Data-tourism Spatialization: a New Methodology Useful for Landscape Planning Assessment

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Abstract

A new innovative methodology for the tourism data distribution is the main aim of this paper, in order to provide useful tools for spatial planning choices. The fine-tuning of our methodology is the result of the substantial experience in research matured by the L.a.co.s.t.a. Laboratory in the University of Molise.
The main problem in spatial analysis is the transition from discrete data distributions to continuous distributions. Most methods consist in relating discrete data with reference to variables to have mostly distribution in the study area.
This study provides to evaluate the distribution of tourist facilities according to localization factors related to the tourism supply, by including landscape features and cultural, environmental, spiritual, healthy concerns. Landscape features are calculated with reference to the elevation gradient and land coverage, while the proximity analysis uses G.I.S. functions to higher is distance from the attraction centers, lower are the values assigned to each point. Through a multivariate regression model, it has been possible to extrapolate the localization factors by administrative units (eg. Municipalities) to subunits of equal dimension (eg. squared cells) and estimate the accommodation density associated with each subunit.

Key words: Spatial econometrics, G.I.S., Tourism, Landscape, Planning.

JEL Classification: O2 Development Planning and Policy; R12 Size and Spatial Distributions of Regional Economic Activity; R15 Econometric and Input–Output Models • Other Models; R52 Land Use and Other Regulations; R58 Regional Development Planning and Policy

1 Introduction

The aim of this paper is to develop a methodology for tourism data spatialitation, exportable to other disciplinary contexts that have a territorial matrix, which takes into account the contextual factors of the observed phenomenon.

In the official statistics, tourism data are collected at the Municipal level and therefore they have a little value for strategic decisions in the land use planning, which however requires a restricted zonal level.

The increased awareness of the relevance of spatial interactions, spatial externalities and networking effects among actors, evoked the area of spatial econometrics that focuses on the specification and estimation of regression models explicitly incorporating such spatial effects (Anselin, 1988; Anselin and Bera, 1998; Florax and Nijkamp, 2004; LeSage et al., 2009).

Spatial statistical and econometric data analysis started in the late 1940s and early 1950s (Moran, 1948, 1950; Geary, 1954; Whittle, 1954). Although the initial development of the field of spatial econometrics has been rather slow (Getis, 2008), the Dixit-Stiglitz revolution (1977) and the emergence of the New Economy Geography (Fujita et al., 1999; Fujita and Krugman, 2004), as well the availability of georeferenced data (Florax and Vlist, 2003) have been instrumental in uplifting the significance and the use of spatial data analysis techniques. The use of spatial data analysis techniques was used in applications dealing with agricultural (Lark, 2000; Florax et al., 2002; Holloway et al., 2002; Anselin et al., 2004; Baylis et al., 2011), environmental and natural resource topics (Bockstael, 1996; Nelson and Hellerstein 1997; Rupasingha and Goetz, 2001; Anselin, 2001a; Deschenes and Greenstone, 2007; Albers et al., 2008): the spread of contaminated water, the diffusion of air pollution (both point- and non-point-source pollution), the location of waste management and other hazardous facilities, the effect of environmental policy on foreign direct investment and the potential of environmental dumping, contamination patterns of animal disease, land use, and the valuation of nature areas and pollution all constitute subjects to which spatial econometric techniques can be fruitfully applied. Spatial models are an important tool for agricultural economics as well as the related disciplines of regional sciences, geography, urban and real estate economics, economic geography, public economics, and local public finance (Baltagi et al., 2007). In social sciences, similar attention shifts have occurred. Increasingly, the popularity of neighborhood effects in sociology, associated with the Chicago school, and the revival of social interaction theory have caused researchers to think about spatial interaction, spatial spillovers, and spatial dependence (Anselin 2003). However spatial patterns are very useful for planning purposes. Our methodology is designed to verify the real tourism enterprises distribution and it is proposed for the New Landscape Plan for the Molise Region (Italy). It could contribute to the measures for landscape features conservation, to the recovery and rehabilitation of degraded areas, and to the appropriate transformation in the landscape context. In the Italian framework planning, the Landscape Plan is a normative reference of particular importance, which has been refined in recent years by the additions of the so-called Urbani Code. Great attention is paid not only to the areas where it is accepted high landscape value, but also to "those significantly compromised or degraded", to emphasize the need to provide "lines of urban development and construction are compatible with the different levels of value recognized", pointing out the requirements for the protection of UNESCO World Heritage sites but also for the "agricultural areas", which for the first time are taken into strong consideration (Cialdea, 2007a, 2012, Cialdea and Mastronardi, 2014).

