

Modeling the Determinants of Urban Fragmentation and Compaction Phenomena in the Province of Matera (Basilicata Region - Italy)

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Abstract. The main objective of the present study was to integrate a logistic regression (LR) model and a geographic information system (GIS) technique to analyze the urban transformations patterns and investigate the relationship between urban transformation dynamics and its various determinant forces.

The case study concerns the territory of the province of Matera, in the region of Basilicata (southern Italy) where the main transformation phenomenon corresponds to the dynamics of urban sprinkling. The definition of the variables, corresponding to the dynamics of urban fragmentation and compaction, will be carried out through spatial analyses concerning the temporal variation of the sprinkling index.

The relationships between the dependent variables (Y) fragmentation and compaction and the independent variables (X) referring to different factors will be analyzed through two logistic regressions. The time interval considered is 1998-2013 and the determining factors (driving forces) refer to physical characteristics, proximity analysis to roads or cities, socioeconomic factors and land use policies. The results consist of two maps showing the probability of variation of the dependent variables whose accuracy will be evaluated using the Relative Operational Characteristic Index (ROC).

Keywords: Urban sprinkling · Logistic regression · Fragmentation

1 Introduction

This article shows the preliminary results for the construction of an urban transformation prediction model. The target of zero net land consumption by 2050 (EU Environment Action Programme to 2020 (7th EAP) [1–3] of the European Community are fundamental for fragile and critical territories, among them is undoubtedly the Italian territory [4–7]. The definition and implementation of such policies, rules and actions aimed at reducing soil consumption are urgent. To the phenomenon of land take are strongly linked the dynamics of urban transformation of fragmentation and compaction. In this study we will analyze the main factors that drive these dynamics.

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Over the last 50 years, land occupation in Europe has become more important, leading to the formation of low-density, fragmented settlements. Urban expansions have therefore moved away from the more traditional and recognized dynamics of urban expansion, acquiring different forms and very low settlement rates [8–10]. Characteristic of the internal areas of the Mediterranean is the urban sprinkling phenomenon [11].

The urban sprinkling phenomenon is a transformation dynamic different from that of urban sprawl [12] and characterized by a sporadic, pulverized and dispersed diffusion of urban settlements on the territory. It has very low-density indexes compared to those of urban sprawl, with consequent urban and landscape fragmentation [13]. The phenomenon of urban sprinkling is measured by SPrinkling IndeX (SPX) which is a geometric indicator that, through the subdivision of the study area into homogeneous territorial units, measures the dispersion of urban settlements on the basis of Euclidean distance.

The case study analyzed in this paper includes the territory of the province of Matera, in the region of Basilicata (southern Italy) where, as shown by previous studies [14–16], urban transformations from the 1950s to the present day have occurred on the basis of the urban sprinkling target. Therefore, on the basis of the sprinkling index, the processes of fragmentation and compaction on the territory of the province of Matera have been analyzed. The objective of this article is to model the factors that determine the dynamics of transformation (fragmentation and compaction) with a logistic regression in the period between 1998 and 2013. Among the determining factors (driving forces) considered are physical factors, socio-economic factors, factors of proximity to road infrastructure and main urban centers, factors concerning urban legislation on the transformability of territories. Logistic regression will be carried out once the phenomenon of compaction and the phenomenon of fragmentation have been considered. The results of logistic regression are maps of probability of change of the variable dependent on Y from the initial state "untransformed" to the subsequent state "fragmented" or "compacted".

2 Study Area

The case study concerns the territory of the province of Matera, located in the eastern part of the Basilicata region in southern Italy (Fig. 1). It borders to the west with Calabria, in particular with the province of Cosenza, to the south it is washed by the Ionian Sea, and to the east it borders with Puglia, and in particular with the province of Taranto and Bari. It has a variable orography where plains and hills alternate and slope down towards the sea.



Fig. 1. Geographical context: on the left the location of the Basilicata region in Italy, while on the right the territory of the province of Matera.

