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Abstract

The development of a region is affected, inter alia, by concepts linked to the ability to displace and reach other locations (accessibility) efficiently and to lagging economic conditions connected to contemporary countryside activities (rurality). These topics and their relationships have attracted the interest of scholars who have scrutinized the implications of accessibility and rurality for policy making and planning.

The aim of this paper is to contribute to the theoretical modeling of accessibility and rurality and to develop an empirical study of their spatial patterns, with reference to the municipalities of the region of Sardinia, Italy. We study accessibility through an indicator constructed using a doubly constrained spatial interaction model and propose the Composite Index of Rurality that aims to evaluate rurality in a regional setting employing multivariate analysis. We investigate the spatial dependence of these indicators through general and local spatial autocorrelation analysis to verify the hypothesis that scarcely accessible spatial units are classifiable as rural areas. The results show that, for the case study of Sardinia, this hypothesis is not always true, as some urban areas are not always highly accessible.

Keywords: accessibility; rurality; remoteness; commuting; spatial interaction model; multivariate analysis

1. Introduction

Regional development scientists are currently interested in expanding concepts that include a variety of phenomena that can be evaluated through quantitative and efficacious indicators. Accessibility and rurality fall into this category and concern a number of key concepts. The first key concept refers to the ability of a given society *latu sensu*, i.e., including a certain set of individuals, places, institutions and infrastructures, to allow each citizen to reach locations in a reasonable time and cost. “Changes in accessibility lead to changes in the value of a region’s economic potential” (Vickerman, 1995, p. 227). It is not surprising that the simplicity of this concept has attracted the interest of a rich panorama of studies directed to the construction of suitable models and indicators to elucidate accessibility (De Montis and Reggiani, 2012 and 2013). Remote places are usually scarcely accessible because they are negatively constrained by high travel costs. Commuters, i.e., workers who travel daily to reach workplaces located in different zones from their home, are one of the categories of individuals affected by issues connected to scarce accessibility and high remoteness. The capability to move easily in a territory is crucial for increasing the share of citizens in our contemporary societies (Sampaio et al, 2008). Remoteness is indeed a crucial issue in the definition of rurality. The detection of rural regions is connected to the level of development of a country. A coordinated national development perspective also implies a correct approach to improve lagging regions. In this vein, many researchers have focused on the definition of rurality to scrutinize various concepts, including subsidy distributions, premium attributions, and lagging region status acknowledgement.

The interplay between accessibility and rurality has been the focus of many studies that develop the hypothesis that accessibility is inversely correlated with the rurality of a place (Morrissey et al, 2008; Barnett et al, 2001).

Against this background, the aim of this paper is to scrutinize the relationships between regional accessibility and rurality. For this purpose, we use two indicators. We study accessibility through an indicator constructed using a doubly constrained spatial interaction model (SIM). We propose the Composite Indicator of Rurality (CIR) exploiting multivariate analysis techniques. We test the two indicators for the case study of municipalities in Sardinia, Italy. Finally, the spatial dependence of these indicators is investigated through global and local spatial autocorrelation analyses (SAAs).

The contents of this paper are presented as follows. In the next section, we recall some of the main research findings about the three key issues of this paper: accessibility, rurality and SAA. In the third section, we illustrate our contribution to the field by proposing a combined index of accessibility and the CIR, and we introduce the reader to SAA. The accessibility indicator is obtained as a weighted linear combination of the incoming and outgoing commuting accessibilities calibrated through a doubly constrained SIM. The CIR is a multi-component indicator obeying a weighted linear combination. Weights in both accessibility indicator and CIR are derived through principal component analysis. In the fourth section, we present the results from the application of the two indicators for the case study of Sardinia and study their spatial correlation. The fifth section concludes this paper with comments and final remarks on the main results of our investigation.

2. State-of-the-art summary

Accessibility is a crucial concept in transport and city planning. The widespread adoption of this concept stems from the pioneering works of Hansen (1959) and Weibull (1976), who defined it for the first time with a systematic approach. The main idea underlying these studies is that accessibility can be measured as a potential of opportunities, which can be reached from a given place at the cost of overcoming the friction associated with the movement through space/time. A number of studies have applied this concept and developed several methods and indicators of accessibility (see, inter alia, Baradaran and Ramjerdi, 2001; De Montis and Reggiani, 2012 and 2013; Geurs and van Wee, 2004; Handy and Niemeier, 1997; Jones, 1981; Martín and Reggiani, 2007; Wu and Hine, 2003). In this respect, the spatial interaction models introduced by Wilson (1970) are currently broadly adopted to scrutinize accessibility. With reference to the aim of this paper, some studies have focused on studying accessibility patterns for commuters (see, inter alia, Caschili and De Montis, 2013; Patuelli et al, 2007). In this case, accessibility also appraises the efficiency of transportation systems, as commuters make use of transport infrastructure for their daily home-workplace-home trips. O'Kelly et al (2012) have used spatial interaction modeling to study the implied benefits of relatively accessible locations for commuters and verified the hypothesis that '*locational advantages and accessibility can be inferred from a spatial interaction process*'. Thus, accessibility modeling is a crucial factor for scholars and practitioners in the field of transport policy planning and making.

Another important concept in regional planning is linked to the description and assessment of a reliable measure of rurality. Contemporary landscapes are characterized by a variety of land uses that cannot be encapsulated through traditional dichotomous concepts such as city and countryside. Hybrid spaces emerge and lead researchers to coin new concepts such as peri- or rur-urbanization (see, inter alia, Sobrino, 2003; Sullivan et al, 2004; Theobald, 2001; Zacharian, 1988). The construction of a quantitative indicator of rurality is crucial to guide decision makers in distributing public subsidies for disadvantaged regions: severe shortcomings may arise if the indicator is poorly defined (see, inter alia, Sherval, 2009). Hence, an interesting stream of research focuses on methodologies useful for designing and constructing suitable rurality indicators. A number of works has shown a general tendency that takes into account i) the insurgence of hybrid spaces, and ii) the multi component character of those spaces. Studies in this respect have been proposed by Bogdanov et al (2008), Dijkstra and Poelman (2008), Higgs and White (2000), Mountrakis et al (2005), Perlín (2010), Pizzoli and Xiaoning (2007), Smith and Parvin (1971), van Eupen et al (2012) and Waldorf (2006).

Finally, it is of interest for this work to recall the background of SAA that we use to evaluate spatial patterns of accessibility and rurality in a regional setting. SAA consists of a group of techniques able to detect the geographical proximity and spatial distribution of a given variable. In other words, SAA helps one to assess whether a variable shows spatial dependences, i.e., similar (in case of positive) or different (in case of negative) spatial patterns in neighboring locations. A very popular measure of global spatial autocorrelation is the index introduced by Moran (1950); the local spatial autocorrelation (LISA) was first introduced by Anselin (1995) and is still broadly adopted to investigate spatial correlations on the local scale. Our interest in this paper is directed to spatial analyses of commuter movements between towns. Many authors have applied spatial autocorrelation analysis to ascertain the geographical dependence of commuter behavior. Griffith (2007) studied commuting in Germany at the NUTS3[1] level and found that distance decay and spatial autocorrelation are highly intermingled. Vandenbulcke et al (2011) applied spatial autocorrelation analysis in conjunction with other spatial statistical tools to inspect bicycle commuting in Belgium. Wang (2001) developed a number of statistical analyses to study the intra-urban variations of average commuting time and distance in Columbus, OH, USA. His goal was to reduce the distortive effects of positive spatial autocorrelation among intra-urban data by introducing a spatially lagged dependent variable. Kawabata and Shen (2007) developed spatial analyses to investigate the association between job accessibility and commuting time for public transit and private cars within the San Francisco Bay area. With respect to SAA applications in the realm of rurality and rural issues, we acknowledge a rich panorama of case studies in various geographical contexts. Ceccato and Dolmen (2011) investigated the determinants of crime in rural Sweden and adopted SAA to analyze spatial agglomeration of illegal misbehavior in certain zones. Ceccato and Persson (2002) applied SAA to study the dynamics of employment in rural areas of Sweden. Pizzoli (2013) applied SAA to study the distribution of rurality in Italian municipalities. Benson et al (2005) used SAA to scrutinize geographical patterns of poverty in rural areas of Malawi. Do Vale and da Silva (2011) applied SAA to inspect rurality in northeastern Brazil on the local scale of municipalities. Liu and Li (2010) developed SAA to understand the criticalities of per capita income growth in rural areas of China at the provincial level.

[1] NUTS is the acronym for Nomenclature of Units for Territorial Statistics, which is a geocode standard for referencing the subdivisions of European countries for statistical purposes.

