Environmental and Ecological Statistics
https://doi.org/10.1007/s10651-022-00541-8

Exploring land use determinants in Italian municipalities: comparison of spatial econometric models

Gennaro Punzo[1] · Rosalia Castellano[2] · Emma Bruno[1]

Received: 11 April 2022 / Accepted: 24 June 2022

Abstract

This study sets up a spatial econometric framework to explore the factors that best describe land consumption in Italy at the municipal level. By modelling the different types of spatial interactions and geographical proximity between all Italian municipalities, the direct effects of land use drivers are assessed together with spillover effects. Land use data are drawn from the ISPRA-SNPA 82/18 Report and cover all 7,998 Italian municipalities. The results highlight the existence of endogenous and exogenous interaction effects and the crucial role of the demographic, socio-economic and institutional structure on land use intensity. Hence the need for a planning policy aimed at: *i*) strengthening institutional cooperation to deal with excessive administrative fragmentation; *ii*) improving institutional and governmental quality to trigger virtuous mechanisms for sustainable land use management.

Keywords Land use · Environment · Municipalities · Spatial models · Italy

Communicated by Luiz Duczmal.

✉ Gennaro Punzo
gennaro.punzo@uniparthenope.it

Rosalia Castellano
lia.castellano@uniparthenope.it

Emma Bruno
emma.bruno@studenti.uniparthenope.it

1 Department of Economic and Legal Studies, University of Naples Parthenope, via Generale Parisi 13, 80132 Napoli, Italy

2 Department of Management and Quantitative Studies, University of Naples Parthenope, via Generale Parisi 13, 80132 Napoli, Italy

1 Introduction

The progressive artificialization of natural soils has severe implications for land degradation, which entails a greater risk of flooding, global warming, and climate change (Ferris and Frank 2021; Aldieri and Vinci 2020; Haines-Young 2009; Polasky et al. 2004). Awareness of the disproportion of land consumption to the actual needs of the population, which violates every premise of sustainability with social and economic consequences, has only raised in recent decades (United Nations, 2019; European Environmental Agency 2017).

The United Nations 2030 Agenda for Sustainable Development Goals (SDGs) emphasizes the crucial role of land use in achieving many SDGs related to zero hunger, good health and well-being, affordable and clean energy, sustainable cities and communities, and responsible production and consumption. In particular, the Agenda plans to strengthen inclusive urbanization and the capacity for participatory and integrated planning and management of human settlement in all countries, as well as long-term sustainable land use by 2030. Therefore, it is desirable to create more sustainable land management systems to reverse current trends in land consumption (UNEP, 2012). To this end, it is necessary to assess the factors underlying land consumption that would help policy makers in evaluating existing planning tools or in developing new environmentally friendly policies for more sustainable urban development (Punzo et al. 2022; Chakir and Le Gallo 2013; De Sá et al. 2013). Knowledge of the factors that regulate land use processes is strategically important to combine community needs with the sustainable management of natural heritage and resources.

Based on the above, this study aims to investigate the main determinants of land consumption in Italy from a spatial perspective. Using data on all 7,998 Italian municipalities, the study specifically concentrates on land consumption, that is, the artificial covering of originally non-artificial surfaces (e.g. agricultural, forest, other natural or seminatural land), as a result of anthropogenic activities. Land consumption rate (LC%, hereafter) is officially defined as the percentage of land consumed on the total surface, net of water bodies (ISPRA-SNPA, 2018).

Italy is an interesting case study due to its socio-economic, territorial and land use characteristics that could bring a high value to the scientific debate for several reasons. First, land consumption in Italy is oversized compared to the real demand and carrying capacity of the territories (Ispra 2015), characterized by urban sprawl and dispersed settlements that have often blurred the boundaries between urban and rural areas (Salvati and Carlucci 2016). With about 7.6% of artificial land in 2016 (against an EU average of 4.6%), Italy ranks fifth after Malta and the Benelux countries and ahead of Germany, Denmark and the United Kingdom (European Environmental Agency 2017). Second, Italy has historically been characterized by a huge north-south economic gap (Ciccarelli and Fenoaltea 2013), inevitably reflecting significant territorial differences in land consumption (ISPRA-SNPA, 2018). In 2016, five out of eight regions with LC% above the national average belonged to northern Italy. Third, Italy has a large number of small and independent municipalities with decision-making autonomy regarding territorial planning strategies, regardless of their size and number of inhabitants. The detection of spatial spillover effects could help overcome the excessive administrative fragmentation regarding land use and identify the key elements to trigger a virtuous circle that would limit urban sprawl in adjacent areas. The spatial dimension is considered in light of *i*) the assumption that human activities impact spatially on the environment (Mellino and Ulgiati 2015; Bateman et al. 2002); *ii*) the scarcity of land resource, which causes its consumption to generate externalities readily (Wu et al. 2021). Both the previous aspects give rise to a land use data generating process that makes the use of spatial econometrics particularly suitable. Our approach builds on aggregated land-use models using aggregate data at the municipality level. Depending on the type of spatial effects, different spatial econometric models are proposed to estimate both direct and indirect (spillover) effects and validate the results' consistency. Fourth, to the best of our knowledge, this is one of the first studies investigating the determinants of land consumption in Italy at such a high level of geographic resolution, explicitly considering spatial effects whose omission could lead to biased and/or inefficient parameter estimates and unreliable statistical inference (Anselin 2003). Aggregated data models help predict changes in aggregate-level land use patterns and examine the effects of policies (Chakir and Le Gallo 2013). Some works have examined land use in Italy (see, among others, Bimonte and Stabile 2017; Salvati et al. 2016; Romano et al. 2015) or its specific territorial realities and regions (Guastella et al. 2017; Fiorini et al. 2017; Savini and Aalbers 2016; Smiraglia et al. 2016; Romano and Zullo 2014a, b; Mazzocchi et al. 2013; Salvati et al. 2012; Pileri and Maggi 2010). However, the vast majority have explored land use drivers by assuming spatial independence, while land use data generating processes are fundamentally spatial in nature (Overmars et al. 2003).

The remainder of the paper is structured as follows. Section 2 discusses the theoretical framework and the main characteristics of the study area. Sections 3 and 4 show the methodological details of the spatial econometric models and the data used, respectively. The main results and policy implications are discussed in Sections 5 and 6. Section 7 concludes.

2 Background

2.1 Theoretical framework

Since land is a resource characterized by location and scarcity, land use changes in a given area tend to spread to surrounding ones, inevitably generating externalities (Wu et al. 2021; Aguiar et al. 2007). Spillover effects can result when neighbouring local authorities independently plan land use without multi-jurisdictional coordination mechanisms (Sciara 2020).

Multiple economic theories have been developed for analyzing land use patterns taking spatial interactions into account (Feng et al. 2018; Ay et al. 2017; Verburg et al. 2004a). Among these, agent-based modelling (Irwin and Bockstael 2002) can effectively help capture spatially complex processes driven by local agents. Modelling spatial land use processes associated with local agents allows one to consider the effect of local and neighbouring factors on land use decision-makers and the effect of potential spatial interactions between spatially distributed local agents. This reasoning finds even more foundation in this study which builds the analysis on data with a high geographical resolution (municipalities). Since the municipality is the administrative division corresponding to the economic reality of the relationships between agents, agent-based modelling represents a sound theoretical framework for inferring the estimation results that can help explain the complexity of the land use processes resulting from the interactions between behavioural and structural factors (Briassoulis 2019; Overmars and Verburg 2005).