The New Landscape Plan should realize the landscape quality aims which must combine with potential interventions on the land and which must organize different actions managing to the conservation, the rehabilitation or the economic development. Therefore, we are studying interventions and actions of territorial transformation and we are investigating new methods for mitigating the impacts of the interventions on the environment and local context. These landscape quality aims are divided into general and specific objectives. The first ones aim to control the transformation dynamics through distinct indicators for the different resource systems. They highlight the relationship between the condition of the landscape identified scope and its territorial context, the impact that some components have on the environment and the establishment of a framework of potential quality objectives (Cialdea, 2007b).

2 Methodology

Spatial effects is a catchall term referring to both spatial dependence and spatial heterogeneity. Spatial dependence (or autocorrelation) and heterogeneity are usually not easily discernable in an empirical sense (Anselin 2001b).

In the spatial statistical and econometric literature, however, substantially more attention has been given to testing for spatial autocorrelation as compared to spatial heterogeneity because the extent of heterogeneity can be assessed using standard statistical tools (Cliff and Ord 1981). Currently, several statistics measuring the extent of spatial autocorrelation are available, and their asymptotics and small sample behavior are well documented. Moran's I and the G statistic of Getis and Ord (1992) are the most commonly used statistics.

Except for a limited number of direct representation cases, most spatial econometric models are spatial process models. In many contexts such in spatial planning, there is a widespread need to transform discrete distributions of spatial data (point values) in continuous distributions (areal values) through geostatistical interpolation techniques based on the distribution of the data in the study area, especially the type IDW (Philip and Watson, 1982, 1985), Kriging (Royle et al., 1981; Burrough, 1986, Oliver, 1990).

The limitation of these techniques is to proceed automatically through algorithms implemented in G.I.S. software without taking into account the possible factors that can influence the observed distribution, ie, assuming the same distribution as the date and derived from a set of latent variables of unknown influence. In this scenario, this paper aims to develop and implement an appropriate methodology for data tourism spatialization that we define Explained Variance Factors (EVF): therefore we assume a specific set of variables connected to the local context and that can influence the distribution of regional level data. In our case study, the spatial data are represented by the density of accommodation Td (Beds/sq km) – as a dependent variable - in the Molise Region (Italy): it is defined at the Municipal level (m_i for 136 Municipalities) and it is related to the k context variables that represent the preferential localization factors, such as proximity (ie, the minimum distance) with respect to the environmental and cultural attractors. The variables used are shown in Table 1.

Tab. 1 The Indicator's description

	Indicator	Description
NATURE	NAS	Natural Sights
	WPR	Woods, oasis, Parks and Reserves
	SRL	Springs, Rivers and Lakes
	SEA	Sea
	SKI	Ski
CULTURE	CSC	Church, Shrines and Cathedrals
	CTV	Castles, Towers, Palaces, Fountains and Walled Villages
	ARS	Archaeological Sites
	MCE	Museums and Crafts Exhibitions
OTHER ATTRACTIVES	TFO	Typical Food
	FOL	Folklore
	CHS	Care Homes and Spas
	EAC	Easy Accessibility
FILTER	PDE	Population Density (ab./km^2)