Starting from this theoretical background, in the next section, we introduce the index of accessibility and the CIR, which we apply to the case study of the Region of Sardinia.

3. Methods: Spatial Interaction Model, Multivariate Analysis and Spatial Autocorrelation Analysis

The analyses developed for this manuscript are based on three methodologies. First, we calibrate a doubly constrained spatial interaction model to construct an indicator of accessibility at the municipal level. Subsequently, we apply multivariate analysis to construct the Composite Indicator of Rurality. Finally, we use SAA to study the geographical patterns of the two above indicators. In the following subsections, we introduce the methodologies applied in developing this work.

3.1. Accessibility and Spatial Interaction Model

We consider two different versions of accessibility indicators, which are based on the framework of spatial interaction models (Hansen, 1959; Wilson, 1970). We define the outgoing accessibility indicator Acc_i^{out} as the potential of opportunities for interaction of municipality *i* with other municipalities *j* of our domain. Acc_i^{out} measures the propensity of economic actors to reach certain economic activities/destinations *j*, and it is expressed by the following form:

$$Acc_i^{out} = \sum_j D_j \, f(\beta_i, d_{ij}) \qquad (1)$$

D_j is the sum of economic activities accessible to municipality *i*, $f(\beta_i, d_{ij})$ is a discounted factor that takes into account travel time/distance costs d_{ij}, measured as the road distance between municipality *i* and municipality *j*; β_i is a cost sensitivity parameter assigned to each municipality that accounts for the relative importance of travel costs.

If Acc_i^{out} measures the potential of opportunities for interaction of municipality *i*, Acc_j^{in} measures the propensity of a municipality *j* to be reached by people residing in other municipalities *i*. We define Acc_j^{in} as follows:

$$Acc_j^{in} = \sum_i O_i \, f(\beta_j, d_{ij}) \qquad (2)$$

where O_i represents the number of opportunities for interaction of municipality *i* with municipality *j*. There is a slight, but significant, difference between the two indicators: whereas Acc_i^{out} measures the ease with which the population that resides in a zone *i* moves to another zone *j*, Acc_j^{in} estimates the ease of zone *j* to be reached from another zone *i*. In our empirical application, we use an exponential form for the discounted factor $f(\beta_i, d_{ij})$ that has been verified to provide better results in estimating regional flows (see, inter alia, Wilson, 1971):

$$f(\beta_i, d_{ij}) = e^{\beta_i d_{ij}} \tag{3}$$

To account for both the attractiveness of a town and the potential for interaction, we define the total accessibility of a town as a weighted combined indicator that, in a general version, can be written as follows:

$$Acc_i^{tot} = \alpha_{out} * Acc_i^{out} + \alpha_{in} * Acc_i^{in} \tag{4}$$

Principal Component Analysis (PCA) is used to assess the contribution of the two accessibility indicators to the determination of the Acc_i^{tot} and the values of the parameter weights. We use entropy maximizing SIM to extrapolate the sensitivity parameters for the empirical application of the accessibility indicators in Equations (1-3). A doubly constrained SIM has been used to calibrate the model parameters. Written as an equation, the doubly constrained spatial interaction model for regional commuting in the region of Sardinia takes the form:

$$T_{ij} = A_i B_j O_i D_j f(\beta_i, d_{ij}) \tag{5}$$

where T_{ij} refers to the number of commuters moving between an origin municipality i and a destination municipality j. The road distance between municipalities i and j is expressed by the term d_{ij}. O_i is the total number of trips (i.e., commuter movements) from municipality i to other municipality j and is expressed by the equation:

$$O_i = \sum_j T_{ij} \tag{6}$$

D_j is the total number of trips (i.e., commuter movements) from municipality j but to other municipalities i:

$$D_j = \sum_i T_{ij} \tag{7}$$

A_i and B_j are balancing factors that ensure that the estimates of T_{ij} , when summed across both rows and columns of the matrix, equal the known O_i and D_j. Balancing factors can be calculated using the following equations:

$$A_i = \frac{1}{\sum_j B_j D_j f(\beta_i, d_{ij})} \tag{8}$$

$$B_j = \frac{1}{\sum A_i O_i f(\beta_i, d_{ij})} \tag{9}$$

The difficulty of calculating these balancing factors and the time-distance cost sensitivity parameters resides in finding a solution for A_i, B_j and β_I, which all depend upon each other. Fortunately, this problem can be solved using an iterative routine with the solution ‘guaranteed’ by Brouwer’s fixed point theorem that assures the existence of a point of convergence (i.e., the existence of a solution).

3.2. Composite Indicator of Rurality: a multivariate analysis

Rurality is a complex concept that is often associated with remoteness and spatial disadvantage (Higgs and White, 2000). Several authors have revolved their research interests around the concept of rurality and have investigated possible drawbacks of policies driven by incorrectly built rurality indicators (Sherval, 2009; Bryant and Pini, 2011). Scholars have investigated rurality according to both qualitative (see, inter alia, Sobrino, 2003) and quantitative indicators (see, inter alia, Waldorf, 2006). In this work, we apply a quantitative approach based on a multivariate analysis of the principal components that influence rurality. We have constructed a new index, the Composite Indicator of Rurality (CIR) based on three quantitative works: Rural Urban Index (RUI) introduced by Smith and Parvin (1973), Index of Relative Rurality (IRR) by Waldorf (2006) and Index of Multiple Deprivation (IMD) by Higgs and White (2000). In Table 1, we have summarized the factors (variables) that have been used to construct the three indicators.

Indicator of rurality	Variable
Rural Urban Index (RUI)	Population density
	Population in rural areas
	Total population
	Employees in agriculture, fishery and mining activities
	Employees in medical jobs
	Employees in recreational activities
	Employees in the tertiary sector
	Demographic fluctuation

	People living on farms
Index of Relative Rurality (IRR)	Total population Population density Extension of developed area Remoteness
Index of Multiple Deprivation (IMD)	Average income per capita Employment rate Mortality causes Environmental quality Service provision

Table 1. Indicators of rurality and variables used for the work of Smith and Parvin (1971), Waldorf (2006) and DRES-RAS (2009).

We have scrutinized the articulation of these three indicators into subcomponents in the perspective to construct the CIR that encompasses all possible facets and minimizes redundancy of variables used in the three indicators. Finally, we have grouped the selected variables into three pillars: "Demography" (D), "Economics" (E) and "Settlement" (S). Each of the three pillars is composed of a number of variables that have been selected on the basis of a multivariate analysis (Table 2). In general and mathematical terms, the CIR of a spatial unit i is expressed by a linear combination of variables belonging to D, E, and S:

$$CIR_i = \phi_i * D_i + \varphi_i * E_i + \gamma_i * S_i \tag{10}$$

D_i, E_i and S_i are the three pillars with ϕ_i, φ_i and γ_i accounting for the importance of each pillar in the determination of the CIR for the spatial unit *i*. Each pillar is, in turn, determined as the linear combination of the following variables:

$$D_i = w_1 \cdot POP_i + w_2 \cdot PD_i + w_3 \cdot PG_i \tag{11}$$

$$E_i = w_4 \cdot PS_i + w_5 \cdot I_i + w_6 \cdot H_i \tag{12}$$

$$S_i = w_7 \cdot DA_i + w_8 \cdot EXU_i \tag{13}$$

Parameter weights from w_1 to w_8 account for the importance of each factor. The descriptive statistics of each variable are reported in Table 2. Principal component analysis (PCA) has been applied to verify whether there are latent dimensions within the set of variables adopted and to assess the contribution of each pillar to the determination of the CIR and the values of the parameter weights.

3.3. Spatial autocorrelation analysis

In this study, we are interested in investigating whether there is a spatial correlation for accessibility and rurality of geographical units and whether there is a spatial correlation between them. For this purpose, we apply an SAA to investigate the pattern of spatial distribution of accessibility indicators and CIR as introduced in Formula (4) and Formula (10).

SAA is a statistical methodology that takes into account the spatial relationships (adjacency, contiguity, proximity, etc.) between locations where a phenomenon evolves. The first law of geography by Tobler (1970) asserts that "*Everything is related to everything else, but near things are more related than distant things*", which is indicative of the basic concepts supporting spatial autocorrelation. This concept is relevant, as most statistical analyses are based on the assumption that each sample of observations is independent of the others (Getis, 2007). However, exogenous variables are sometimes dependent; this dependency occurs, in particular, for spatial phenomena. SAA measures the strength of spatial dependence and tests for spatial independence of observations. Spatial autocorrelation is positive when variables have similar trends in neighboring locations, and it is negative when variables have dissimilar trends in close spatial association.