Alongside agent-based modelling, we followed the theoretical approach developed by Turner et al. (2020), a flexible and open framework composed of key elements to which the potential determinants of land consumption and their combinations can be traced. Its core consists of four main groups of characteristics – i.e. sociodemographic conditions, economic structure, institutions, and actors' attributes – that can influence land demand (Meyfroidt 2016).

Since the behaviour of economic agents is often related to demographic and social characteristics, the latter can influence land pressures, increase land use demand and urban growth (Getzner and Kadi 2020). Characteristics such as population density, family size, and availability of services, in turn, depend on the land supply (absolute availability and relative access) and could contribute to changes in access to land or resources (Salvati et al. 2018).

From the economic perspective, there could be a close relationship between economic activity and land use (such as built-up areas). Economic development, observed through levels of employment, income, and living standards, can affect land demand for housing and industrial areas and incentivise housing supply (Getzner and Kadi 2020; Deng et al. 2010).

Institutions play a crucial role in land use management (Barbier and Tesfaw 2015; Wolfersberg et al., 2015) as they are the primary decision-makers in land planning by addressing land access and regulating social interaction with territorial systems, both formal and informal (Tellman et al. 2021). Stable governance systems can ensure efficient land control and natural resource protection policies. Otherwise, weaker institutions, characterized by political instability, corruption and the absence of adequate regulatory interventions, could fail in regulating land access and guaranteeing sustainable land management (Galinato and Galinato 2013).

There is a not negligible interconnection between institutions and society's demographic and economic structure. Actors' attributes, meant as the main characteristics of local governments and institutions, are crucial for most land use explanations, such that a change in one of them can affect demand, access and management of land. Therefore, the proposed framework cannot ignore that an actor's land use decision may be influenced by the sociodemographic, economic and institutional characteristics of spatially proximate decision-making units and their interaction.

In light of this framework and Italian legislation, which recognizes that each municipality has autonomy in decision-making regarding land use, our analysis was carried out at the municipal level. In compliance with national legislation, the primary role played by municipalities in spatial planning can produce multiple adjacent jurisdictions of neighbouring areas (Sciara 2020; Towe et al. 2017; Cho and Linneman 1993). This means, for example, that local binding control of land use can affect the outcome of surrounding communities and that the more or less restrictive regulations adopted by a municipality can influence the decisions of the neighbouring municipalities, causing interlinked spillover effects that cannot be ignored in the estimation process (Ji and Tate 2021; Wang et al. 2020).

2.2 Study area

The high granularity of the administrative units (municipalities), which are in charge of land zoning, makes Italy an interesting case study. In fact, the representation of national land consumption is the result of the programmatic choices made by about 8,000 municipalities – of which approximately 99% have less than 50,000 inhabitants – with the same power regardless of their surface or number of inhabitants (Guastella et al. 2017)[1].

By analyzing data from Ispra (Italian Institute for Environmental Protection and Research), LC% are quite differentiated throughout the Italian territory. In 2016, LC% values higher than the national value (7.63%) mostly concerned the regions of northern Italy. Lombardy (12.96%) and Veneto (12.21%) reached the highest level of land consumption, followed by Campania (10.76%) and Emilia Romagna (9.77%). By contrast, Aosta Valley (2.91%), Basilicata (3.38%), Sardinia (3.75%), and Molise (4.03%) showed the lowest LC%. The provinces of northern Italy (except for the Alpine ones) showed LC% above the national value, along with coastal provinces of Tuscany, Latium, Campania, Marche, and above all, southern Sicily and Apulia (except for Foggia).

Several municipalities exceed 50%, and sometimes 60%, of land consumption. These are small or middle-small sized municipalities that often show land use linked to the urbanization process of the provincial city to which they belong, or very small size communities with coinciding administrative limits with the urbanized area. With a few exceptions, the 50 municipalities with the highest LC% (above 55%) belong to Lombardy (especially the provinces of Milan and Monza and Brianza) and Campania (Naples).

Figure 1 plots (a) the spatial distribution by decile of LC% in Italy at the municipal detail, (b) the global spatial autocorrelation of LC% at the municipal level, (c) the local indicators of spatial autocorrelation (LISA), and (d) their significance level. All spatial statistics were obtained using the first order binary contiguity matrix in row-standardised form (W_I); thereby, two municipalities are adjacent ($w_{ij} = 1$) if they share an administrative boundary of non-zero length.

With a significant global Moran's I of 0.7652, LC% are highly spatially correlated. This means that land use levels do not occur independently in each municipality, but each development directly affects the behaviour of neighbouring municipalities. Graphically, being the vast majority of municipalities located in the first and third quadrants of Moran's scatter plot, LC% are connected according to a 'high-high' and 'low-low' relationship. That is, municipalities showing high (low) LC% are usually surrounded by municipalities with as many high (low) levels of land consumption.

[1] In Italy, the territorial planning authorities should operate hierarchically, and the regions should legislate within the national guidelines to outline the structure that local authorities follow in preparing statutory land use plans. However, Italy does not yet have organic land use regulation; therefore, the role of the regions and provinces is often limited to providing general guidance.

The global Moran's I offers only averages, giving an overall picture of the spatial pattern of land consumption in Italy; it may hide interesting territorial micro-concentrations of spatial interactions in land use patterns. LISAs help understand exactly which municipalities are similar to those in their neighbourhood. In particular, the local Moran's I detects significant spatial clusters of similar values, identifying 'hot' and 'cold' spots where municipalities with high or low LC% are adjacent. The local Moran's I also finds areas where adjacent communities exhibit significantly different values, that is, municipalities with high LURs are surrounded by municipalities with low LURs and vice versa[2]. Significant clusters of high LURs are detected in specific areas of the country, i.e. a wide range of municipalities of Lombardy and Veneto, the provinces of Asti and Turin (Piedmont), Modena and Reggio Emilia (Emilia Romagna), Rome (Latium), Naples (Campania) and Lecce (Apulia), and clusters of low LURs along almost throughout the rest of the peninsula.

3 Method

The occurrence of spatially dependent data could invalidate the OLS assumption of uncorrelated residuals, resulting in biased estimates of the model parameters. With this in mind, our empirical strategy was oriented towards spatial econometric models. Based on the type of spatial interaction, all specifications of spatial models (Elhorst 2010; Anselin 1988) are generalized restrictions of the General Nesting Spatial (GNS) model (Manski 1993):

$$Y = \rho WY + \alpha i_N + X\beta + WX\theta + u \tag{1}$$

$$u = \lambda Wu + \epsilon \tag{2}$$

where β is the vector of parameters for exogenous covariates X, α is the intercept (i_N is the vector of ones), W is the spatial weights matrix; ρ is the scalar for the endogenous interaction effects (WY) referred to as spatial autoregressive, θ for exogenous interaction effects (WX), λ for the spatial correlation effect of errors; u is the vector of auto-correlated errors, Wu is the interaction effects among the disturbance terms, and ε is the vector of independently and identically distributed error terms with zero mean and constant variance.