The starting hypothesis is that the facilities (eg. Agritourism Farm) tend to be located in the vicinity of the major factors of tourist attraction, with distances that decrease as the weight of each factor: moreover they are variables depending on the degree of spatial dispersion of the same factors. For our purposes, the elements of attraction were assigned to a point in space that corresponds to the Municipal city, since it is assumed that the facilities tend to be located where they are concentrated mainly service activities, except for the beach resorts and ski resorts, where the reference point is represented respectively by the beach resorts and sports stations. Our data were organized in a matrix in which rows shown the Municipalities (*m*) and columns the *k variables*: the dependent variable, the density accommodation (*Td*) is continuous, while the explanatory variables (F_i) are discrete. To take into account the different value of these variables (landscapes, natural and cultural) have been defined three level value [0,1,2] with scores assigned on the basis of expert assessments (from tourist guides, or through surveys). Moreover, for a linear regression model, it is necessary to estimate a function:

[1] $$\mathbf{Td = A_0 + A_1\, F_1 + \ldots.. + A_k\, F_k}$$

where F_i is the i-th factor of attraction (variable) and A_i (i = 1, ..., k) is the coefficient or marginal contribution of that factor to the observed variable.
A preliminary investigation allowed us to select the variables with greater explanatory power, which is the subset k <= n of variables that makes the maximum R^2 of the regression for a given value of significance.
Through spatial interpolation techniques in G.I.S. (Inverse Distance Weighted, IDW) it was possible to transform the point distribution of each factor F_i in a continuous distribution for the entire study area. In the IDW method it is assumed that the weight P_i - related to the i-th variable - is directly proportional to its magnitude or the relative power of attraction (expressed as normalized values) and inversely proportional to the distance from the point of conventional location (beach, ski resort or administrative center):

[2] $$\mathrm{Pi} = \mathrm{f}\left(\frac{\mathrm{M_i}}{\mathrm{d^s}}\right)$$

where M_i is the magnitude and d^s is the distance from the center of attraction, elevated to a scale factor *s* that can take discrete values between ½ and 3 in relation to the overall variability in the pattern of distribution. The scale factor *s* has been obtained from analysis of the density differences $\Delta Td_{ij} = |Td_i - Td_j|$ for each couple of points i,j to vary the reciprocal distance d_{ij}, within a predetermined threshold, that in view of the scope of object study was identified in 10 km. The IDW method adopts the interpolation formula for the prediction of a generic Z value at the point g_0, which is based on a weighted sum of the values observed (usually 12) in a neighborhood of the point of variable radius:

[3] $$\mathbf{Z(g_0) = \sum^{p} \varphi_p\, Z(g_p)}$$

The unknown weights φ_p depends only on the distance from the observation point and the partial derivatives of the distance (power function). The locational potential of the town j-th PL_j can be interpreted as the sum of the potential P_{ij} of each factor F_i, weighted by the relative importance of that factor λ_i:

[4] $$\mathbf{PL_j} = \sum_{j}^{i} \lambda_i\, P_{ij} \qquad \text{per } i = 1,\ldots,k \text{ variables}$$

where $\lambda_i = A_i/\sum A_i$ is the relative marginal contribution of each factor according to the parameters of the regression. The potential PL_J can be considered equivalent to the probability of a generic facility to locate a point in the territory according to the distribution of location factors F_i. Under G.I.S., we can calculate it through a weighted overlay of information layers in raster format, obtained from the application of the algorithms of spatial distributions of observed points. The estimated value of the density accommodation Td^e in the generic point g_p is then given by:

$$[5] \qquad Td^e\,(gp) = Td(gp)_{min} + \left[\frac{PL(g_p) - PL(gp)_{min}}{PL(gp)_{max} - PL(gp)_{min}}\right] * \left(Td(gp)_{max} - Td(gp)_{min}\right)$$

However, it is possible to compare different estimates using spatial interpolation techniques different from each other. If the final layer range (ΔPLg_p) is divided into h regular intervals, you can assign for each class h = 1, ... m of estimated density Dh^e the corresponding value equal to:

$$[6] \qquad Dh^e = Dh_{min} + \frac{h}{m} * \Delta Dh$$

To validate the model, we can compare the result of the spatial IDW to the result of Explained Variance Factors (IDW_EVF) with the spatial IDW classic, obtained by the application of the technique, with the same parameters of the model, directly to the observed density values for each Municipal city Td_m and reclassifying these values according to size classes similar to those defined by the model. If you assign to each class the intermediate value h (sum of the two extremes) it is possible to estimate the average value of the density μTd^e, obtained with each technique for each joint and calculate the squared residuals Td^2_{res} between the actual density Td_m and the density estimated μTd^e.

