

Analyzing the Driving Factors of Urban Transformation in the Province of Potenza (Basilicata Region-Italy)

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Abstract. The main transformation dynamics in the province of Potenza territory (Basilicata region in the south of Italy) correspond to those of urban sprinkling. The urban sprinkling phenomena is typical of mainly mountainous internal areas with indices of settlement density and artificial coverage ratios very low. The temporal and spatial analysis of the urban sprinkling phenomenon gives a picture of the transformation dynamics of the territory, i.e. the phenomena of fragmentation and compaction of the urban territory. Through a logistic regression, the driving factors that have affected the dynamics of urban transformation and specifically the phenomena of fragmentation and compaction between 1998 and 2013 will be analyzed. The two transformation phenomena (dependent variables Y), will be analyzed separately and built on the basis of the variation of the sprinkling index in the analyzed period. In the model, eleven independent variables concerning physical characteristics, proximity analysis, socioeconomic characteristics and the urban policies or constraints, have been considered.

The result of the logistic regression consists of two probability maps of change of the dependent variable Y from non-urban to fragmented or compacted. The indexes of the relative operational characteristic (ROC) of 0.85 and 0.84 respectively for compaction and fragmentation, testify the goodness of the model.

Keywords: Urban sprinkling · Logistic regression · Fragmentation · Low-density

1 Introduction

Land take is the phenomenon of land area conversion from its original (natural) to its anthropic (urban) use [1, 2]. The phenomenon of soil consumption is becoming more and more widespread all over the world despite the implementation of various policies to contain its consumption [3–5]. European commission has legislated for soil protection by setting a target of zero net land consumption by 2050 (EU Environment Action Programme to 2020 (7th EAP)). This can be achieved by aligning soil consumption growth with real population growth by 2030. The demographic trend is crucial in the urban expansion process of a territory. In Italy, but also in other European

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countries, more and more often urban expansion is not justified by real settlement demand [6, 7]. In many contexts of low density and continuous depopulation, urban expansion is coupled with a negative demographic trend (decoupled growth) [8–10].

The phenomenon of land take in Europe, assumes more relevance considering that since the 1950s it has been largely driven by urban expansion characterized by a sharp decrease in urban density with decentralization of urban areas [11, 12]. This has led to changes in the shape of urban settlements from compact to fragmented and dispersed around the territory. The urban expansions in the last fifty years have detached from the more traditional and recognized dynamics of urban sprawl acquiring different forms and very low settlement indexes. Characteristic of internal Mediterranean areas is the phenomenon of urban sprinkling [13] recognized in Italy, Spain and Africa [9, 14–16].

Urban sprinkling is a transformation phenomenon different from that of urban sprawl [17] and characterized by a sporadic, pulverized and scattered diffusion of urban settlements on the territory. It has very low-density indices compared to those of urban sprawl, resulting in urban and landscape fragmentation [18]. The urban sprinkling phenomenon 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 SPX index, analyzed in the temporal dimension, returns a picture of the transformation dynamics of a territory in terms of fragmentation and compaction.

The case study analyzed is the territory of the province of Potenza, in the Basilicata region (southern Italy) where, as demonstrated by previous studies [9, 19, 20], the urban transformations from the 1950s to the present day have occurred on the basis of urban sprinkling rules. Therefore, on the basis of the sprinkling index the processes of fragmentation and compaction on the territory of the province of Potenza have been analyzed.

The aim of this article is to model the factors determining the dynamics of transformation (fragmentation and compaction) with a logistic regression in the period between 1998 and 2013. Analyzing all these factors is of fundamental importance in order to understand what are the driving forces behind the dynamics of transformation of the territory and also to obtain information about future transformations to be used as a support in the work of policy makers. The determining factors (driving forces) considered include physical factors, socio-economic factors, proximity factors to road infrastructure and major urban centers, factors concerning urban legislation on the transformability of territories. Logistic regression will be carried out once considering the phenomenon of compaction and once considering the phenomenon of fragmentation. The results of the logistic regression are probability maps of change of the dependent variable Y (fragmentation or compaction) from the initial state "untransformed" to the subsequent state "fragmented" or "compacted".