Following the combined approach proposed by Elhorst (2010) to select the most appropriate spatial model, we first run the LM tests (Anselin 1988) and their robust (RLM) versions (Anselin et al. 1996) to formally verify the spatial autoregressive ($\rho \neq 0$) and/or residual autocorrelation structures ($\lambda \neq 0$). Then, we perform LR

[2] Contrary to the Moran's scatter plot, which fails to be fully explanatory, the LISA cluster map well illustrates that most of the Italian municipalities are significantly connected to each other according to a 'low-low' (27.59%) rather than 'high-high' relationships (12.18%). A very low share of municipalities is significantly connected according to a 'low-high' (0.26%) or 'high-low' (0.34%) relationships, while the remaining share is made up of municipalities that are not significantly connected to each other (59.45%) and neighbourless (0.18%).

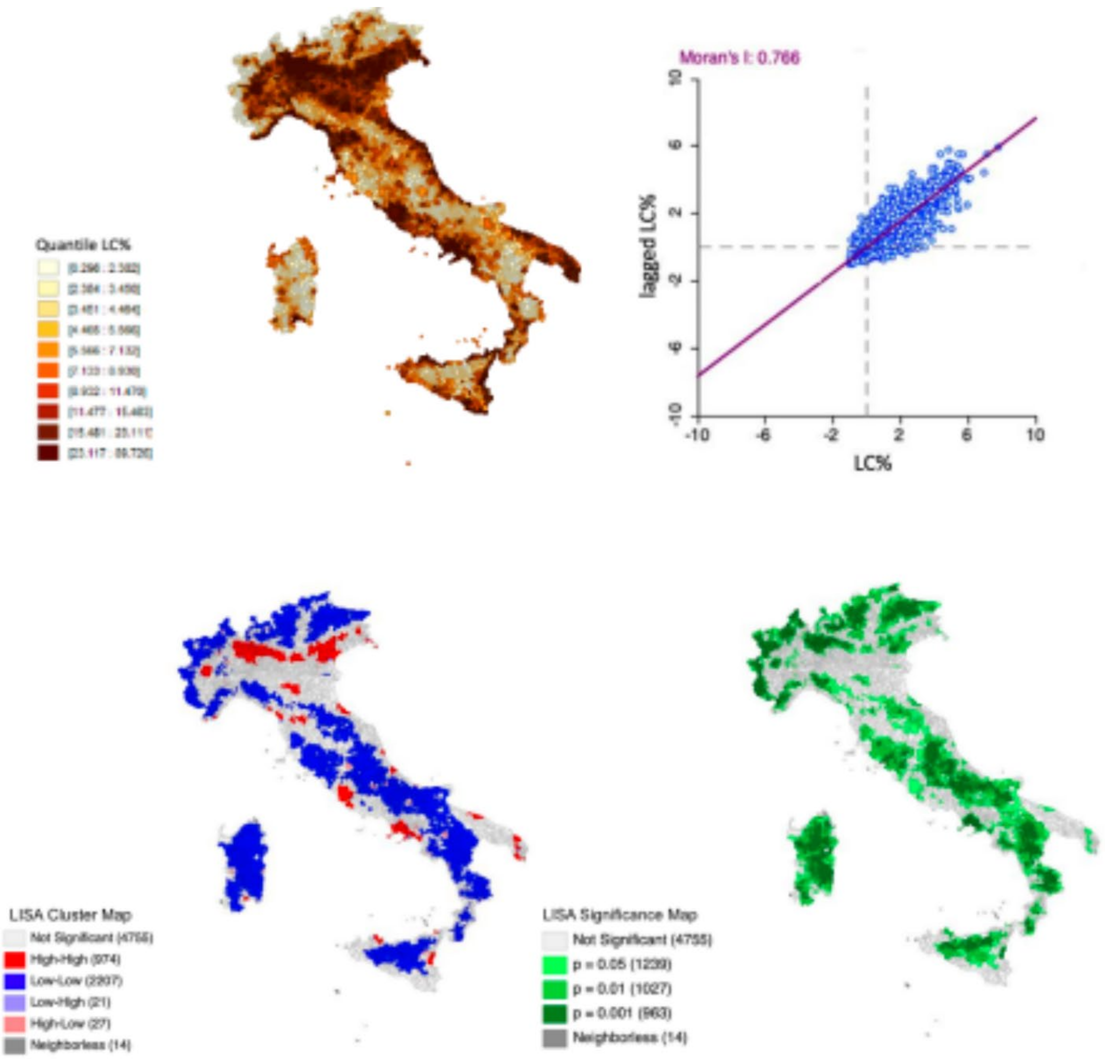

Fig. 1 LC% in Italy (2016): Spatial distribution by decile (a), Moran scatterplot (b), LISA cluster map (c), LISA significance map (d)

tests ($\theta \neq 0$;$\theta + \rho\beta \neq 0$) to detect the presence of a potential spatial autocorrelation in the covariates[3], which would also imply exogenous interactions.

Although technically the GNS model can be estimated, the parameters cannot be meaningfully interpreted as the different types of interaction effects cannot be distinguished from each other due to overparameterization (Burridge et al. 2016; Elhorst 2010; LeSage and Pace 2009). To overcome this limitation, we followed the procedure suggested by most of the empirical literature (Halleck Vega and Elhorst 2015), which removes one of the three types of spatial interaction effects. Therefore, we estimated three types of models deduced from the GNS model, depending on the constraint used.

[3] Both classic and robust versions of the Lagrange Multiplier (LM) tests are based on the residuals of the OLS model and follow a chi-squared distribution with one degree of freedom. Moreover, the first Likelihood Ratio (LR) test examines whether the Spatial Durbin Model (SDM) can be simplified to the Spatial Lag Model (SAR), in which the structure spatial effect enters only endogenously through the spatial autoregressive term. The second LR test verifies whether the SDM can be simplified to the Spatial Error Model (SEM), in which the spatial effect concerns only the residual autocorrelation structure. Both LR tests follow a chi-squared distribution with k degrees of freedom.

First, placing the constraint on the residual autocorrelation structure ($\lambda = 0$), the Spatial Durbin Model (SDM) was estimated. The structure spatial effects enter both endogenously through the spatial autoregressive term to reflect the impact of land consumption in neighbours and exogenously to reflect the consequence for each unit of the change in an exogenous variable (LeSage and Pace 2009). The SDM does not impose prior restrictions on the magnitude of spatial spillover effects, which can be global or local and be different for different covariates; moreover, the SDM provides unbiased coefficient estimates even in the presence of spatial error dependence (Elhorst 2010).

Second, placing the constraint on the spatial autoregressive structure ($\rho = 0$), the Spatial Durbin Error Model (SDEM) was obtained, in which there is no endogenous interaction, and the focus is on neighbourhood externalities.

Third, constraining only exogenous interactions, the Kelejian-Prucha (1998; 2010) model, also referred to as Spatial Autoregressive Confused (SAC), provided the double spatial component, i.e. a spatial autoregressive model with autoregressive disturbances.

As the spatial lagged dependent variable is usually correlated with the disturbance term, the SDM and SAC suffer from endogeneity, which can be addressed by using a set of instruments (Anselin 2001), i.e. variables that are correlated with the spatially lagged variable (instrument relevance) and independent of the errors (instrument exogeneity).