$$[7] \qquad Td^2_{res} = (Td_m - \mu Td^e)^2$$

we can compare these two distributions through some statistical tests on the average or median: the expected value of the technique IDW_EVF must be significantly lower than that obtained from the IDW classical technique.

3 Results

In order to meet the standard criteria of goodness of the model (Table 2), starting from the 14 initial variables we asked to the exploratory algorithm to select a minimum number of 2 and a maximum number of 7 variables.

The algorithm has identified a set of regression models that meet the requirements. Among these models, we selected the model with the highest number of significant explanatory variables that maximizes the variance explained.

Tab. 2 Percentage of Search Criteria Passed

	Criterion	Cutoff	Trials	% Passed
Min Adjusted	R-Squared	> 0.50	9893	41.34
Max Coefficient	p-value	< 0.05	9893	0.32
Max	VIF Value	< 7.50	9893	100.00
Min Jarque-Bera	p-value	> 0.10	9893	0.00
Min Spatial Autocorrelation	p-value	> 0.10	21	90.48

As can be seen from the data in Table 3, the 5 selected variables explain about 2/3 of the total variability. It is important that only 3 variables interpret almost 55% of the observed variability. Among these, the most significant variables are the seaside resorts (SEA), which correspond to 30% of the total variability and ski resorts (SKI) (16% of the variability). Among the variables that explain the remainder, the most important is the density of the population (just over 9%).

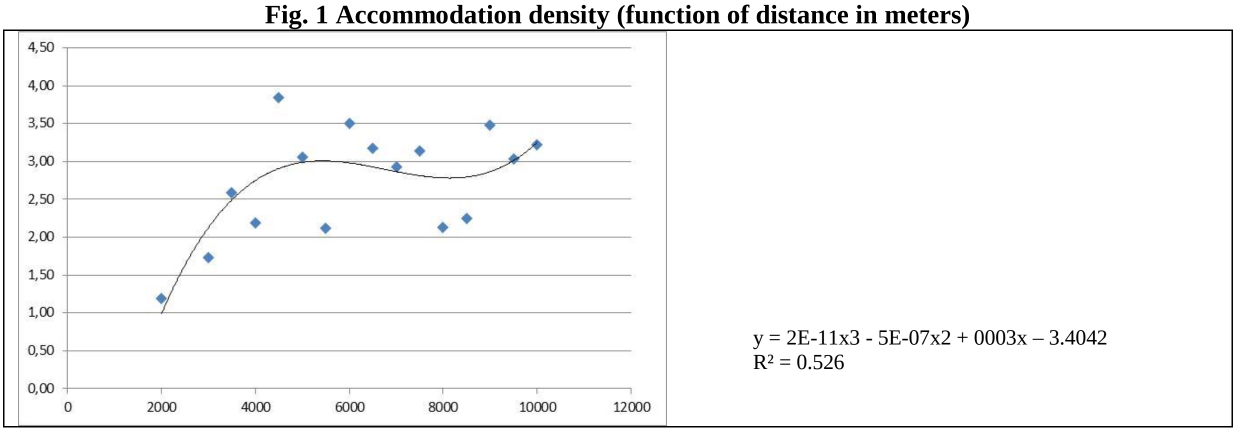
Tab. 3 Summary of OLS Results - Model Variables