Moran (1950) proposed a measure of spatial autocorrelation as follows:

$$I = \frac{\left(n\sum_i \sum_j w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \mu\right)\right)}{\left(\sum_i \sum_j w_{ij} \sum_i \left(x_i - \mu\right)^2\right)} \tag{14}$$

In equation (14), μ represents the mean of the variable x for n observations, x_i and x_j are the observations in location i and j, and w_{ij} represents the so called "spatial weight". The spatial weight w_{ij} is a term that takes into account spatial interconnectedness (i.e., number of neighbors, length of shared boundary or distance between locations). Moran's index ranges between –1 and +1: values close to +1 represent a strong positive spatial autocorrelation (similar close located trends), while values close to –1 indicate negative autocorrelations (dissimilar close located trends).

Moran's index measures spatial autocorrelation across a set of spatial units (global approach). There are significant limitations in the identification of local spatial units when spatial autocorrelation is more significant. Anselin (1995) proposed a measure called Local Indicators of Spatial Association (LISA) to overcome this limitation. According to Anselin, any statistical measure can be considered a LISA if it satisfies two requirements: i) each observation conveys an indication about significant spatial clustering in its neighborhood, and ii) the summation of all observations is proportional to a global indicator of spatial association. LISA provides spatial clusters where autocorrelation is significant under a chosen significance (Anselin, 1995).

In this study, SAA is implemented both in general and local terms and is referred to the municipalities of the island of Sardinia, Italy. The accessibility indicator is also studied through a bivariate SAA with respect to the CIR. We aim at ascertaining the similarities and dissimilarities in the spatial trends of the two indicators above developing on the intuitive assertion that higher values of accessibility should mirror or even be explained by similarly lower values of rurality.

4. Case study of Sardinia, Italy

The aim of this section is to introduce a general overview of the socio-economic conditions of the island of Sardinia and to present the results of the implementation of the two indicators of accessibility and rurality introduced in section 3. We complement the analysis with an SAA.

4.1. The island of Sardinia: a general overview

The Italian island of Sardinia corresponds to an administrative region of approximately 24,000 square kilometers, the second largest Mediterranean island after Sicily. Its central location and landscape characteristics have favored an important history of relations with external populations and the development of a strong social identity and of important political movements. The Sardinian population consists of approximately 1,600,000 inhabitants (2.8% of the total Italian population); approximately 42% live in only 14 municipalities (out of 377) that have more than 20,000 inhabitants (ISTAT, 2001a). Approximately 43% of the residents live in 239 medium-low size towns (1,000-10,000 inhabitants), while the remaining population lives in small villages of less than 1,000 inhabitants. Cagliari, the capital town of Sardinia, has a resident population equal to 160,000 inhabitants, while its metropolitan area hosts approximately 47% of the total population of the island. The richest municipalities are (or have been) provincial capital towns: Sassari, Oristano, Olbia and Nuoro. The distribution of municipal personal income also reflects the evidence that in Sardinia, population and productive activities concentrate mostly on coastal areas.

Sardinia has historically been characterized by a depressed economy: the main socioeconomic indicators such as industrial production (-4% in 2012) and employment (-1.1% in 2012) describe a significant contraction (Banca d'Italia, 2013). The economy still presents a very weak industrial system. Industrial settlements were installed since the 1960s under the aegis of a pole-based development framework of capital-intensive activities. Decision makers and politicians are steering the development of post-industrial activities able to re-launch local know-how and resources: agricultural production, manufacturing, landscape and cultural assets, renewable energy sources and tourism. These policies were confronted with the most severe international financial and economic crisis in 2008 (Banca d'Italia, 2013). The transport infrastructure is dominated by roads and a weak railway system. The use of railway as a means of transport is very low due to the limited frequency and speed (three hour journey between Cagliari and Sassari - 200 km). The entire Sardinian transport infrastructure is dependent on the use of traditional energy sources (fossil fuels), as the majority of vehicles are fueled by gas, gasoline or oil while the railway system is not electrified yet. The main road infrastructure of Sardinia, the National Road n. 131, connects Cagliari to Sassari via Oristano and Olbia via Nuoro. Another important road infrastructure is the National Road n. 130 that connects the metropolitan area of Cagliari and the Campidano, the main plain of the island, to southwestern Sardinia, one of the main industrial and productive areas of the island. Apart from the areas served by those major infrastructures, many centers are not easily accessible (in more than one hour from the principal intermodal towns). The whole island is weakly connected to the mainland through a system including slow and fast vectors, as ferries (six to twelve hours) and airplanes (one to two hours) still present relatively high fares, low frequency and difficult connections via Rome and Milan.

4.2. Data

Information of commuting traffic used for the calibration of the spatial interaction model (Formula from 5 to 9) has been obtained from the Origin-Destination Table provided by the Italian National Institute of Statistics (ISTAT, 2001b) and referred to 2001 Census (ISTAT, 2001a).

Pillar	**Code**	**Variable**	**Code**	**Definition**	**Unit of measure**	**Influence**	**Source**	**Time period**	**Mean**	**Standard Deviation**
Demography	D	Population	POP	Residential population on December 31, 2005	-	Negative	Census, Italian National Institute of Statistics	2005	4,391.72	12239.68
		Population density	PD	Residential population per unit of surface area	Inhabitants per km^2	Negative	Census, Italian National Institute of Statistics	2001	76.85	209.51
		Population growth	PG	Resident population percentage change	Percentage change	Negative	Census, Italian National Institute of Statistics	2001	-0.30	1.34
Economics	E	Employees in the primary sector	PS	Percentage of employees hired in agriculture, fishery and forestry activities over total number of employees	Percentage	Positive	Census, Italian National Institute of Statistics	2001	16.79	12.90
		Income per capita	I	Average income per resident inhabitant	Euro per inhabitant	Negative	Census, Italian National Institute of Statistics	2001	17,962.60	2,478.28
		Health service provision	H	Percentage of employees in sectors connected to health service management over total number of employees	Percentage	Negative	Census, Italian National Institute of Statistics	2001	6.17	2.94

Settlement	S	Extension of developed area	DA	Percentage of developed land over total municipal surface area	Percentage	Negative	Sardegna Geoportale	2005	0.24	0.40
		Extra Urban Roads	EXU	Percentage of of extra urban roads	Percentage	Negative	Own elaboration on Sardegna Geoportale data set	2005	0.74	0.71

Table 2. Pillars and variables of the composite indicators of rurality: characteristics and simple statistics.

This data set has been used and studied in a number of studies (inter alia, see De Montis et al, 2007, 2011a, 2011b). We refer to these works for a thorough description of commuter movements in Sardinia. Distance between municipalities has been calculated using the shortest road distance (EXU variable in Table 2).

This information has been elaborated within ARCGIS 10 and its extension Network Analyst. We have used two spatially referenced data sets to elaborate this information: the graph of extra-urban roads and the centroids of the urban centers of each municipality.

The calculation of CIR has initially involved a larger number of variables which have been reduced through sampling adequacy tests for avoiding redundant information to the list of variables reported in Table 2. The variables in Table 2 have been clustered by pillar groups, as described in section 3. While the predominant source is the 2001 Italian Census (ISTAT, 2001b), variables in the Settlement pillar are extracted (or elaborated) from Sardegna Geoportale and referenced to the year 2005. CIR is an indicator of rurality; thus all variables, with the exception of PS, influence CIR negatively.

4.3. Results for the accessibility indicator

The calibration of the doubly constrained spatial interaction model[2] (coefficient of determination $R^2 = 0.85$) for the estimation of accessibility for municipalities in Sardinia has made use of commuting movements; therefore, we construct indicators able to take into account incoming and outgoing commuters from each municipality.

The contribution of the two accessibility indicators to the total accessibility has been evaluated using PCA. The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO test equal to 0.50) and the Bartlett test (p-value < 0.001 and chi-square equal to 389.66) indicate that the data set is adequate to describe the phenomenon and that it is suitable to be studied through PCA.

Component	Initial Eigenvalues			Extraction sums of squared loadings		
	Total	Percentage of variance	Cumulative	Total	Percentage of variance	Cumulative

[2] In Appendix A we report the values of the β_i cost sensitivity parameters estimated for each municipality.

1	1.804	90.209	90.209	1.804	90.209	90.209
2	0.196	9.791	100.00			

Table 3. Results of the principal component analysis over the two accessibility indicators.

The communality matrix (Table 4) shows the percentage of variance explained along the principal component extracted for each variable considered. The communality matrix illustrates the intensity of the contribution of each variable and suggests the appropriate value to attribute to the weights in the functional relationship explaining the total accessibility according to Formula (4).