2 Study Area

The territory of the Province of Potenza in the Basilicata region presents a significant orographic range with the presence of many mountain peaks, especially in the southern part of the territory where there is the Pollino massif where the maximum provincial

and regional altimetry is reached (2238 m above sea level). The province of Potenza has a territorial extension of 6594 km^2, includes 100 municipalities and has a total population of 368,251 inhabitants (ISTAT 2019 [21]).

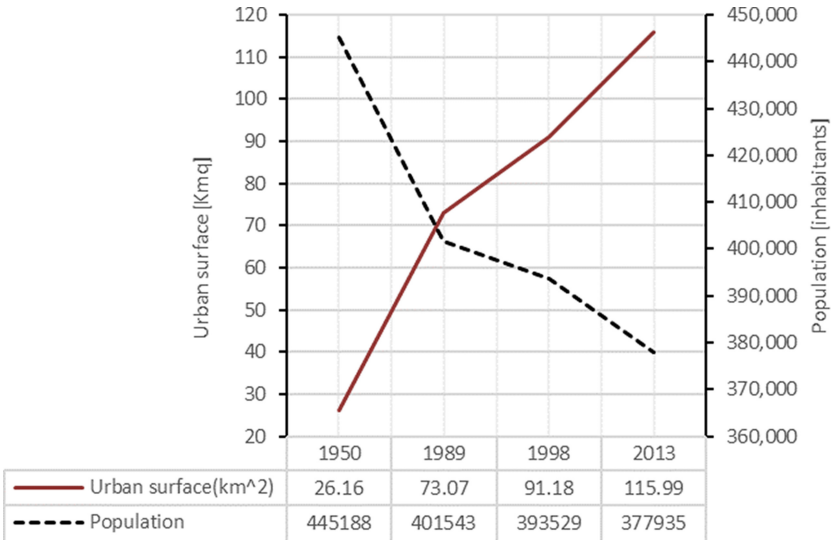


Fig. 1. Comparison from demographic trends and urban surface (in square kilometers) from 1950 to 2013 in the Province of Potenza.

The largest city for population is the municipality of Potenza (67168 inhabitants) which is also the regional capital. The other municipalities are small in size. Specifically, 6 municipalities on 100 have population between 10000 and 20000 inhabitants, 12 municipalities on 100 have population between 5000 and 10000 inhabitants and the rest (81 municipalities on 100), representative of the majority of the provincial municipalities, has population less than 5000 inhabitants. The graph in Fig. 1 shows a comparison between population growth and urban expansion measured in square kilometers of urban area from 1950 to 2013. The urban area in this case is defined as the surface occupied by buildings and road infrastructure. A disaggregated trend of the two variables emerges: as the population decreases, the urbanized area increases. This trend is still active all over the region, which, in the face of a negative demographic trend and a high rate of depopulation, sees its urban areas increase. Land take is therefore unsustainable in the absence of demand for settlement.

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 11 driving forces as independent variables (X). The dependent variables (Y) will be derived from the sprinkling index and will be in a first case fragmentation and in a second case compaction.

3.1 Dataset

The dependent variables include the dynamics of urban transformation and specifically: fragmentation and compaction. These layers were obtained from the analysis of the sprinkling index calculated on the whole regional territory in previous studies [9, 20]. The sprinkling index has a range of values between 0 and +∞ and is an expression of the distribution of urban aggregates on the territory divided into homogeneous territorial areas. Large values of the index indicate a high degree of fragmentation of the territory. Analyzing the variation of the index from an initial time t_0 to a final time t_1 we obtain:

- $\Delta SPX_{(t_1-t_0)} > 0$ Urban fragmentation
- $\Delta SPX_{(t_1-t_0)} < 0$ Urban compaction
- $\Delta SPX_{(t_1-t_0)} = 0$ No transformation

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

According to the existing scientific literature [22–24] and the characteristics of the territory, 11 independent (predictive) variables (X) have been identified that include physical factors, proximity factors, socioeconomic factors and urban planning legislation.