Time lagged values of endogenous variables are less likely to be influenced by current dynamics, ensuring no correlation with the error term (Anselin 1988). Following this reasoning, we used as instruments the time lag of the potentially endogenous dependent variable (LC%). The coefficient of the spatially lagged dependent variable was estimated through the two-stage least squares (TSLS) estimator (Kelejian and Robinson 1993; Kelejian and Prucha 1998, 2010; Lee 2003, 2007), using the time lag of four periods (year 2012) of the spatial lag of LC% to instrument the endogenous variable (Reed 2015; Anselin and Lozano-Gracia 2008; Fingleton and Le Gallo 2008). The strength of the instrumental variable was verified using the first-stage F-test. The F-statistics (11,022) was above the rule of thumb threshold of 10 proposed by Staiger and Stock (1997).

The presence of spatially lagged variables implies that the parameters associated with the covariates cannot be interpreted as in the usual framework of the linear model. Because of spatial interactions, the change in a covariate in a given municipality *directly* affects the dependent variable in that area and *indirectly* affects the dependent variable in all other municipalities (Elhorst 2010; LeSage and Pace 2009). In the presence of the spatial autoregressive term (SDM and SAC models, in this paper), being different for each unit, the direct and indirect (spillover) effects were first computed for each municipality, and then the average was proposed. While the average direct effect can be interpreted similarly to that of the β coefficients of linear OLS models, the average total effect is the average of the n effects by the change of a unit of variable X in the i^{th} area across all areas. Finally, the average indirect effect is given by the difference between the average total effect and the average direct effect. In the presence of exogenous interactions without endogenous interaction (SDEM), the direct and indirect effects of a covariate are given by the vector of the response coefficients (β) and that of its spatial lag (θ). Therefore, SDEM has an important char-

Table 1 Direct and indirect effects of different model specifications

	Direct effects	Indirect effects
OLS	β_k	0
SDM	Diagonal elements of $(I-\rho W)^{-1}(\beta_k+W\theta_k)$	Off-diagonal elements of $(I-\rho W)^{-1}(\beta_k+W\theta_k)$
SDEM	β_k	θ_k
SAC	Diagonal elements of $(I-\rho W)^{-1}\beta_k$	Off-diagonal elements of $(I-\rho W)^{-1}\beta_k$

acteristic of spillover effects, which are *local* and not *global*, as they only occur in areas that, according to W, are connected to each other without involving all the other areas that are unconnected (Anselin 2003; Halleck Vega and Elhorst 2015). The direct and indirect effects of the model specifications used in this paper are shown in Table 1.

We also run global Moran's I and spatial econometric models using three other weight matrix configurations (Stakhovych and Bijmolt 2009; Case et al. 1993). They are: *i*) row-standardised second order binary contiguity matrix including the first order neighbours as well (W_2), in which two municipalities are considered neighbours ($w_{ij}=1$) if they share an administrative boundary of non-zero length or have borders that touch the first-order neighbours. *ii*) row-standardised distance-band weight matrix based on the centroid distance (W_3) in which two municipalities are treated as neighbours ($w_{ij}=1$) whenever they fall within the critical distance cut-off ($d_{ij}\leq\delta$). The critical distance cut-off (δ) was set such that each municipality had at least one neighbour[4]. The distance-band matrix reflects the hypothesis that the intensity of a spillover effect decreases with the distance. *iii*) k-nearest neighbour matrix (row-standardised) (W_4) where k is the number of neighbours that is set equal to the mean of the neighbours in the binary contiguity matrix (k=5).

4 Data and variables

The data are drawn from official statistical sources and cover all 7,998 Italian municipalities (NUTS-5/LAU-2 level of the Eurostat classification) for 2016. Official land use data were merged with a set of information taken from Istat (Italian Institute of Statistics) and SIEPI (Italian Society of Economics and Industrial Policy). The choice of potential explicative variables was based on the dominant literature in this field while considering the constraints related to the data availability at such a high level of geographic resolution. According to Turner et al. (2020) conceptual framework, the selected variables concern the three main groups of sociodemographic, economic and institutional characteristics while controlling for the geomorphological elements that can influence people's ability to transform the land.

Table 2 details all selected variables that could help explain land use patterns in Italy, also including references to the relevant literature and their expected relationship with LC%.

[4] 14 municipalities (islands made up of one municipality) were neglected, since the criterion 'the largest of the nearest neighbour distances' would have meant choosing a distance-band too long causing computational problems.

Table 2 Explanatory variables

Dimensions	Variables	Description	Expectation	References
Geomorphologic	Overall Surface	Square kilometres of the entire municipality	*Negative*: land use is higher in smaller areas	Guastella et al. 2017.
	Elevation above mean sea level	A measurement in metres of the elevation of a location in reference to the mean sea level	*Negative*: it affects the operational complexity of the land use activities	Huang et al. 2019; Silveira and Dentinho 2018; Verburg et al. 2004b; Overmars et al. 2003.
Demographic	Population Density	Ratio between the total population and the total square kilometres of the municipality	*Positive*: land use is greater in more populous areas	*Handavu et al.,2019;* Shu et al. 2018; *Wolfersberg et al., 2015;* Skonhoft and Solem 2001
	Per capita housing	Ratio between the total number of houses (i.e. buildings, apartments) and the total population	*Positive*: An increase in the demand for housing generates an increase in land use	Guastella et al. 2017.
	Metropolitan Area	Dummy for the metropolitan area: 1 if the municipality belongs to a metropolitan area (Rome, Milan, Naples, Turin, Bari, Florence, Bologna, Genoa, Venice, Reggio Calabria, Palermo, Catania, Messina, Cagliari) and 0 otherwise	*Positive*: A higher degree of urbanization leads to greater land consumption *Negative*: A higher cooperation favour agglomeration effects	European Committee of the Regions, 2019; Guastella et al. 2017; Mazzocchi et al. 2013.
Socio-Economic	Employment Rate	Share of employed people aged 16–64 out of the working-age population	*Positive*: high level of employment implies a higher propensity to investments in land for business or housing	Meyfroidt et al. 2013; Bradshaw and Muller 1998.
	Per capita GDP	Value of all goods and services produced in one year in the country divided by the total population	*Positive*: Economically more prosperous areas may finance land use *Negative*: Higher levels of economic prosperity may lead to a more rational land use	Getzner and Kadi 2020; Handavu et al. 2019; Shu et al. 2018; *Wolfersberg et al., 2015;* Galinato and Galinato 2013; Skonhoft and Solem 2001; Bradshaw and Muller 1998
	Per capita enterprises	Total number of enterprises out of the total population	*Positive*: A high level of economic activity requires more land availability	Meyfroidt et al. 2013; Bradshaw and Muller 1998.

Table 2 (continued)

Dimensions	Variables	Description	Expectation	References
Institutional Quality	IQI	A measure of Italian institutional quality. It is composed of five dimensions: - Voice and accountability - Government effectiveness - Regulatory quality - Rule of law - Corruption	*Negative*: Greater institutional and governmental quality leads to a more rational land use	Barbier and Tesfaw 2015; *Wolfersberg et al., 2015;* Galinato and Galinato 2013; Schneider and Pontius 2001.