The provincial territory includes three regional nature reserves, the Natural Park of Gallipoli Cognato, the Archaeological and Historical Natural Park of the Rupestrian Churches of Matera, also known as the Murgia Materana Park, and finally a small portion of the Pollino National Park. Basilicata includes a total of 131 municipalities, 31 of which reside in the province of Matera. The largest city is Matera, also capital of the province, with 60351 inhabitants [17]. Three municipalities have a population between 10000 and 50000 inhabitants: Bernalda, Pisticci and Policoro. The remaining part has a population of less than 10000 inhabitants.

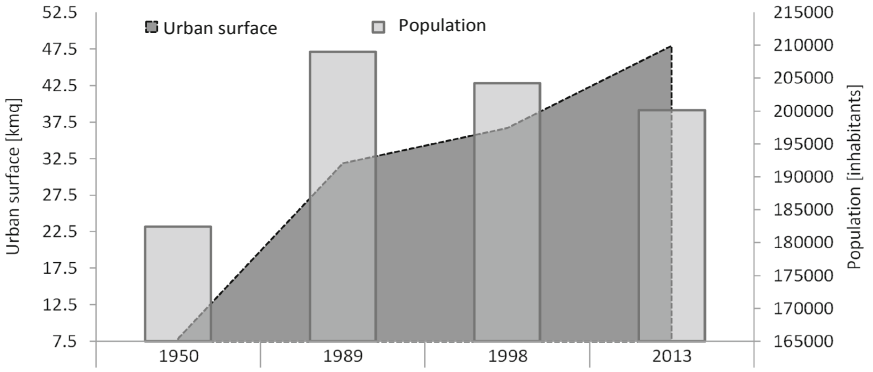


Fig. 2. Comparison from demographic trends and urban surface (in square kilometers) from 1950 to 2013 in the Province of Matera.

The graph in Fig. 2 shows the dynamics of urban expansion and population growth from the 50s to 2013 in order to highlight the general growth trend of the territory. From 1950 to 1989 the demographic trend is positive, in the following years a decrease

in population starts instead. The urban expansion, after a strong increase between 1950 and 1989, continues to grow until 2013 in contrast with the demographic trend. This decoupled growth trend is characteristic of the all regional territory [16].

3 Materials and Methods

The aim of this study is to model the determinants of urban transformation dynamics (fragmentation and compaction) with two logistic regressions in the time interval 1998-2013 considering 10 driving forces as independent variables (X). The dependent variables (Y) will be derived from the sprinkling index (analyzed in previous studies at regional level [14, 16]), as reported in the Table 1, and will be in a first case fragmentation and in a second case compaction.

Table 1. Urban transformation dynamics.

SPX	Urban transformation dynamics
$\Delta SPX_{(2013-1998)} > 0$	Urban fragmentation
$\Delta SPX_{(2013-1998)} < 0$	Urban compaction
$\Delta SPX_{(2013-1998)} = 0$	No transformation

The index was calculated on a 200 × 200 m grid for the years 1998 and 2013. For each transformation dynamics, 2 binary rasters were created in which the value 0 corresponds to no transformation and the value 1 to fragmentation or compaction.

According to the existing scientific literature [18–20] and the characteristics of the territory, 10 independent (predictive) variables have been identified (X).

Variable X_1: elevation, in raster format and with pixels at a resolution of 5 × 5 m; variable X_2 slope in percentage obtained from the elevation; X_3 proximity to secondary roads; X_4 proximity to local roads; X_5 proximity to railway stations; X_6 proximity to large cities, i.e. those with a population of more than 50000 inhabitants (city of Matera); X_7 proximity to medium-sized cities, i.e. those with a population between 10000 and 50000 inhabitants (municipalities of Montescaglioso, Bernalda, Policoro and Pisticci); X_8 population density in 2001 at municipal level; X_9 employment rate (source: Urbistat [21]); X_{10} raster of transformability containing all the constraints of inedificability present in the territory. All variables have been rasterized with 200 × 200 pixel resolution and standardized, with the exception of variable X_{10} which is categorical (0–1).