Specifically, the independent variables analyzed are: X_1 elevation, in raster format and with pixels at 5 × 5 m resolution; X_2 slope in percentage obtained from elevation; X_3 proximity to highways; X_4 proximity to secondary roads; X_5 proximity to local roads; X_6 proximity to railway stations; X_7 proximity to big cities, i.e. those with a population greater than 50000 inhabitants (Potenza city); X_8 proximity to medium-sized cities, i.e. those with a population between 10000 and 50000 inhabitants (Avigliano, Venosa, Lauria, Rionero in Vulture, Lavello and Melfi municipalities); X_9 population density in 2001 at municipal level; X_{10} employment rate (source: Urbistat [25]); X_{11} raster of transformability containing all the constraints of inedificability present in the territory. Except for variable X_{11}, all variables have been rasterized with 200 × 200 resolution pixels and standardized. The X_{11} variable is categorical (0–1) and the other variables are continuous, in meter, percentual or number.

3.2 Logistic Regression

Logistic regression is a statistical method used to analyze a dataset in which there are one or more independent variables that determine a result [26]. Logistic regression can also 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. Logistic regression is usually used in estimating 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 value 1 (positive response) following the logistic curve. The probability of the dependent variable assuming value 1 is expressed by the formula (1):

$$P(Y = 1|X) = \frac{\exp(\sum \beta x)}{1 + \exp(\sum \beta x)} \quad (1)$$

Where: P is the probability that the dependent variable Y becomes 1; X are the independent variables; β are the estimated parameters, the regression coefficients for each independent variable X.

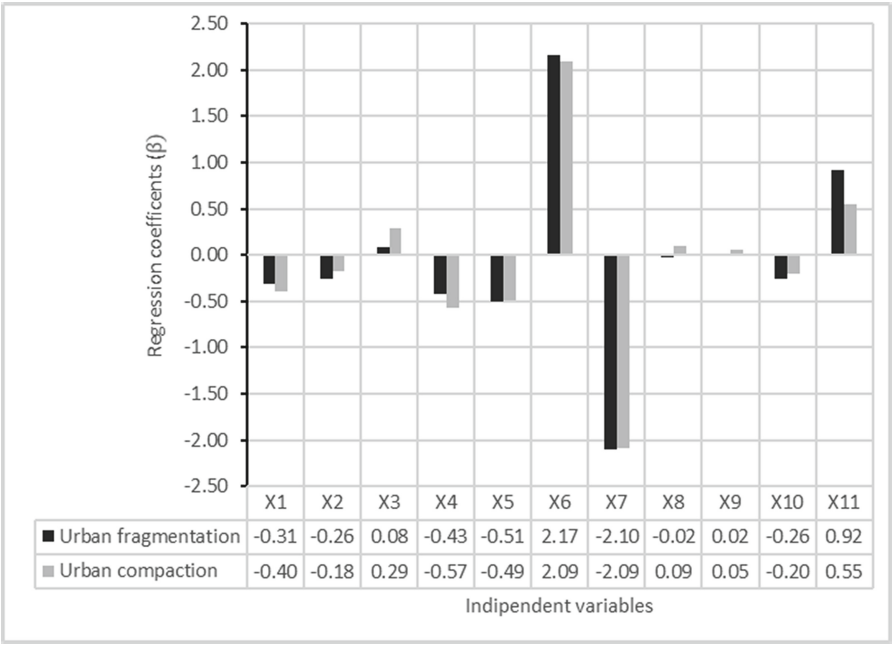
The goodness of fit of the model calibration is estimated by *Pseudo R_square* which estimates the goodness of setting the logistic regression model. *Pseudo R_square* equal to 1 indicates a perfect fit, *Pseudo R_square* equal to 0 indicates no relationship.