Variable code	Extraction	w
Acc^{in}	0.902	1
Acc^{out}	0.902	1

Table 4. Communality matrix and weights w of the variables related to the two accessibility indicators.

In Figure 1, we visualize the total accessibility Acc_i^{tot}. For the case of Sardinia, the total accessibility of a municipality *i* is equally determined by the two accessibility indicators (Table 4), named incoming and outgoing accessibility in Equation (1) and (2), thus $\alpha_{out} = \alpha_{in} = 1$ in Equation (4). The results of Figure 1 uncover a general high accessibility in the southern part of Sardinia with emphasis on the Campidano (the larger plain of Sardinia). The main regional freeway that connects the capital town Cagliari and Oristano is located in this area. The metropolitan area of Cagliari shows remarkable figures of accessibility.

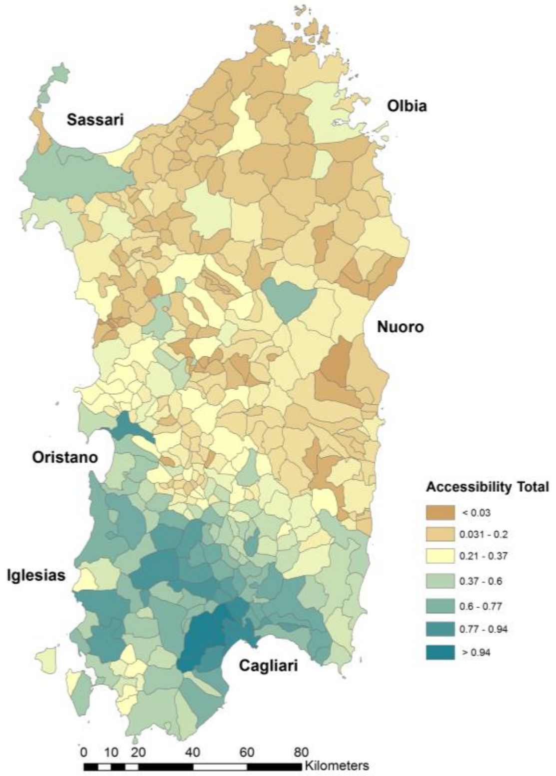

Figure 1. Map of total commuters accessibility indicator Acc_i^{tot}.

In Appendix 1, we have also plotted Acc_i^{out} and Acc_j^{in} (Figures A1 and A2). Outgoing accessibility Acc_i^{out} appears to be a wider phenomenon than incoming accessibility Acc_j^{in}: many municipalities display relevant figures of Acc_i^{out}, while incoming accessibility Acc_j^{in} in the central and northern parts of the island typically affects the main provincial towns such as Nuoro, Sassari and Olbia.

4.4. Analysis and results for the composite indicator of rurality (CIR)

The construction of the CIR is based on the linear combination of the three pillars presented in section 3.2. Variables have been normalized and weights investigated through multivariate analyses, according to the nested pattern proposed in Table 2. Subsequently, the CIR has been obtained as the unweighted sum of the descriptors of each pillar: in other words, we assume that $\phi = \varphi = \gamma = 1$ in Equation (10).

With respect to the Demography (*D*) pillar, we have developed a correlation analysis and verified that the variables involved are not significantly correlated (Table 5).

	POP	**PD**
POP		
PD	0.52	
PG	0.17	0.13

Table 5. Correlation analysis of variables in the "Demography" pillar.

The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO test equal to 0.53) and the Bartlett test (p-value < 0.001 and chi-square equal to 132.14) indicate that the data set is adequate to describe the phenomenon through PCA. The analysis of the extraction of components in Table 6 reveals that one principal component can be identified and associated with one eigenvalue greater than 1 and that three variables (POP, PD and PG) fairly well represent the "Demography" macro dimension. This component explains 53.37% of total variance of information contained in the entire dataset.

Component	**Initial Eigenvalues**			**Extraction sums of squared loadings**		
	Total	**Percentage of variance**	**Cumulative**	**Total**	**Percentage of variance**	**Cumulative**
1	1.60	53.37	53.37	1.60	53.37	53.37
2	0.92	30.81	84.18			
3	0.47	15.82	100.00			

Table 6. Results of the principal component analysis over the variables related to the "Demography" macro component.

The component matrix reported in Table 7 shows the percentage of variance explained along with the principal component extracted for each of the three variables considered.

Variable code	Extraction	w
POP	0.695	0.96
PD	0.723	1
PG	0.184	0.26

Table 7. Communality matrix and weights w of the variables related to the "Demography" pillar.

The communality matrix illustrates the intensity of the contribution of each variable. We have assigned to each variable a weight proportional to the variance explained. We assign a value w=1 to the variable with the highest value of explained variance while the other values are assigned proportionately to the extraction value and the highest value extracted. The functional relationship that describe the "Demography" pillar in Equation (11) assumes the following expression:

$$D = -0.96 * POP - PD - 0.26 * PG \tag{14}$$

With reference to the "Economics" pillar, the correlation analysis in Table 8 indicates a negative correlation among the variables involved, except between income and health services provision.

	PS	I
PS		
I	-0.29	
H	-0.21	0.15

Table 8. Correlation analysis of the variables related to the "Economics" pillar.

The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO test equal to 0.54) and the Bartlett test (p-value < 0.001 and chi-square equal to 53.008) indicate that the data set is adequate to describe the phenomenon at hand and that the data set is suitable to be studied through PCA. The extraction of the components in Table 9 reveals that one principal component can be identified and associated with one eigenvalue greater than 1 and that the data set fairly well represents the "Economics" macro dimension. This component explains 47.91% of the total variance, conveying a fairly great portion of information contained in the entire dataset.

Component	Initial Eigenvalues			Extraction sums of squared loadings		
	Total	**Percentage of variance**	**Cumulative**	**Total**	**Percentage of variance**	**Cumulative**
1	1.44	47.91	47.91	1.44	47.91	47.91
2	0.86	28.75	76.67			
3	0.7	23.754	100			

Table 9. Results of the principal component analysis over the variables related to the "Economics" pillar.

The communality matrix reported in Table 10 shows the percentage of variance explained along with the principal component extracted for each of the four variables considered.

Variable code	Extraction	w
PS	0.57	1
I	0.50	0.88
H	0.36	0.63

Table 10. Communality matrix and weights w of the variables related to the "Economics" macro component.

Using the same procedure illustrated for the "Demography" component, we have assigned the weights *w* that enter in Equation (12) as follows:

$$E = PS - 0.88 * I - 0.63 * H \qquad (15)$$

It is important to stress that the "Economics" macro-dimension originally included, beyond the three variables processed above, two additional variables, i.e., the percentage of employees in the service sectors and the percentage of employees in the recreational service. The application of PCA led us to identify two principal components, a sign that two hidden dimensions are present in the data set. Under these circumstances, the pillar *E* could have been incorrect. We have decided to exclude the fourth and fifth dimensions, thereby reducing the number of principal components to one.

We have followed the same outline for the analysis of the "Settlement" pillar, which includes two variables (DA and EXU) that are positively correlated (correlation coefficient equal to 0.80).

The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO test equal to 0.50) and the Bartlett test (p-value < 0.001 and chi-square equal to 387.78) indicate that the data set is adequate to describe the phenomenon and that it is suitable to be studied through PCA. The extraction of the components reveals (Table 11) that one principal component can be identified and associated with one eigenvalue greater than 1 and that the data set represents the macro dimension "Settlement" fairly well. This component explains 90.15% of total variance, conveying a fairly great portion of information contained in the entire dataset.

Component	Initial Eigenvalues			Extraction sums of squared loadings		
	Total	**Percentage of variance**	**Cumulative**	**Total**	**Percentage of variance**	**Cumulative**
1	1.803	90.154	90.154	1.803	90.154	90.154
2	1.197	9.846	100.00			

Table 11. Results of the principal component analysis over the variables related to the "Settlement" pillar.

The communality matrix reported in Table 12 shows the percentage of variance explained along the principal component extracted for each of the four variables considered.

Variable code	Extraction	w
DA	0.949	1
EXU	0.949	1

Table 12. Communality matrix and weights w of the variables related to the "Settlement" macro component.

The communality matrix illustrates the intensity of contribution of each variable and suggests the appropriate value to attribute to the weights in the functional relationship explaining the first pillar according to Formula (12):

$$S = -DA - EXU \tag{16}$$

In this case, because the analysis of explained variance has provided us with the same values for both DA and EXU, we have assigned a weight w equal to 1 to both variables in Equation (16). According to the analyses developed thus far, we can rewrite the CIR general functional relation in Equation (10) as follows:

$$CIR = -0.96 * POP - PD - 0.26 \cdot PG + PS - 0.88 * I - 0.63 * H - DA - EXU \tag{17}$$

In Figure 2, we have mapped the values of CIR for each municipality in Sardinia. The index was rescaled from 0 to 1 to obtain a better understanding of the spatial patterns of rurality in Sardinia: higher values of CIR (yellow to red coloration in Figure 2) correspond to more rural municipalities.