The Institutional Quality Index (IQI) is a measure of the quality of Italian institutions proposed by Nifo and Vecchione (2014), inspired by the World Governance Indicator (Kaufmann et al. 2011). IQI is a composite indicator that involves five dimensions, each measuring a specific aspect of the quality of local governments: *i*) Corruption, as a measure of the degree of corruption of those who perform public functions and crimes against the public administration; *ii*) Government effectiveness that evaluates the quality of public service and the policies of local governments; *iii*) Regulatory quality, representing the government's ability to promote and formulate effective regulatory interventions; *iv*) Rule of law that quantifies the crime levels, shadow economy, police force, and magistrate productivity; *v*) Voice and accountability, assessing the degree of freedom of the press and association. IQI ranges between 0 and 1. The closer the IQI is to 1, the higher the quality of the local institution.

Table 3 shows the summary statistics of the outcome variable LC% and the explanatory variables and the global Moran's *I* according to the four spatial weight matrix configurations. All descriptive statistics were computed on the original variables, without any transformation or pre-processing of the data. The logarithmic transformation was performed for the purpose of spatial econometric models. For metropolitan area we report the percentage of municipalities belonging to metropolitan city (metropolitan area = 1) and not belonging to (metropolitan area = 0). For the variable

Table 3 Descriptive statistics

Variable	Min	Max	Mean	St. deviation	Moran's I (W_1)	Moran's I (W_2)	Moran's I (W_3)	Moran's I (W_4)
LC%	0.296	89.726	10.488	10.141	0.765	0.684	0.640	0.758
Overall Surface	11.990	128,583.54	3,813.48	5,078.96	0.440	0.359	0.309	0.331
Elevation above sea	0	2,035	357.173	298.088	0.784	0.702	0.706	0.765
Population Density	0.008	122.750	3.044	6.496	0.735	0.632	0.548	0.722
Per capita housing	0.046	19.191	0.758	0.725	0.456	0.355	0.355	0.384
Employment Rate	18.000	74.020	44.927	7.942	0.820	0.794	0.806	0.801
Per capita GDP	14,505.50	53,231.32	26,628.31	7,750.85	0.654	0.649	0.659	0.655
Per capita enterprises	0.002	0.718	0.066	0.027	0.287	0.233	0.202	0.256
IQI	0	1	0.607	0.210	0.797	0.764	0.804	0.829
Dummy variable			%					
Metropolitan Area	-	1	16.59					
	0		83.41					

Table 4 Spatial dependence tests

OLS vs. SEM H_0: $\lambda=0$		OLS vs. SAR H_0: $\rho=0$		OLS vs. SAC H_0: $\lambda=\rho=0$	
LM lag:	11,753***	LM error:	2,225.9***	LM lag + error:	12,070***
RLM lag:	9,844.6***	RLM error:	317.5***		
SDM vs. SAR H_0: $\theta=0$		SDM vs. SEM H_0: $\theta+\rho\beta=0$			
LR SDM vs. SAR:	138.59***	LR SDM vs. SEM:	2,119.7***		

'metropolitan area', the percentage of municipalities belonging to the metropolitan city (metropolitan area = 1) and not belonging to (metropolitan area = 0) is reported.

5 Results

The results of LM tests and their robust versions provided significant evidence for both the autoregressive term and the autocorrelation structure; moreover, both LR tests point to a significant spatial autocorrelation in the covariates as well (Table 4). Therefore, the existence of all three forms of spatial relationships is proved: *i*) endogenous interaction, i.e. the patterns of land use in a given municipality depend on its neighbours, *ii*) exogenous interaction, i.e. these patterns also depend on the observable characteristics of neighbours; *iii*) spatial correlation of the effects due to the unobserved characteristics.

Table 5 shows the estimation results of the three spatial models using the first order binary contiguity matrix in row-standardised form (SDM, SDEM, SAC). Estimations of the linear model without spatial effects (OLS) are also presented. The log-log specification allows the coefficients to be interpreted as percentage variations and the derivative is the elasticity, i.e. the percentage change in land use rates for a unit percentage change in a given covariate. Table 6 shows the direct, indirect and total effects of each explanatory variable.

Comparing the three spatial models suggests that the SDEM gives the best specification. It shows the highest log likelihood function value, allows a direct interpretation of spillover effects and corrects the omission of potential spatially related attributes of municipalities from the model.

Following Stakhovych and Bijmolt (2009) and Case et al. (1993), we also run spatial models using the other three definitions of spatial weights (see Sect. 2), whose results are shown in Tables A1-A2-A3-A4-A5-A6 (Appendix A)[5]. The comparison between the estimation results of the three spatial models, on the one hand, and between the estimation results of the same models with the four configurations of the spatial weight matrix, on the other one, confirms the overall consistency of the estimates, which is also proven by all diagnostic tests (LeSage and Pace 2014).

[5] Tables A1-A2 show, respectively, the estimation results of the three spatial models and the direct, indirect, and total effects of each explanatory variable obtained using the second order binary contiguity matrix in row-standardised form. Tables A3-A4 show the estimation results obtained using the distance-band binary matrix based on the centroid distance in row-standardised form. Table A5-A6 show the estimation results obtained using the *k*-nearest neighbour matrix in row-standardised form.

Table 5 Estimates of spatial models using first order binary contiguity matrix, row-standardised

	OLS		SDM		SDEM		SAC	
Variable	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
Intercept	-0.3253	(0.1981)	0.2366	(0.1586)	0.824**	(0.3847)	0.366	(0.3778)
Elevation above sea	-0.0004***	(0.00001)	-0.00002	(0.00002)	-0.0001***	(0.00002)	-0.0002***	(0.00002)
Population density	0.5422***	(0.0038)	0.5077***	(0.0044)	0.509***	(0.0042)	0.5097***	(0.0044)
Per capita housing	0.0922***	(0.0103)	0.1555***	(0.0101)	0.1468***	(0.01)	0.15***	(0.0102)
Metropolitan area	-0.1335***	(0.0105)	-0.0701***	(0.0186)	-0.0651***	(0.0218)	-0.1032***	(0.016)
Employment rate	0.1636***	(0.0335)	0.1109***	(0.0303)	0.1039***	(0.0325)	0.1166***	(0.0335)
Per capita GDP	0.2072***	(0.0237)	0.1648***	(0.0209)	0.1103***	(0.0398)	0.1206***	(0.0375)
Per capita enterprises	0.1008***	(0.0109)	0.1108***	(0.0087)	0.1228***	(0.0094)	0.1124***	(0.0096)
IQI	0.0138	(0.0291)	-0.1017*	(0.0575)	-0.0585	(0.0712)	0.0461	(0.0485)
W* Elevation above sea			-0.0001***	(0.00002)	-0.0004***	(0.00004)	-	
W*Population density			-0.3316***	(0.0077)	0.0726***	(0.0085)	-	
W*Per capita housing			-0.1402***	(0.0141)	-0.0424*	(0.0224)	-	
W*Metropolitan area			0.0233	(0.0196)	-0.0733**	(0.0286)	-	
W*Employment rate			-0.0783*	(0.0414)	0.02	(0.0744)	-	
W*Per capita GDP			-0.1141***	(0.0171)	0.0152	(0.0303)	-	
W*Per capita enterprises			-0.0379***	(0.0145)	0.0422*	(0.0238)	-	
W*IQI			0.099*	(0.0585)	0.1252	(0.084)	-	
ρ			0.6899***	(0.0098)	-	-	**0.1661*****	**(.0100)**
λ			-	-	0.7126***	(0.0098)	**0.635*****	**(.0136)**
Number of observations	7,998		7,998		7,998		7,998	
Log likelihood	-		353.2774		435.8007		256.1629	
AIC	-		-668.55		-833.6		-488.33	
Adjusted R-squared	0.8834		-		-		-	