As mentioned in [27], pseudo R_square greater than 0.2 is considered a relatively good fit. To verify the absence of multi-collinearity between the independent variables, the Variance Inflation Factor (VIF) was calculated. VIF values less than 5 show the absence of multi-collinearity while VIF values greater than 5 indicate the presence of multi-collinearity between the independent variables [28, 29]. The overall adaptive fit of the model is assessed using the Relative Operative Characteristic (ROC) index which must be greater than 0.5 [30].

4 Results

The results of the logistic regression carried out first for the dependent variable fragmentation and then compaction for the period 1998–2013 are shown below. The Fig. 2 shows the regression coefficients of the two transformation dynamics. The independent variable X1 has a negative correlation coefficient for both transformation dynamics and is more influential for the compaction phenomenon. The negative correlation indicates that the probability of the cell becoming 1 (compaction/fragmentation) increases as the elevation decreases. The variable X2 shows negative correlation with a higher coefficient for the fragmentation process which, compared to compaction, tends to occur more as the slope decreases. The probability that a cell changes its state from non-urban to compact increases with increasing distance from highways (variable X3). Compact urban centers, in fact, are located far away from highways. The variables X4 and X5 have a negative correlation index with both transformation phenomena. The probability of finding compacted or fragmented cells increases as the distance from secondary and local roads decreases. The variable X6 is among the most influential variables and shows positive correlation. The probability of finding compacted cells increases as the distance from railway stations increases. Usually urban transformations take place near railway stations, this anomalous behavior is justified by the concentration of railway stations mainly in the northern part of the study area. The variable X7 shows a strong negative correlation. It represents the distance from large cities, i.e. the city of Potenza. The probability that a cell undergoes transformation increases as the distance from large cities decreases.

Differently, for variable X8 the correlation is positive and higher for the compaction process. The transformations take place, therefore, far from medium-sized cities.



	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Urban fragmentation	-0.31	-0.26	0.08	-0.43	-0.51	2.17	-2.10	-0.02	0.02	-0.26	0.92
Urban compaction	-0.40	-0.18	0.29	-0.57	-0.49	2.09	-2.09	0.09	0.05	-0.20	0.55

Fig. 2. Comparison of the regression coefficients of the two transformation dynamics.

The coefficient of variable X_9 is very small, which shows that in the case study urban transformations are not driven by a real settlement demand. The variable X_{10} shows negative correlation: the probability that a cell undergoes transformation increases as the employment rate decreases. This correlation is quite unusual because the employment rate is an expression of the economic level of an area and it is quite irrational to build in areas where the employment rate is low. Finally, for the last variable X_{11} the correlation is positive, transformations increase near transformable territories and the greatest correlation is for the fragmentation process.

The *Pseudo R_square* for the fragmentation process was 0.25 and for compaction process 0.23; these coefficients, according to [27], show a good adaptation of the regression model.

The maps in Fig. 3 shows the final result of logistic regression: the change probability maps for both dependent variables: fragmentation and compaction. The maximum probability of change for fragmentation is 69% and for compaction 52%. This shows that the territory will be more subject to transformation dynamics regarding fragmentation. The ROC indices of 0.85 and 0.84 for compaction and fragmentation, respectively, testify to the goodness of the model.

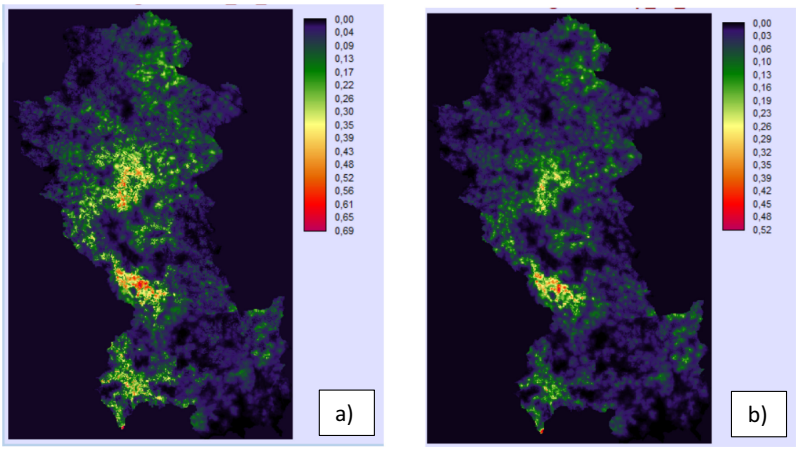


Fig. 3. Predicted dependent variables: a) fragmentation, b) compaction.