Logistic regression can be considered as a special case of linear regression when the result variable is categorical, so it predicts the probability of an event occurring by adapting the data to a logit function [22]. Logistic regression is usually used in the estimation of a model that describes the relationship between one or more continuous independent variables and binary dependent variables. The dependent variable can only assume two values: 0 and 1. The basic assumption is that the probability of the dependent variable assumes the value 1 (positive response) following the logistic curve.

Pseudo R_square estimates the goodness of the logistic regression model setting. *Pseudo R_square* equal to 1 indicates a perfect fit, *Pseudo R_square* equal to 0 indicates no relationship. According to [23], the *Pseudo R_square* greater than 0.2 is considered a relatively good fit. The multi-collinearity test between the independent variables will be done with the Variance Inflation Factor (VIF). VIF values below 5 show the absence of multi-collinearity, while VIF values above 5 indicate the presence of multi-collinearity between the independent variables [24, 25]. The overall adaptive fit of the model is evaluated using the Relative Operative Characteristic Index (ROC) which must be greater than 0.5 [26].

4 Results and Conclusions

Below are the results of the logistic regression carried out first for the fragmentation of the dependent variable and then for the compaction for the period 1998-2013. The multicollinearity test has a VIF less than 5 so all variables were considered in the logistic regressions. Figure 3 shows the regression coefficients of the two transformation dynamics.

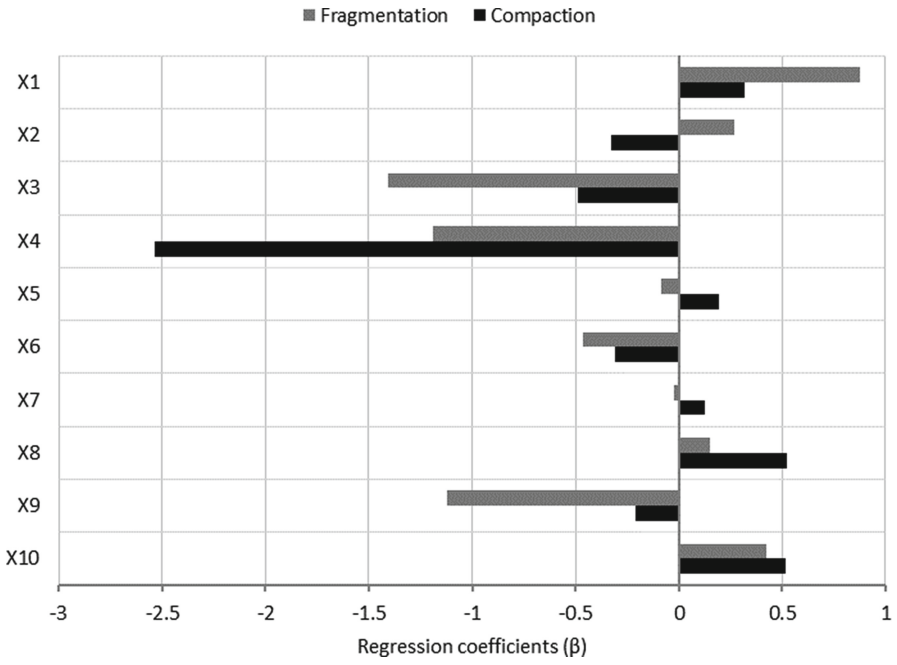


Fig. 3. Comparison of the regression coefficients of the two transformation dynamics.