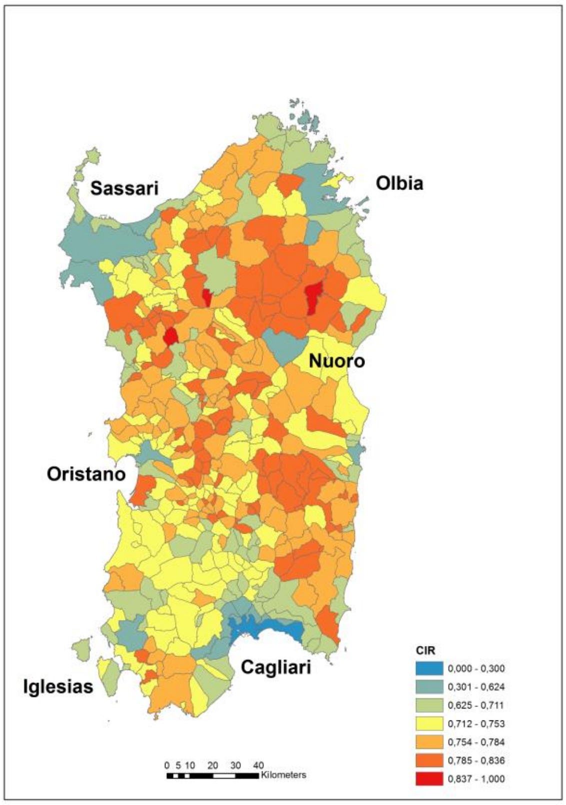

Figure 2. Map of Composite Index of Rurality: we display the most rural areas in red.

The spatial distribution of CIR appears to be coherent with our hypotheses: there is a high level of rurality in the region of Sardinia (red tones), and only the major provincial capitals (i.e., Cagliari, Iglesias, Sassari, etc.) show a structured urban organization. Observing Figures 1 and 2, we note that areas with medium-high accessibility sometimes show a moderate rural nature. To precisely interpret the results of CIR, we need to investigate the spatial correlation between accessibility and rurality quantitatively. In the reminder of this section, we discuss the results of the univariate SAA for accessibility and bivariate SAA between accessibility and rurality indicators for the 377 municipalities in Sardinia.

4.5. Univariate and Bivariate Spatial Autocorrelation Analysis

We apply SAA to inspect whether we can observe a spatial structure in the accessibility and rurality of municipalities in Sardinia and if it is possible to detect a spatial correlation between rurality and accessibility.

Correlation analysis has been implemented constructing a weighted spatial matrix (WSM) of proximity relationships among spatial units. In the WSM, each element has been calculated according to the Queen contiguity rule (Cliff and Ord, 1969): we have considered contiguous units as those that share an administrative border.

Univariate global SAA has been implemented to investigate the mutual spatial dependence in the accessibility of municipalities in Sardinia. We apply the Moran I index for this scope. This index ranges between -1 and 1; -1 indicates a negative autocorrelation, +1 a positive autocorrelation while 0 indicates the absence of autocorrelation. In Figure 3, we plot the values of univariate autocorrelation for the accessibility index (Moran I index = 0.715, p-value < 0.05[3]).

[3] Test run with 99, 199, 499 and 999 permutations

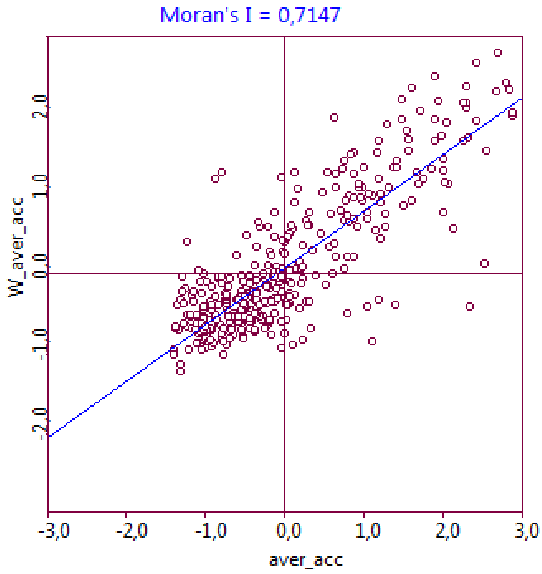

Figure 3. Univariate spatial autocorrelation analysis: Moran's scatterplot for the accessibility index Acc_i^{tot}**.**

The Moran I index has a high and positive value, thus indicating a strong positive autocorrelation for accessibility. This strong positive autocorrelation is visually confirmed by Figure 3, where most of the points are in the first and fourth quadrants of the plot. Distance is a determinant factor for spatial correlation of accessibility for municipalities. Municipalities with a high Acc^{out} are located close to municipalities with a high Acc^{in} because people tend to live outside metropolitan areas but within a commuting journey time (30 minutes on average). Accessibility for municipalities thus has a strong spatial dependence: in general, municipalities with high values of accessibility are spatially located around municipalities with high values of accessibility, while municipalities with small values of accessibility tend to be surrounded by municipalities that are not very accessible as well. We have implemented a univariate analysis for CIR to investigate the possible presence of spatial dependence between municipalities. The WSM used in this step is the same as the previous SAA for the accessibility indicator. In Figure 4, we plot the value of the univariate spatial autocorrelation for CIR (Moran index I = 0.537, p-value < 0.05[4]).

[4] Test run with 99, 199, 499 and 999 permutations.

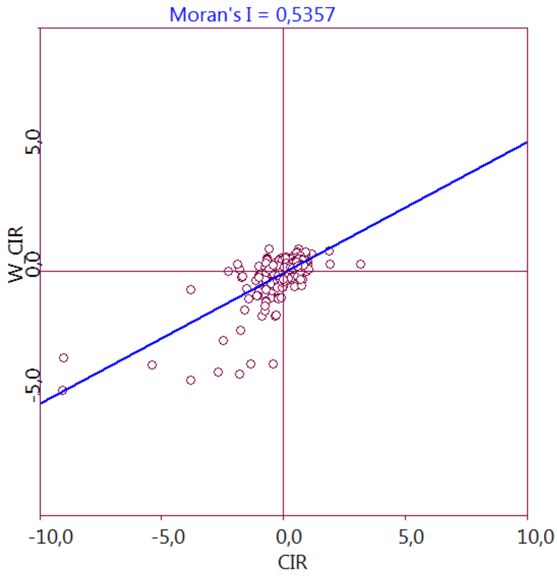

Figure 4. Moran's scatterplot for CIR index.

This value of Moran's I indicates the presence of spatial autocorrelation, although it is not very strong. A rural municipality tends to influence the rural level of the surrounding municipalities in a positive way. Therefore, rural municipalities tend to be closed to other rural municipalities, whereas urban municipalities are closed to municipalities with a low level of rurality.

This finding brings us to a further analysis. We now want to investigate whether there is a spatial autocorrelation between accessibility and rurality. This study can be performed using a bivariate autocorrelation analysis, which enables the analyst to relate the value assumed by a variable in a given location to the value(s) of another variable at a neighboring location. As in the univariate SAA, the bivariate SAA includes a general and a local approach. In the first case, the Moran's index ranges between –1 and 1. For Moran's index approaching 1, we report a positive SA: the first variable shows a value in a location that is sensibly distant from its mean and is accompanied at neighboring locations by values of the other variable that are similarly distant from the mean. In case of a negative SAA, the opposite trend applies, as the variables show an inverse behavior. The local approach implies a bivariate LISA that is able to find specific and significant areas where the two variables intertwine at neighboring locations by showing values according to the well-known four quadrant scheme: high-high, low-low, high-low and low-high.

In this case, we would like to inspect how accessibility values appear in a certain municipality in relation to rurality values in contiguous municipalities, and vice versa. The results are illustrated in Figures 5 and 6. According to the Moran index (equal to -0.351), accessibility and rurality are intertwined through a small negative spatial correlation.