5 Conclusions

The objectives target of zero net land consumption by 2050 (EU Environment Action Programme to 2020 (7th EAP) of the European Community are fundamental especially for territories that are fragile and critical, among them there is undoubtedly the Italian territory [31–33]. The definition and implementation of such policies, rules and actions aimed at reducing soil consumption are urgent [34]. The results of this study show that the likelihood of land change will generate more fragmentation processes. In the case analyzed but, more generally, in the Basilicata region, fragmentation has also been caused, in recent years, by other components of the settlement system such as renewable energy installations [19, 35] and oil wells [20]. Urban transformations have a significant impact on the quality of the landscape, the ecosystem services provisioning [36–38] and the costs to the population of transforming the city in no sustainable way [39, 40]. More generally, the dynamics of urban transformation can have a significant impact and cause considerable damage to cultural heritage, and due to the dynamics that develop following an uncontrolled transformation of the territory (landslide movements) can be a cause of risk to human life [41–43].

The results shown in this work are preliminary and will provide a model for predicting the dynamics of urban transformation in the future.

References

1. European Commission: Guidelines on best practice to limit, mitigate or compensate soil sealing (2012). https://doi.org/10.2779/75498
2. European Union: FUTURE BRIEF: No net land take by 2050? (2016). https://doi.org/10.2779/537195
3. Brown, L.A.: The city in 2050: a kaleidoscopic perspective. Appl. Geogr. **49**, 4–11 (2014). https://doi.org/10.1016/j.apgeog.2013.09.003

