density (Figures 2 and 3) is a rough measure which needs a deeper analysis. Moran index and Getis and Ord (1992) function give a further interpretation of phenomena considering contiguity not in all directions but only in some zones.

The exclusion rules (Figure 6) have been considered in the present study: areas included within a distance of 150 m from rivers, streams and springs, slopes higher than 35%, Nature 2000 sites, hydro-geological risk zones, areas higher than 1200 m a.s.l., landslides, areas close to railways and road networks.

Figure 6 shows the flow chart of the land suitability procedure for the location of Peri-urban fringe. All these rules have been combined using map algebra techniques. Figure 7 quantifies the reduction of suitable areas achieved after the procedure.

The results are illustrated as geographic components in Figure 8. Location of the contiguity belt is determined by the highway, which determines two gates for the town. In these areas urban sprawl is more intensified, particularly in the eastern part where the other road,

Figure 6. Scheme of the land suitability procedure for the location of Peri-urban fringe

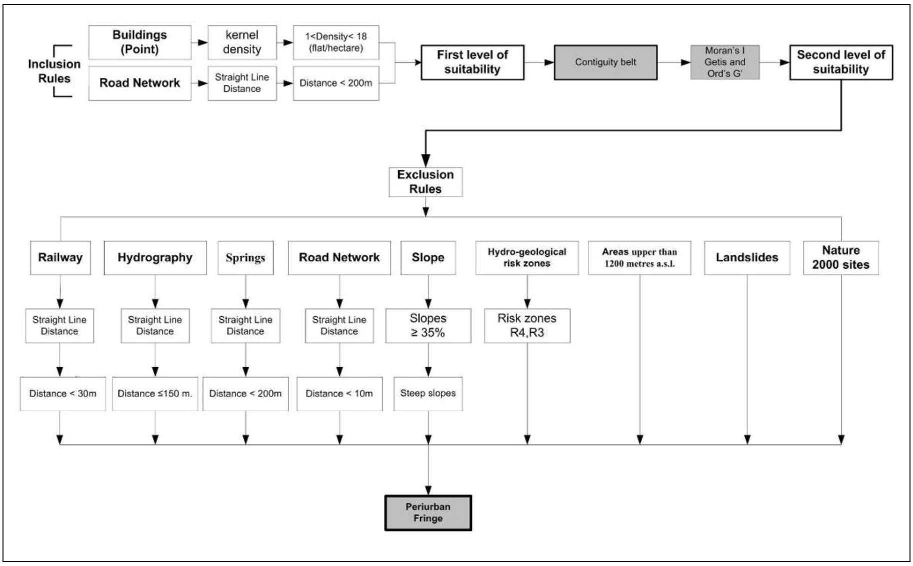
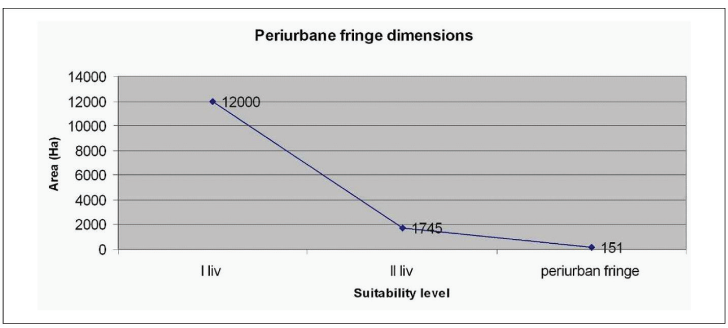


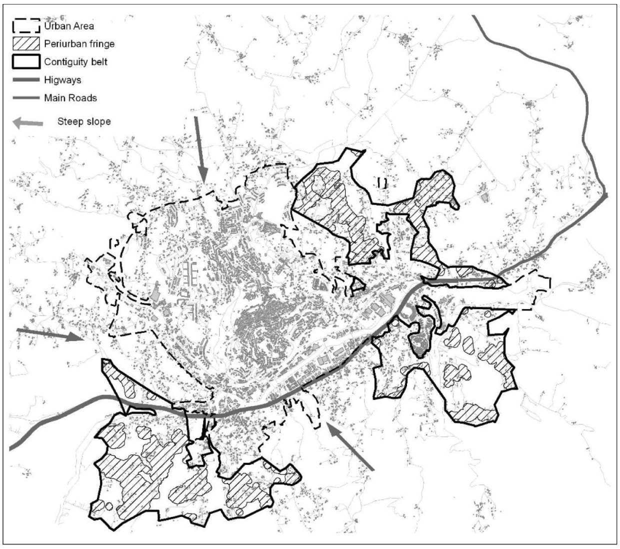
Figure 7. Size of suitable areas



which connects the industrial areas of Potenza with FIAT factory, amplifies the phenomenon. Steep slope obstructs urban growth in other zones. Periurban fringe (oblique hatch in Figure 8) considers contiguity belt after the exclusion rules and represents areas suitable for the location of new settlements or for intensifying the existing ones.

After the theorization by Tobler (1970), the first law of geography is reported here: "Everything is related to everything else, but near things are more related than distant things". More experience exists of the use of spatial statistics in geographical analysis; for instance Kernel density has been applied for the location of epidemics (Gatrell et al., 1995), in urban renewal analyses (Murgante et al., 2008), in defining damage scenarios (Danese et al., 2008; Danese et al., 2009) and studies on spreading of city services (Borruso & Schoier, 2004), while these techniques have not been used enough in the field of territorial planning. In this paper several kinds of spatial statistic functions have been applied for a deeper knowledge of territory and to give urban planners a better support for planning choices.

Figure 8. Periurban fringe after the land suitability procedure (oblique hatch)



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