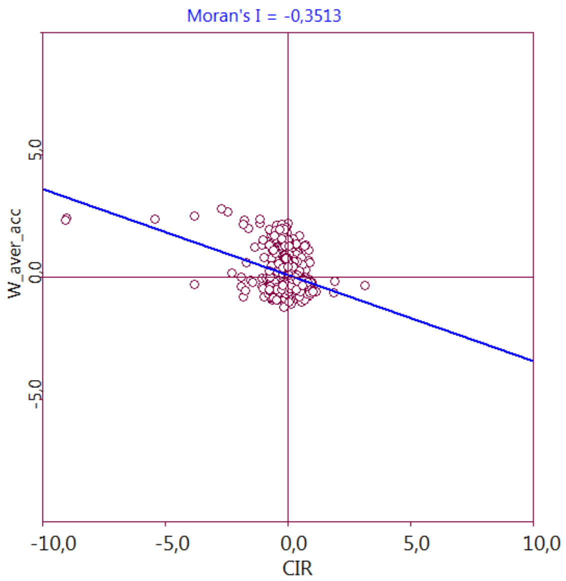

Figure 5. Bivariate analysis between accessibility and rurality: Moran's scatter plot for Acc_i^{tot} vs CIR.

In general terms, a rural municipality has a low level of accessibility while all urbanized areas have a high level of accessibility. We observe this behavior comparing the maps of accessibility and CIR. Sardinian municipalities are mostly rural (high value of CIR) and show a low level of accessibility. An exception is the area along the Campidano Plain (between Cagliari and Oristano), where high levels of accessibility are observed despite municipalities that are moderately rural in that area because it is easier to access a flat area, and the level of infrastructures is higher compared to the rest of Sardinia. This portion of the region is crossed by the main regional freeway (National road n. 131) and many town centers have been developing along this road.

We conclude the SAA by implementing a local univariate analysis (both for accessibility and CIR) and local bivariate analysis (between accessibility and rurality indicators). In this case, we want to investigate locally whether it is possible to detect clusters of municipalities with similar behaviors. Figure 6 reports cluster and significance maps for the univariate analysis. Zones with significant levels of correlation are reported in green on the map of significance. A positive correlation between municipalities with high accessibility is detected in Southern Sardinia (cluster in red) while areas where we detect spatial correlation between municipalities with low accessibility (clusters in blue) are spread across Sardinia in Ogliastra (Mideastern) and Gallura (Northeastern). These areas are characterized by being rocky and mountainous: accessibility is therefore limited and infrastructures are overall not very well developed.

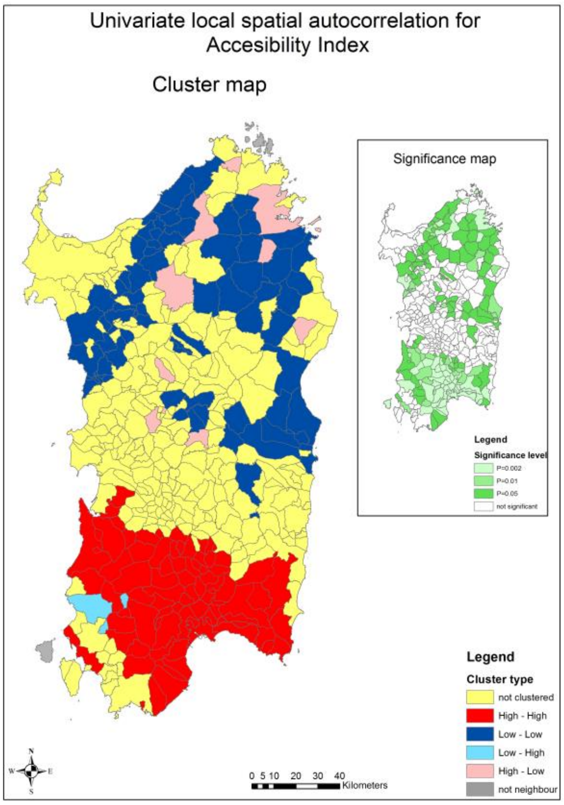

Figure 6. Cluster map of local univariate autocorrelation for accessibility index Acc_i^{tot}.

The pink clusters in Figure 6 represent municipalities with higher values of accessibility compared to their surrounding neighbors. Among these towns, some municipalities (such as Ozieri and Olbia) represent relevant settlements and poles of provision of service (i.e., schools, hospitals, etc.).
The univariate analysis for the rurality indicator CIR demonstrates the emergence of a limited number of significant clusters mostly indicating a high-high spatial autocorrelation pattern. Sardinian municipalities, with a few exceptions, display a fairly high level of the rurality indicator CIR. As Figure 7 shows, the blue clusters identify groups of municipalities with a low level of CIR: the metropolitan area of Cagliari in the South, the industrial and tourist zones of Alghero and Porto Torres in the North. Red clusters with a high value of CIR are located in central-northern and in central-southeastern Sardinia. The groups include municipalities where the economy is comparatively still strongly based on the primary sector. Furthermore, the municipalities are small, i.e., with limited urban area and number of inhabitants. A few other municipalities fall into the cyan clusters, where a low-high pattern emerges, as municipalities with relevant economic and service systems are reference poles for lower level surrounding municipalities.

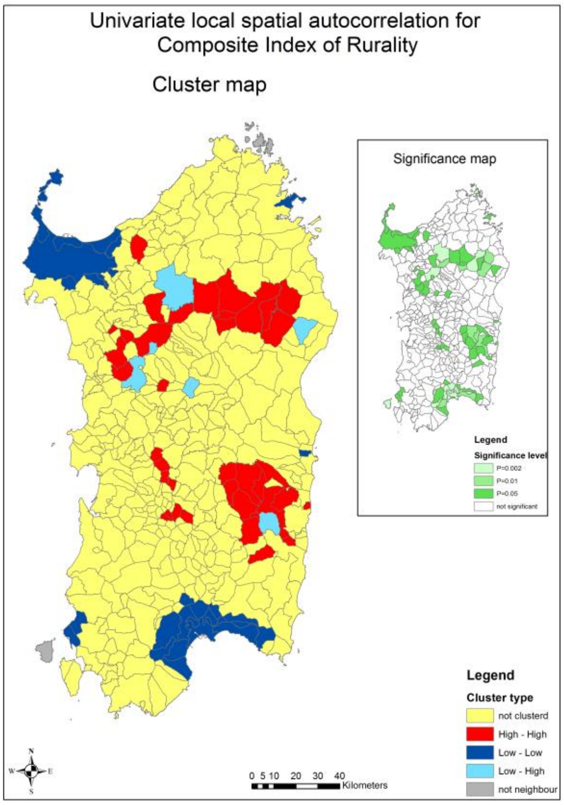

Figure 7. Cluster map of local univariate autocorrelation for the rurality index CIR.

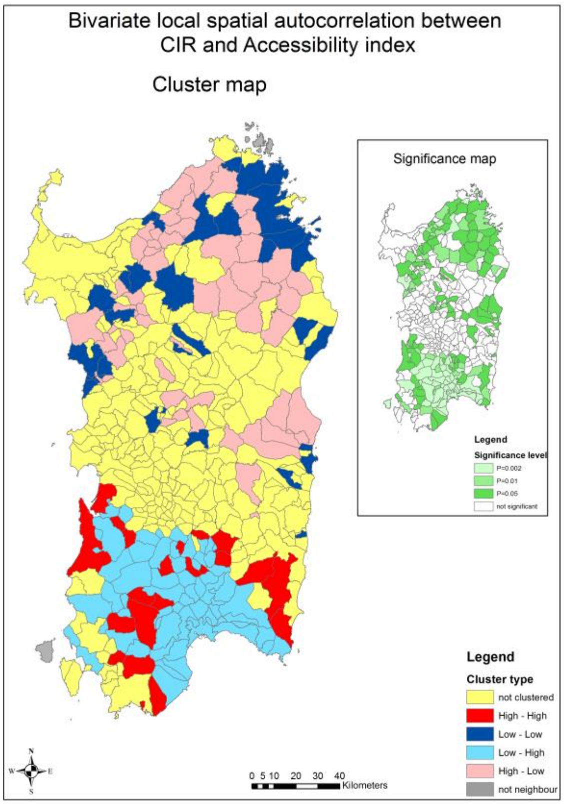

Figure 8. Cluster and significance maps for bivariate spatial autocorrelation analysis between accessibility index Acc_i^{tot} and rurality indicator CIR.