4. United Nations Department of Economic and Social Affairs/Population Division: World Urbanization Prospects The 2018 Revision (2018)
5. Cobbinah, P.B., Aboagye, H.N.: A Ghanaian twist to urban sprawl. Land Use Policy **61**, 231–241 (2017). https://doi.org/10.1016/j.landusepol.2016.10.047
6. Murgante, B., Borruso, G., Balletto, G., Castiglia, P., Dettori, M.: Why Italy first? Health, geographical and planning aspects of the Covid-19 outbreak. Preprints (2020). https://doi.org/10.20944/preprints202005.0075.v1
7. Murgante, B., Las Casas, G., Sansone, A.: A spatial rough set for locating the periurban fringe (2007)
8. Rienow, A., Goetzke, R.: Supporting SLEUTH - enhancing a cellular automaton with support vector machines for urban growth modeling. Comput. Environ. Urban Syst. **49**, 66–81 (2015). https://doi.org/10.1016/j.compenvurbsys.2014.05.001
9. Saganeiti, L., et al.: Assessing urban fragmentation at regional scale using sprinkling indexes. Sustainability **10**, 3274 (2018). https://doi.org/10.3390/su10093274
10. Angel, S., Parent, J., Civco, D.L., Blei, A., Potere, D.: The dimensions of global urban expansion: estimates and projections for all countries, 2000–2050. Prog. Plann. **75**, 53–107 (2011). https://doi.org/10.1016/j.progress.2011.04.001
11. Siedentop, S., Fina, S.: Monitoring urban sprawl in Germany: towards a gis-based measurement and assessment approach. J. Land Use Sci. **5**, 73–104 (2010). https://doi.org/10.1080/1747423X.2010.481075
12. Nolè, G., Lasaponara, R., Lanorte, A., Murgante, B.: Quantifying urban sprawl with spatial autocorrelation techniques using multi-temporal satellite data. Int. J. Agric. Environ. Inf. Syst. **5**, 19–37 (2014). https://doi.org/10.4018/IJAEIS.2014040102
13. Romano, B., Zullo, F., Fiorini, L., Marucci, A., Ciabò, S.: Land transformation of Italy due to half a century of urbanization. Land Use Policy **67**, 387–400 (2017). https://doi.org/10.1016/j.landusepol.2017.06.006
14. Xu, G., et al.: Urban expansion and form changes across African cities with a global outlook: spatiotemporal analysis of urban land densities. J. Clean. Prod. **224**, 802–810 (2019). https://doi.org/10.1016/j.jclepro.2019.03.276
15. Urbieta, P., Fernandez, E., Ramos, L., Méndez Martínez, G., Bento, R.: A land-cover based urban dispersion indicator suitable for highly dispersed, discontinuously artificialized territories: the case of continental Portugal. Land Use Policy **85**, 92–103 (2019). https://doi.org/10.1016/J.LANDUSEPOL.2019.03.048
16. Romano, B., Zullo, F., Fiorini, L., Ciabò, S., Marucci, A.: Sprinkling: an approach to describe urbanization dynamics in Italy. Sustainability **9**, 97 (2017). https://doi.org/10.3390/su9010097
17. Nechyba, T.J., Walsh, R.P.: Urban sprawl. J. Econ. Perspect. **18**, 177–200 (2004). https://doi.org/10.1257/0895330042632681
18. Saganeiti, L., Pilogallo, A., Scorza, F., Mussuto, G., Murgante, B.: Spatial indicators to evaluate urban fragmentation in Basilicata region. In: Gervasi, O., et al. (eds.) ICCSA 2018. LNCS, vol. 10964, pp. 100–112. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-95174-4_8
19. Saganeiti, L., Pilogallo, A., Faruolo, G., Scorza, F., Murgante, B.: Territorial fragmentation and renewable energy source plants: which relationship? Sustainability **12**, 1828 (2020). https://doi.org/10.3390/SU12051828
20. Scorza, F., Saganeiti, L., Pilogallo, A., Murgante, B.: Ghost planning: the inefficiency of energy sector policies in a low population density region. Arch. DI Stud. URBANI E Reg. (2020). (in press)
21. Istat.it. https://www.istat.it/. Accessed 05 Apr 2019