First order binary contiguity matrix, row-standardised

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 6 Direct, indirect and total effects of spatial models using first order binary contiguity matrix, row-standardised

	SDM	SDEM	SAC
Direct effects	-0.0001***	-0.0001***	-0.0003***
Elevation above sea	0.5116***	0.509***	0.5124***
Population density	0.1486***	0.1468***	0.1508***
Per capita homes	-0.0753***	-0.0651***	-0.1037***
Metropolitan area	0.1105***	0.1039***	0.1172***
Employment rate	0.1647***	0.1103***	0.1212***
GDP per capita	0.1188***	0.1228***	0.113***
Per capita enterprises	-0.0958**	-0.0586	0.0464
IQI			
Indirect effects	-0.0005***	-0.0004***	-0.00003***
Elevation above sea	0.0561***	0.0726***	0.0988***
Population density	-0.0993***	-0.0424*	0.0291***
Per capita homes	-0.0757**	-0.0733**	-0.02***
Metropolitan area	-0.0054	0.02	0.0226***
Employment rate	-0.0015	0.0152	0.0234***
GDP per capita	0.1162***	0.0422*	0.0218***
Per capita enterprises	0.0868	0.1252	0.0089
IQI			
Total effects	-0.0005***	-0.0004***	-0.0002***
Elevation above Sea	0.5677***	0.5816***	0.6112***
Population density	0.0494	0.10442***	0.1798***
Per capita homes	-0.1511***	-0.1384***	-0.1237***
Metropolitan area	0.1051	0.1239	0.1398***
Employment rate	0.1632**	0.1255**	0.1446***
GDP per capita	0.235***	0.165***	0.1348***
Per capita enterprises	-0.0089	0.0666	0.0553
IQI			

First order binary contiguity matrix, row-standardised

*Significant at 10%; **Significant at 5%; ***Significant at 1%

According to a stepwise procedure, all the presented covariates (Table 1) were adequately tested. About the spatial effects, as expected, both the spatial autocorrelation (ρ) and autoregressive (λ) coefficients are highly significant and positive, and all models with exogenous interactions show significant spillover coefficients. This means that interactions between municipalities play a crucial role in sketching the actual profile of land consumption in Italy, and local patterns mutually depend on those of neighbouring municipalities.

The estimated direct effects of population density are consistent throughout the models and indicate that, on average, an increase in population density causes an increase in land consumption. In particular, being the population size corrected for the space it occupies, the results imply that the response of municipalities to population increases as the average size of the municipality decreases, highlighting that land consumption directly depends on low-density spatial settlement (Guastella et al. 2017). The SAC results also show a trend towards growing land use with the increasing population of adjacent municipalities. This implies that land consumption is greatly influenced by crowding in a broad sense (Skonhoft and Solem 2001) in line with the literature that recognizes demographic and social developments as determinants of land use (Salvati et al. 2018; Wolfersberger et al. 2015). The consistency of the estimation results is also verified for per capita housing, as the coefficients are consistently positive for all spatial models and their magnitude varies little.

This direct relationship between residential demand and land consumption (Zoppi and Lai 2015) also finds historical reasons in that the growth of cities and almost all human settlements have been determined by population and, more recently, by the increased demand for housing (Bimonte and Stabile 2017; Guastella et al. 2017). Moreover, the ageing of society, the greater presence of smaller families or the higher number of singles in households (Getzner and Kadi 2020; Colsaet et al. 2018) are just some of the main social changes that can lead to an increase in land consumption. However, both direct and indirect (spillover) effects confirm the negative impact of altimetry on land use, showing the difficulty of sorting operations in adverse morphologic areas. Given the structural and non-modifiable nature of the morphology, these territories are usually characterized by a lower population density, a greater housing dispersion and a lower economic activity that negatively affect land consumption. The results show that belonging to a metropolitan area – meant as a set of neighbouring and independent municipalities that gravitate around one or more densely populated urban cores in commuting-conjunction with the suburban zone – tends to decrease land consumption both directly and indirectly. Metropolitan regions are internally more integrated, as municipalities would favour cooperation to maximize the positive effects of agglomeration advantages. A policy organising urban development in a metropolitan region is challenged to enable development on adequate sites while exerting less pressure on land, which allows metropolitan areas to be recognized a potential more efficiency in land use management (European Committee of the Regions, 2019; Guastella et al. 2017).

Moving to the economic dimension, it is worth noting that there is, as expected, a positive effect of economic activity on land use for all spatial regressions. In particular, per capita GDP[6] appears to be a significant direct determinant of land consumption[7]. Bimonte and Stabile (2017) found that increasing land use is coupled with income growth, meaning that the greater the developable land, the greater its consumption. Consistent with the theoretical prediction, the positive impact of employment rate and per capita enterprises on land consumption rate confirm that land tends to be converted into new developments when economic activity in the areas becomes flourishing (Skonhoft and Solem 2001). As employment and income increase, the general upgrading in local living conditions may incentive the housing demand in those areas and, therefore, land use demand for built-up zones and infrastructures (Getzner and Kadi 2020). Except for the SAC model, the estimated indirect effects of two out of three economic variables turn insignificant. This means that municipali-

[6] As LC% and GDP can be codetermined, i.e. land consumption can be related to GDP and vice versa, a 4-year lag (2012) in the measurement of GDP is used as an instrument in TSLS estimation to address potential endogeneity problems (Deng et al. 2015; Reed 2015; Jiang et al. 2013; Staiger and Stock 1997).

[7] The hypothesis that land use rises as economic growth increases up to a given turning point (Getzner and Kadi 2020; Wolfersberger et al. 2015), after which economic growth can be further achieved while land use no longer increases or increases at a diminishing rate, was also tested by including a quadratic functional form for the GDP in spatial models. However, the estimation results did not provide significant evidence for this specific pattern in our data.

ties with a relatively high per capita economic activity are more likely to have a high amount of land use, but the same land use intensity is less affected by the economic development of neighbouring municipalities.

Institutional quality may help explain territorial imbalance due to differences in the size of the informal sector and shadow economy (Di Liberto and Sideri 2015; Rodríguez-Pose 2013). The direct effects of IQI as a proxy for virtuous management of public affairs are significantly negative, implying that the higher the institutional quality, the lower the land consumption in Italy. In general, a more efficient legal system and a lower propensity to corruption play a significant role in preserving land use, in line with the strand of economic literature (Barbier and Tesfaw 2015; Wolfersberger et al. 2015; Galinato and Galinato 2013) proving that better institutional and regulatory quality could curb the rise in land use. By contrast, the institutions' weakness makes the local political bodies more vulnerable to illegal activities and speculative interests, making the land use process more difficult to manage.

6 Discussion

In recent years, European institutions have increasingly perceived the issue of land use as one of the major challenges facing Europe (European Committee of the Regions, 2019). However, the progressive increase in land consumption in Italy as well as in other European countries shows the frequent inability of local institutions to put EU concerns into practice.