In the case of bivariate analysis (accessibility versus rurality), a slight different picture emerges (Figure 8). Clusters are distributed differently between southern and northern Sardinia. In southern Sardinia, we observe two clusters that exhibit a high-high (in red) and a low-high (in cyan) spatial autocorrelation pattern. Municipalities in red are mostly located in the Campidano Plain, where the main freeway efficiently provides access, and hence show high values of accessibility despite the high levels of rurality indicator CIR. Municipalities in cyan are in the majority included in the metropolitan area of Cagliari, the capital town of Sardinia, and display low values of rurality indicator CIR surrounded by municipalities with high values of accessibility. In northern Sardinia, we observe two clusters of municipalities displaying a high-low (in pink) and a low-low (in blue) spatial autocorrelation pattern. Blue Municipalities are located mostly in northeastern Sardinia and are characterized by a low level of accessibility and rurality. This counterintuitive result is explained by geographical and economic reasons: municipalities belong to Costa Smeralda, the well-known exclusive tourist location that has been planned so that overall urban conditions parallel a relatively lower level of infrastructure provision. Municipalities in pink are mostly distributed in northern-central Sardinia and show high values of rurality CIR with low values of accessibility. As we have discussed for the global SAA, we do not find any significant spatial autocorrelation (p-value > 0.05) for a large number of municipalities (in yellow).

The causal relationship between accessibility and rurality, conceived above as accessibility versus rurality, may also be modeled according to the opposite influence (rurality versus accessibility).

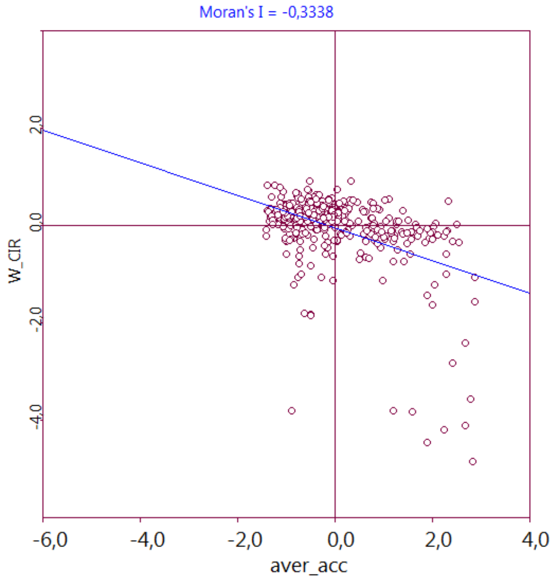

Figure 9. Bivariate analysis: Moran's scatter plot of rurality versus between accessibility indicators.

To clarify this causal relationship, we have performed a further bivariate spatial autocorrelation analysis. In this case, the independent variable is the accessibility, while the dependent variable is the rurality index CIR. As Figure 9 indicates, a similar level of spatial autocorrelation (Moran's I = -0.334) is confirmed. A finer inspection using LISA reveals a substantially different cluster distribution.

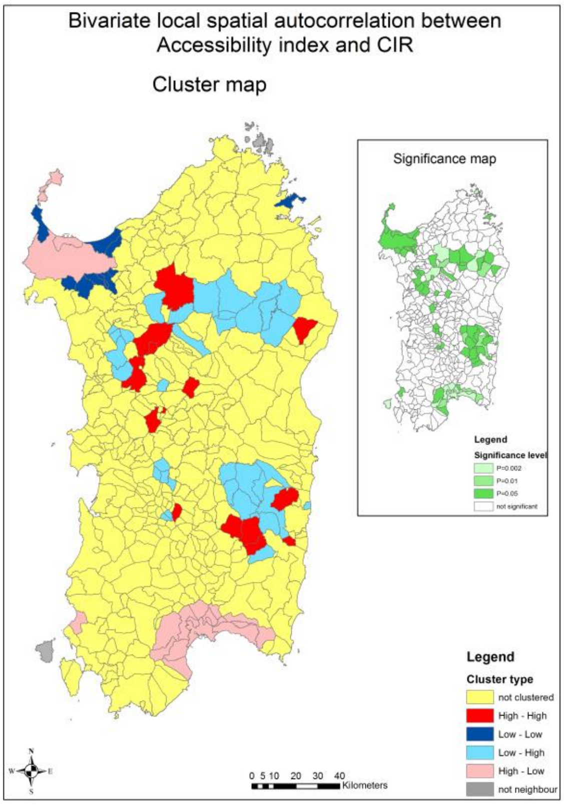

Figure 10. Cluster and significance maps for bivariate spatial autocorrelation analysis between rurality indicator CIR and accessibility indicator Acc_i^{tot}**.**

As Figure 10 shows, cluster distribution, apart from the colors, is fairly similar to the pattern emerging in the univariate spatial autocorrelation analysis of the rurality indicator CIR. The cluster (in yellow) including municipalities without significant spatial autocorrelation values is clearly larger than in the case of the bivariate analysis illustrated in Figure 8. By contrast, the clusters with significant spatial autocorrelation display a substantial contraction. In particular, municipalities now represented in pink, due to the opposite variable selection, and corresponding to the metropolitan area of Cagliari, are clearly reduced. In addition, no municipalities located in the Campidano and in Costa Smeralda are included in clusters with significant spatial autocorrelation values. We therefore have reasons to believe that the causal relationship of accessibility vs. rurality, i.e., rurality influences accessibility, holds with a higher significance than the opposite influence relation.

5. Discussion and Concluding remarks

In this paper, we propose two new spatial indicators to evaluate the level of rurality and accessibility for regional units and have applied them to municipalities in the region of Sardinia, Italy.

The accessibility indicator that we have proposed is based on the modeling framework of Spatial Interaction Models – SIMs - (Wilson, 1970; 2000) that have a long tradition in transport and urban planning. We have introduced two novelties compared to standard applications (Geurs and van Wee, 2004; Martín and Reggiani, 2007): first, we have calibrated a doubly constrained spatial interaction model in which the cost sensitivity parameters β_i have been calibrated separately for each spatial unit instead of being calculated as a unique "average" value for the set of all municipalities. This procedure has allowed us to obtain a very high level of reliability for the SIM ($R^2 = 0.85$) and thus also a better estimation of the accessibility indicator. In Figure A3, we have mapped the spatial distribution of β_i exponents, which range between -0.86 and -0.22 (mean = -0.44 and standard deviation = 0.07). The spatial patterns are very similar to the three indicators of accessibility that we have introduced in section 3.1 (Figure 1, A1 and A2) with the cost sensitivity parameter as one of the major determinants in the formulation of accessibility. The most inaccessible areas are those that are more remotely located from the main backbones of the regional road network. We have discussed in sections 1 and 2 that poorly accessible zones are often classified as rural areas where the predominant activities are linked to farming or to the exploitation of natural resources. In this instance, one of the goals of this work is to discuss whether accessibility and rurality are spatially correlated. For this purpose, we have proposed a new index of rurality (Composite Index of Rurality, CIR). Given that De Montis et al (2012) tested five different indices of rurality, finding that each index provides different results, we have proposed a new index, which accounts for three macro determinants (Demography, Economics and Settlement) that have been extracted from the work of Smith and Parvin (1973), Higgs and White (2000) and Waldorf (2006) on indicators of rurality. The application of CIR for our case study has shown that in Sardinia, municipalities are mostly rural. This condition is particularly clear in parts of the island where we observe a low infrastructural level. The orography of those zones (i.e., Ogliastra, Central-Eastern Sardinia) is very sharp and thus creates a sense of isolation for the populations that live in these territories. From the perspective of an urban planner, one of the central applications for this case study is to understand whether this condition needs to be improved or if it should be preserved (because it represents part of the historical structure of those territories). Furthermore, in a period of growing financial crisis that involves not only the international financial system but also national systems, thus reducing the public investments available, is it sustainable to contemplate investing in rural zones to transition those areas with a rural propensity towards a model of dispersed urbanity? If we take into account the population that resides in the region of Sardinia, the majority live in or around the four major urban poles (Cagliari, Sassari, Nuoro and Olbia). The benefit that the whole Sardinian community could earn from investments in these areas would be limited. In this historic moment, urban planners and stakeholders should carefully take into account these factors when planning vast regional areas. In this context, it is the opinion of the authors that the majority of the investments in infrastructures should be directed towards the creation of axes connecting the major urban poles and thus rationalizing public spending. Rural municipalities should anyway play an active role in the regional economic and social activities. One of the paths that they can take to support their economies is to cooperate with each other forming thematic networks to sustain, rationalize and expand their existing activities as well as propose new ways to live within their territories without distorting their historical attitudes.

In the vein of a speculative analysis, we have investigated whether there is a spatial correlation between accessibility and rurality of an area. For the case study of Sardinia, we have found that this indication of spatial correlation is not always true for the majority of municipalities where it is possible to find a correlation. We have found a small negative correlation (Moran's I index = -0.351), and in the cluster map in Figure 8, we confirm that areas with high accessibility are surrounded by areas with low rurality. We have found an opposite behavior in northeastern Sardinia where not very accessible zones are not rural. This zone is the tourist area of Gallura, which is characterized by a high quality of tourism which usually tends to stay within this area (Costa Smeralda). Many tourists access this area through the airport in Olbia (the main hub of the area) or use the network of tourist ports located along the cost. Thus, the economy of this area, which has been based on farming activities for centuries, is now mostly connected to the service industry that supports tourism in the region.