22. Traore, A., Watanabe, T.: Modeling determinants of urban growth in Conakry, Guinea: a spatial logistic approach. Urban Sci. **1**, 12 (2017). https://doi.org/10.3390/urbansci1020012
23. Salem, M., Tsurusaki, N., Divigalpitiya, P.: Analyzing the driving factors causing urban expansion in the peri-urban areas using logistic regression: a case study of the greater Cairo region. Infrastructures **4**, 4 (2019). https://doi.org/10.3390/infrastructures4010004
24. Martellozzo, F., Amato, F., Murgante, B., Clarke, K.C.: Modelling the impact of urban growth on agriculture and natural land in Italy to 2030. Appl. Geogr. **91**, 156–167 (2018). https://doi.org/10.1016/J.APGEOG.2017.12.004
25. Statistiche economicheProvincia di POTENZA. https://ugeo.urbistat.com/AdminStat/it/it/economia/dati-sintesi/potenza/76/3. Accessed 08 May 2020
26. Aldrich, J., Nelson, F.: Linear Probability, Logit, and Probit Models. SAGE Publications, Inc. (2011). https://doi.org/10.4135/9781412984744
27. Clark, W.A., Hosking, P.L.: Statistical Methods for Geographers (Chapter 13). Consortium Erudit, New York (1986). https://doi.org/10.7202/021850ar
28. Kock, N., Lynn, G.S.: Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations. J. Assoc. Inf. Syst. **13**, 546–580 (2012). https://doi.org/10.17705/1jais.00302
29. Belsley, D.A.: A Guide to using the collinearity diagnostics. Comput. Sci. Econ. Manag. **4**, 33–50 (1991). https://doi.org/10.1007/BF00426854
30. Walsh, S.J.: Goodness-of-fit issues in ROC curve estimation. Med. Decis. Mak. **19**, 193–201 (1999). https://doi.org/10.1177/0272989X9901900210
31. Las Casas, G., Murgante, B., Scorza, F.: Regional local development strategies benefiting from open data and open tools and an outlook on the renewable energy sources contribution. In: Papa, R., Fistola, R. (eds.) Smart Energy in the Smart City. GET, pp. 275–290. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-31157-9_14
32. Las Casas, G., Scorza, F., Murgante, B.: Razionalità a-priori: una proposta verso una pianificazione antifragile. Ital. J. Reg. Sci. **18**, 329–338 (2019). https://doi.org/10.14650/93656
33. Scorza, F., Grecu, V.: Assessing sustainability: research directions and relevant issues. In: Gervasi, O., et al. (eds.) ICCSA 2016. LNCS, vol. 9786, pp. 642–647. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-42085-1_55
34. Murgante, B., Borruso, G., Lapucci, A.: Sustainable development: concepts and methods for its application in urban and environmental planning. Stud. Comput. Intell. **348**, 1–15 (2011). https://doi.org/10.1007/978-3-642-19733-8_1
35. Saganeiti, L., Pilogallo, A., Faruolo, G., Scorza, F., Murgante, B.: Energy landscape fragmentation: Basilicata region (Italy) study case. In: Misra, S., et al. (eds.) ICCSA 2019. LNCS, vol. 11621, pp. 692–700. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-24302-9_50
36. Pilogallo, A., Saganeiti, L., Scorza, F., Murgante, B.: Ecosystem services' based impact assessment for low carbon transition processes. TeMA - J. L. Use Mobil. Environ. **12**, 127–138 (2019). https://doi.org/10.6092/1970-9870/6117
37. Scorza, F., Pilogallo, A., Saganeiti, L., Murgante, B., Pontrandolfi, P.: Comparing the territorial performances of renewable energy sources' plants with an integrated ecosystem services loss assessment: a case study from the Basilicata region (Italy). Sustain. Cities Soc. **56**, 102082 (2020). https://doi.org/10.1016/J.SCS.2020.102082
38. Scorza, F., Pilogallo, A., Saganeiti, L., Murgante, B.: Natura 2000 areas and sites of national interest (SNI): measuring (un)integration between naturalness preservation and environmental remediation policies. Sustainability **12**, 2928 (2020). https://doi.org/10.3390/su12072928

39. Manganelli, B., Murgante, B., Saganeiti, L.: The social cost of urban sprinkling. Sustainability **12**, 2236 (2020). https://doi.org/10.3390/SU12062236
40. Dvarioniene, J., Grecu, V., Lai, S., Scorza, F.: Four perspectives of applied sustainability: research implications and possible integrations. In: Gervasi, O., et al. (eds.) ICCSA 2017. LNCS, vol. 10409, pp. 554–563. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-62407-5_39
41. Lasaponara, R., et al.: Spatial open data for monitoring risks and preserving archaeological areas and landscape: case studies at Kom el Shoqafa, Egypt and Shush, Iran. Sustainability **9**, 572 (2017). https://doi.org/10.3390/su9040572
42. Pascale, S., et al.: Landslide susceptibility mapping using artificial neural network in the urban area of Senise and San Costantino Albanese (Basilicata, Southern Italy). In: Murgante, B., et al. (eds.) ICCSA 2013. LNCS, vol. 7974, pp. 473–488. Springer, Heidelberg (2013). https://doi.org/10.1007/978-3-642-39649-6_34
43. Elfadaly, A., Attia, W., Qelichi, M.M., Murgante, B., Lasaponara, R.: Management of cultural heritage sites using remote sensing indices and spatial analysis techniques. Surv. Geophys. **39**(6), 1347–1377 (2018). https://doi.org/10.1007/s10712-018-9489-8