This study demonstrated the presence of significant direct effects of local characteristics on land use patterns and significant spillover effects from adjacent municipalities and neighbours of neighbours. In line with the agent-based approach (Irwin and Bockstael 2002), this allows recognizing the interaction between the different actors operating in space as a fundamental role in decision-making processes relating to land use.

Findings suggest that land consumption is greatly influenced by crowding in the area; that is, the response of municipalities to land use depends directly on the demographic needs of the same municipality rather than on those of neighbouring areas. Similarly, land consumption also heavily depends on the levels of economic development of the municipality and, albeit to a lesser extent, on those of neighbouring communities. In a nutshell, the expansion of population density and dwelling needs and the decentralization of productive activities can be ascribed as the main factors of the uncontrolled land use growth in Italy with expected negative impacts on the environment.

The integration of municipalities in a context of shared identity, such as the metropolitan city, with a common perception of values, challenges and goals, seems to improve institutional cooperation, which in turn can help moderate land consumption. These results highlight the first point of criticism of land use management in Italy. If the territorial decentralization for land use planning, which is the responsibility of the municipalities, could allow direct control of land consumption (Wolfersberger et al. 2015), the high number of small and independent municipalities (approximately

8,000 with an average size of 36 km^2) leads to excessive administrative fragmentation. Therefore, administrative coordination across municipalities could form the basis for developing an integrated system of interaction among the various agents that helps design more effective solutions to hold up the land transformation and prevent over-exploitation (Hytönen et al. 2016). Given the presence of spillover effects, such an integrative approach could trigger a virtuous circle that would limit urban sprawl even in adjacent areas.

The institutionalization in Italy of the metropolitan cities (Law 56/2014) as a new government entity in charge of several functions, including strategic territorial planning, surely represents a fundamental step for structuring coordinated land use management systems and setting limits to municipal actions. However, while covering almost 17% of the total municipalities and about 36% of the national population, metropolitan cities concern only the main 14 Italian urban contexts, without considering the high heterogeneity in terms of wealth generated and the consistent gap to the detriment of southern cities. Therefore, further initiatives are called for promoting coordination and cooperation between metropolitan cities and non-metropolitan areas to develop a more aware land use management to achieve the goal of zeroing net land consumption (ISPRA-SNPA, 2018). This would promote the rehabilitation of degraded land or the repurpose of land already taken to adapt to climate change (Smiraglia et al. 2016) and the compensation for soil sealing with the re-naturalization of other areas that could return to providing the ecosystem services of natural soils.

Moreover, the results suggest that the extent of land consumption also depends on the quality of local institutions, stressing the second point of criticism of land use management in Italy. Poor government quality may hinder the effectiveness of land development strategies aimed at rationalizing land consumption and fighting against illegal activities (Romano and Zullo 2016). Italy is historically characterized by high heterogeneity in institutional performance, and the quality of local governments in southern Italy is far below that of northern Italy (Nifo and Vecchione 2014). Strengthening the qualitative characteristics of local institutions is an essential step to close the regional divides and better manage land use projects. Independently on the policies adopted, the effectiveness of land use actions passes unquestionably through the definition of clear rules of law, low levels of corruption in local administrations and high capabilities of governments to implement land use planning capable of producing a good environment for the creation of new value.

7 Conclusions

The contribution of this study was twofold. First, we set up an econometric framework to explore the main determinants of land consumption in Italian municipalities, thereby adding to the small number of studies that perform spatial econometric models. Second, this is one of the few studies investigating land use determinants at such fine geographic resolution covering the entire national territory, also taking spatial effects into account. It may provide insights into local policymakers who are increasingly called upon to plan and manage the future of sustainable cities.

We performed a set of spatial econometric models that allowed the comparison between estimated direct and spillover effects, which are, in substance, mutually consistent in terms of the sign, magnitude and significance levels, even when adopting different spatial weight matrices. The empirical results corroborated the idea behind the agent-based models that recognize the crucial role of interaction, collaboration and competition among various actors (i.e. local authorities, landlords, firms, investors, developers) in land use decision-making processes, providing an approach to modelling spatial complexity in land use patterns that takes care of the neighbourhood and/or distance between territorial areas.

While providing interesting food for thought for future research, the present work does not come without its limitations. First, the results enabled us to learn more about the main determinants of land consumption in Italy without, however, demanding their generalization to other levels of territorial disaggregation (e.g. regions, provinces). This means that the interpretation of the results is valid for the chosen geographic breakdown (Italian municipalities), which perfectly matches the economic reality of relationships between agents, even though the procedure can be easily applied to other contexts. Second, comparing multiple spatial econometric models allowed the consistency of the results to be assessed by controlling for the different forms of spatial relationship, although it cannot adequately address spatial heterogeneity, i.e. potential local variations due to the non-stationary of the spatial process. Finally, the analysis dealt with land consumption in general, regardless of its specific use. Compatibly with the availability of official data, upcoming further research is called for comparing land use drivers by type of use to establish best-practice guidelines for the management, control and direction of land use, e.g. the implementation of projects of 'land-use zoning', which would allow lands to be ranked based on their best uses. This study also calls for empirical validation in other countries at the same level of geographic detail in order to contextualize the research from an international perspective and provide policymakers with practical guidance.

8 Appendix A

Table A1 Estimates of spatial models using second order binary contiguity matrix

	SDM		SDEM		SAC	
Variable	Coef.	St. error	Coef.	St. error	Coef.	St. error
Intercept	0.1894	(0.1841)	1.1162**	(0.4516)	0.7602**	(0.3322)
Elevation above sea	-0.0001***	(0.00001)	-0.0001***	(0.00002)	-0.0001***	(0.00002)
Population density	0.5392***	(0.0042)	0.5365***	(0.0043)	0.5373***	(0.0043)
Per capita housing	0.1507***	(0.0103)	0.1445***	(0.0103)	0.1449***	(0.0103)
Metropolitan area	-0.0734***	(0.0182)	-0.0518**	(0.0219)	-0.0809***	(0.0178)
Employment rate	0.1326***	(0.0334)	0.1257***	(0.0341)	0.1287***	(0.0326)
Per capita GDP	0.1387***	(0.0209)	0.0472	(0.0457)	0.085**	(0.0334)
Per capita enterprises	0.101***	(0.0094)	0.1062***	(0.0095)	0.1039***	(0.0093)
IQI	-0.1701***	(0.0654)	-0.1214*	(0.0727)	-0.0006	(0.0006)
W* Elevation above sea	-0.000001	(0.00001)	-0.0003***	(0.0001)	-	
W*Population density	-0.437***	(0.0091)	0.025	(0.0153)	-	
W*Per capita housing	-0.1574***	(0.0168)	-0.1012**	(0.0419)	-	
W*Metropolitan area	0.0476**	(0.0211)	-0.0599	(0.0412)	-	
W*Employment rate	-0.1129**	(0.05)	-0.1451	(0.1356)	-	
W*Per capita GDP	-0.1157***	(0.0212)	0.0776	(0.0557)	-	
W*Per capita enterprises	-0.0637***	(0.0208)	-0.0047	(0.0477)	-	
W*IQI	0.1768**	(0.0717)	0.2924**	(0.1138)	-	
ρ	0.8138***	(0.0118)	–	–	**0.1237***	**(.0149)**
λ	–	–	0.8294***	(0.0119)	**0.8089***	**(.0138)**
Number of observations	7,998		7,998		7,998	
Log likelihood	125.3751		167.9819		96.5445	
AIC	-212.75		-297.96		-169.09	