Future research will investigate the evolution of rurality and accessibility in the region of Sardinia using the two indicators proposed in this study. Our objective is to take into account the planning policies that have been implemented over the past few decades. This course of study will help us verify whether political actions were effective in changing the territorial configuration of the region of Sardinia. We seek to ascertain whether rurality and accessibility are static phenomena or if they have evolved towards different models. For this purpose, we will take into account a 30-year time span to verify our hypothesis. Additionally, we aim to extend the CIR to consider not only demographic, economic and spatial factors but also taking into account such factors as features of landscapes and urban settings.

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Appendix A

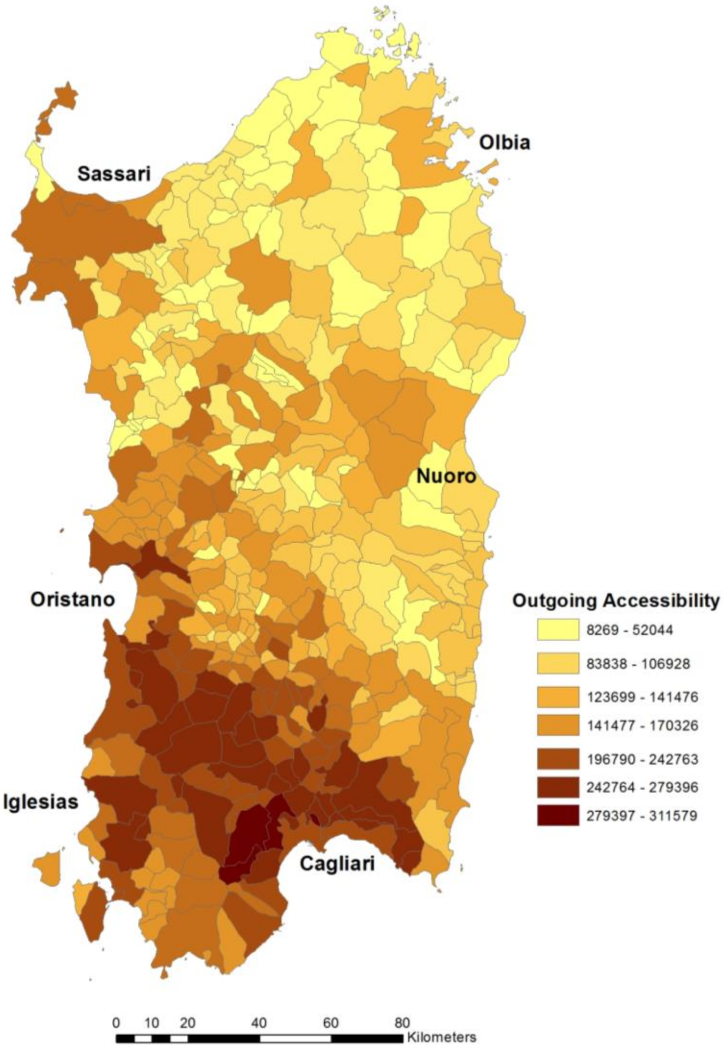

Figure A1: Outgoing accessibility index Acc_i^{out}

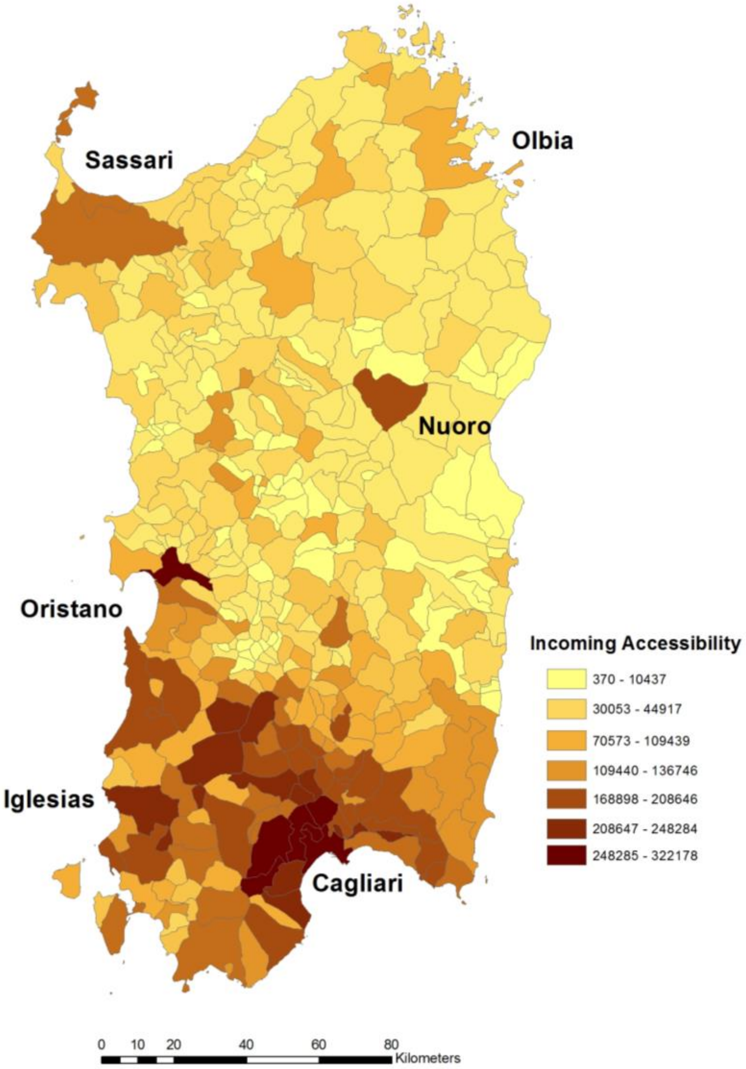

Figure A2: Incoming Accessibility Index Acc_j^{in}

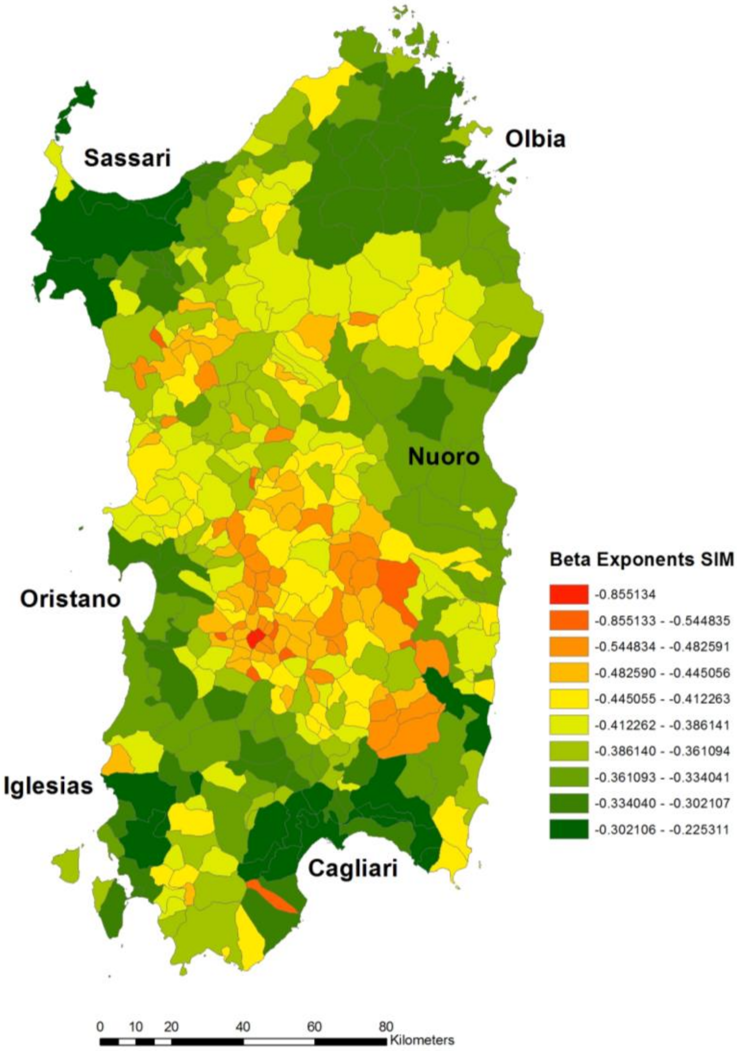

Figure A3: cost sensitivity β_i parameters for each municipality