Variable	Coefficient	StdError	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	-1.8822	0.4920	-3.8253	0.0001*	0.7803	-2.4121	0.0168*	--------
SEA	8.0609	0.6329	12.7348	0.0000*	1.9062	4.2287	0.0000*	1.2026
SKI	4.3785	0.7858	5.5718	0.0000*	2.3991	1.8250	0.0696	1.0028
CSC	0.6328	0.3050	2.0746	0.0394*	0.3176	1.9920	0.0478*	1.0971
CHS	1.8268	1.2511	1.4601	0.1459	0.5197	3.5151	0.0005*	1.0012
PDE	2.5264	0.4228	5.9749	0.0000*	0.6795	3.7181	0.0002*	1.3033

Number of Observations: 190
Multiple R-Squared: 0.6575
Adjusted R-Squared: 0.6482
Prob(>F), (5,184) degrees of freedom: 0.0000*
Prob(>chi-squared), (5) degrees of freedom: 0.0000*
Prob(>chi-squared), (5) degrees of freedom: 0.0000*
Prob(>chi-squared), (2) degrees of freedom: 0.0000*

The result is a framework in which the Molise Region is characterized by a traditional tourism, linked to the sea and ski activities. For these reasons the landscape attractors role, natural and cultural, is secondary. The Figure 1 shows that the variation of density receptive function of the distance between couple of points (Municipalities) within a 10 km radius, was realized by calculating average values of the differences in density within steps of 500 meters. The scale factor is expressed by the degree of the polynomial interpolation function. It is clear that the density of accommodation varies locally so sensitive. The degree of interpolation accuracy also varies according to the uniformity of the distribution of points: if the concentration of the points (Municipal capitals) is higher, the interpolation error degree is lower and vice versa.

Fig. 1 Accommodation density (function of distance in meters)



The estimated values were grouped in classes of increasing amplitude (Figure 2) because, in our study area, the median value of the reception density receptive to the is relatively low and less than 3 persons per km^2. From the figure, confirming what has already been highlighted by the regression model, it is known as the density accommodation is the major urban centers of the Region, such as the two provincial capitals of Campobasso and Isernia where all the service industries and the city of Venafro next to excellent healthcare facilities.

Figure 3 shows a different situation compared to the previous framework: the polarizations around the major attractive elements (the coast and the ski resorts) are less strong; moreover we can see some secondarily attractive centres (the Municipalities of Pietracupa, Castropignano, Vastogirardi, Pesche, Vinchiaturo and Pozzilli.

Fig. 2 IDW_EVF Methodology

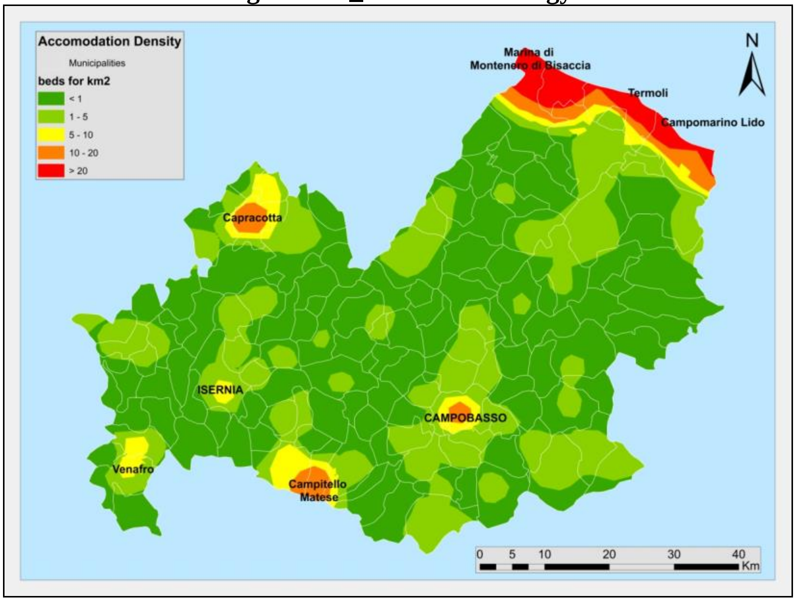
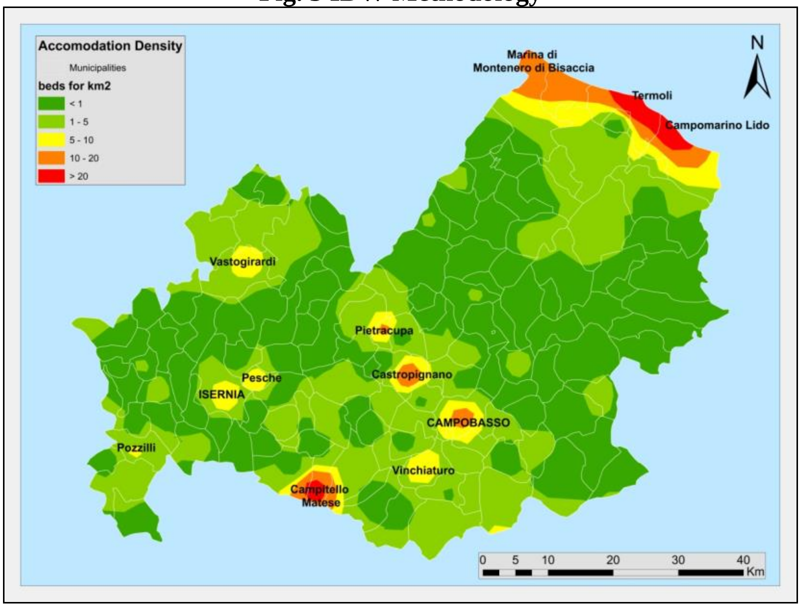