The dependent variable X_1 has a positive coefficient for both transformation dynamics and is more influential for the fragmentation phenomenon. The positive

correlation indicates that the probability that the cell becomes 1 (compaction/fragmentation) increases with increasing elevation. Variable X_2 has negative correlation for compaction dynamics and positive correlation for fragmentation dynamics. The processes of urban transformation concerning fragmentation occur, therefore, at greater slopes than those of compaction. The variables X_3 and X_4 have a negative correlation index with both transformation phenomena and are the most significant factors for both processes. The correlation coefficients are the highest and show that the transformations in this territory are strongly influenced by the proximity of roads. The probability that a cell changes its state from untransformed to fragmented or compacted increases as the distance from secondary and local roads decreases. The probability for a cell to change its state from untransformed to fragmented increases near train stations (variable X_5) while the probability for a cell to change its state from untransformed to compacted increases as the distance from train stations increases. Transformation processes take place more in the vicinity of large cities (variable X_6) and away from medium-sized municipalities (variable X_7). Transformations are positively correlated with population density (variable X_8). The variable X_9 shows a negative correlation: the probability that a cell undergoes a transformation increases as the employment rate decreases. Finally, for the last variable X_{10} the correlation is positive, the transformations increase near the transformable territories and the greatest correlation is for the compaction process.

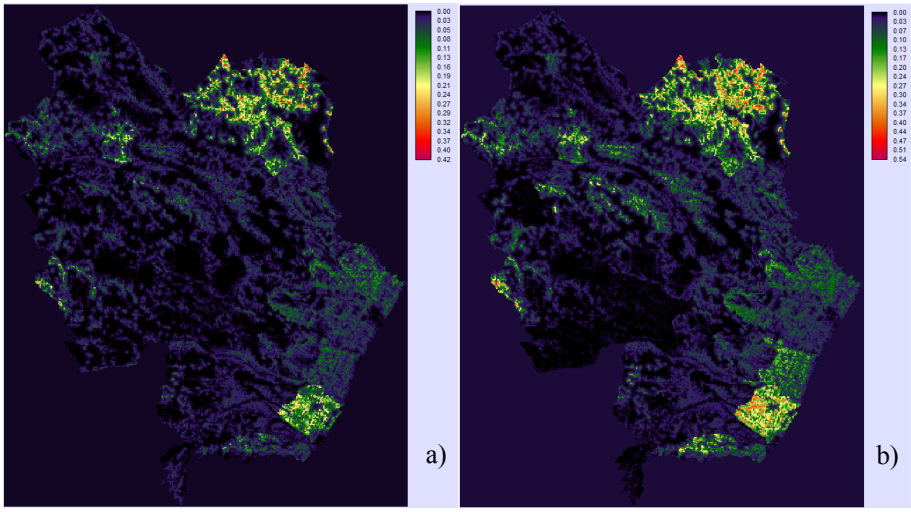


Fig. 4. Predicted dependent variables: a) Compaction, b) Fragmentation.

The *Pseudo R_square* for the fragmentation process was 0.26 and for the compaction process 0.23; these coefficients, according to [23], show a good adaptation of the regression model.

The maps in Fig. 4 show the final result of the logistic regression: the change probability maps for both dependent variables: fragmentation and compaction. The maximum probability of change is 54% for fragmentation and 42% for compaction.

This shows that the territory will be more subject to transformation dynamics with regard to fragmentation. The ROC indices of 0.87 and 0.84 for compaction and fragmentation, respectively, demonstrate the goodness of the model.

This article shows the preliminary results for the construction of an urban transformation prediction model. The results show that the probability of transformation of the territory is more related to processes of urban fragmentation. In the case study analyzed but, more generally, in the whole Basilicata's regional territory, urban fragmentation is the main dynamics of transformation and, in recent years it has also been caused by other components of the settlement system such as renewable energy plants [15, 27] and oil wells [16]. It is crucial to analyze and model urban transformation dynamics as they have a significant impact on the quality of the landscape, the supply of ecosystem services [28–30] and the costs to the population of transforming the city in an unsustainable way [31, 32]. For these and other reasons, analyzing the dynamics of urban transformation is of fundamental importance since they can have a significant impact and cause significant damage to cultural heritage and, because of the dynamics that develop as a result of uncontrolled land transformation (landslide movements) can be a risk to human life [33–35].

The analysis of all these factors is of fundamental importance to understand what are the driving forces of the transformation-transformation dynamics of the territory and also to obtain information on future transformations to be used as a support to the work of policy makers. Future developments of this work will consist in building a model for predicting the dynamics of urban transformation in the future.

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