Fig. 3 IDW Methodology



The tests carried out (Table 4) on the model reveal differences which are not significant in relation to the average value of the estimated density for the entire study area.

However, the calculation of residuals for Municipalities (with the comparison between the Municipality average size in our study area) shows that the distributions of both models are asymmetric and leptokurtic (ie stretched upward), and therefore conventional parametric tests, for the normality hypothesis, cannot be applied. Therefore, the comparison between the proposed model and the classical model was based on the expected value for the median, which in the case IDW EVF (0:58) is much closer to the observed value for the study area

(0:49) compared to IDW (1.12). By analogy, the calculation of the determination coefficient $R^2_{(Me)}$) (related to the adaptation quality) is based on the deviance explained with respect to the median ($ESS_{(Me)}$) instead of the average value, obtaining a value of 0.443 for the model IDW_EVF against the 0.273 for the IDW classic; the probability that this difference is more robust than the random tests (Kolmogorov-Smirnov) is less than 1‰.

Tab. 4 Comparison between the proposed model IDW EVF and the classical model IDW

Statistics	IDW EVF	IDW	Observed (n = 136)
Td average	1.17	1.253	2.78
Td median	0.58	1.12	0.49
Td dev.st	5.97	4.47	9.11
Asymmetry of residuals	-2.75	-5.51	
Kurtosis	19.8	32.7	
Model fit			
ESS(Me)	5276	3258	
TSS (Me)	11923	11923	
R^2(Me)	0.443	0.273	
Model test			*p(same)*
Sign	r=84		2.20E-07
Wilcoxon	W=4736 , z=4.34		1.420E-05
Kolmogorov-Smirnov Permutation p	D=0.25		0.000308 0.0003

4 Conclusions

Our proposed model extends the current scenery of interpolation techniques; it also suggests a methodology that is not limited to mathematically derive spatial data with standardized algorithms, but, instead, it can explain the observed variability across a set of geo-locational factors. The potential of this methodology are not limited to the field of tourism, but it may be extended to all disciplines in which it is appropriate to interpret a spatial distribution related to the factors that affect this distribution. It also can be applied to any geographical area and also exportable to other territories. The preliminary investigation on latent variables that influence the observed phenomena is of particular utility in planning for the implementation of interventions to sub-municipality scale and for evaluating the effectiveness of the operational strategies adopted. The New Regional Landscape Plan, which will cover the entire territory of the Region, must define, for each identified homogeneous area, some specific requirements in order to define actions aimed at the identification of land development, compatible with different value levels and oriented to the correct land use.

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