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table A2 Direct, indirect and total effects of spatial models using second order binary contiguity matrix (including first order neighbours), row-standardized

	SDM	SDEM	SAC
Direct effects	-0.0001***	-0.0001***	-0.0001***
Elevation above sea	0.5394***	0.5365***	0.5378***
Population density	0.1470***	0.1445***	0.1451***
Per capita homes	-0.0746***	-0.0518**	-0.081***
Metropolitan area	0.1321***	0.1257***	0.1288***
Employment rate	0.1384***	0.0472	0.085***
GDP per capita	0.103***	0.1062***	0.104***
Per capita enterprises	-0.166***	-0.1214*	-0.0006
IQI			
Indirect effects	-0.0004***	-0.0003***	-0.00002***
Elevation above sea	0.0087	0.025	0.0754***
Population density	-0.1828***	-0.1012**	0.0203***
Per capita homes	-0.0632	-0.0599	-0.0114***
Metropolitan area	-0.0266	-0.1451	0.0181***
Employment rate	-0.0151	0.0776	0.0119***
GDP per capita	0.0969	-0.0047	0.0146
Per capita enterprises	0.2022	0.2924**	-0.0001
IQI			
Total effects	-0.0005***	-0.0004***	-0.0001***
Elevation above sea	0.5481***	0.5615***	0.6132***
Population density	-0.0358	0.0432	0.1654***
Per capita homes	-0.1379**	-0.1117***	-0.0924***
Metropolitan area	0.1055	-0.0194	0.1468***
Employment rate	0.1233	0.1248*	0.097***
GDP per capita	0.1999**	0.1015**	0.1186***
Per capita enterprises	0.0361	0.171*	-0.0007
IQI			

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table A3 Estimates of spatial models using the distance-band binary matrix based on the centroid distance, row-standardized

	SDM		SDEM		SAC	
Variable	Coef.	St. error	Coef.	St. error	Coef.	St. error
Intercept	0.3351***	(0.1301)	1.4572***	(0.3887)	0.9089***	(0.3996)
Elevation above sea	-0.0001***	(0.00002)	-0.00008***	(0.00002)	-0.0001***	(0.00002)
Population density	0.5458***	(0.0044)	0.5418***	(0.0043)	0.545***	(0.0044)
Per capita housing	0.151***	(0.0106)	0.1422***	(0.0105)	0.1464***	(0.0106)
Metropolitan area	-0.0533**	(0.0225)	-0.0224	(0.0212)	-0.0628***	(0.0205)
Employment rate	0.1365***	(0.033)	0.1122***	(0.0343)	0.1208***	(0.0351)
Per capita GDP	0.1254***	(0.02)	0.026	(0.0393)	0.0582	(0.043)
Per capita enterprises	0.0613***	(0.0075)	0.0737***	(0.0081)	0.0631***	(0.0079)
IQI	-0.0244	(0.0169)	-0.0273*	(0.014)	-0.0237*	(0.0136)
W* Elevation above sea	-0.0001**	(0.00002)	-0.0004***	(0.0001)	-	
W*Population density	-0.4451***	(0.0092)	0.0212	(0.0142)	-	
W*Per capita housing	-0.1795***	(0.0175)	-0.1527***	(0.0394)	-	
W*Metropolitan area	0.0181	(0.0285)	-0.1579***	(0.0408)	-	
W*Employment rate	-0.1503***	(0.0521)	-0.2051	(0.1292)	-	
W*Per capita GDP	-0.0971***	(0.021)	0.1407***	(0.0534)	-	
W*Per capita enterprises	-0.0046	(0.0086)	0.1684***	(0.0398)	-	
W*IQI	-0.0043	(0.0078)	-0.0557	(0.0807)	-	
ρ	0.8094***	(0.0127)	-	-	**0.1246*** **	**(.0155)**
λ	-	-	0.824***	(0.0121)	**0.8156*** **	**(.0139)**
Number of observations	7,984		7,984		7,984	
Log likelihood	73.0559		124.0173		33.6553	
AIC	-108.11		-210.03		-43.311	

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table A4 Direct, indirect and total effects of spatial models using the distance-band binary matrix based on the centroid distance, row-standardized

	SDM	SDEM	SAC
Direct effects	-0.0001***	-0.0001***	-0.0001***
Elevation above sea	0.5455***	0.5418***	0.5455***
Population density	0.1446***	0.1422***	0.1465***
Per capita homes	-0.0561***	-0.0224	-0.0629***
Metropolitan area	0.132***	0.1121***	0.121***
Employment rate	0.1258***	0.026	0.0583
GDP per capita	0.0663***	0.0737***	0.0632***
Per capita enterprises	-0.0271	-0.0273*	-0.0237*
IQI			
Indirect effects	-0.0005***	-0.0004***	-0.00001***
Elevation above sea	-0.0179	0.0212	0.0771***
Population density	-0.2938***	-0.1527***	0.0207***
Per capita homes	-0.1282*	-0.1579***	-0.0089**
Metropolitan area	-0.2046	-0.2051	0.0171***
Employment rate	0.022	0.1407***	0.0082
GDP per capita	0.2308***	0.1684***	0.0089***
Per capita enterprises	-0.1233	-0.0557	-0.0033*
IQI			
Total effects	-0.0006***	-0.0004***	-0.0001***
Elevation above sea	0.5276***	0.5629***	0.6226***
Population density	-0.1491**	-0.0105	0.1672***
Per capita homes	-0.1844***	-0.1803***	-0.0718***
Metropolitan area	-0.0726	-0.0929	0.138***
Employment rate	0.1479	0.1667***	0.0665
GDP per capita	0.2971***	0.2421***	0.0721***
Per capita enterprises	-0.1504	-0.083	-0.027*
IQI			

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table A5 Estimates of spatial models using *k*-nearest neighbour (knn) matrix, row-standardized

	SDM		SDEM		SAC	
Variable	Coef.	St. error	Coef.	St. error	Coef.	St. error
Intercept	0.1387	(0.1923)	0.7237*	(0.3974)	0.4158*	(0.2481)
Elevation above sea	-0.0001*	(2E-05)	-0.0001***	(2E-05)	-0.0002***	(0.00002)
Population density	0.5143***	(0.0045)	0.5153***	(0.0042)	0.5151***	(0.0044)
Per capita housing	0.1632***	(0.0102)	0.1527***	(0.0101)	0.1510***	(0.0101)
Metropolitan area	-0.0597***	(0.0230)	-0.0526*	(0.0221)	-0.1035***	(0.0161)
Employment rate	0.1295***	(0.0321)	0.1206***	(0.0327)	0.1233***	(0.0307)
Per capita GDP	0.1650***	(0.0256)	0.1116***	(0.0405)	0.1086***	(0.0281)
Per capita enterprises	0.1048***	(0.0086)	0.1137***	(0.0094)	0.1026***	(0.0089)
IQI	-0.0602	(0.0575)	-0.0297	(0.0758)	0.0692*	(0.0360)
W* Elevation above sea	-0.0001	(2E-05)	-0.0003***	(4E-05)	-	
W*Population density	-0.3387***	(0.0075)	0.0573***	(0.0087)	-	
W*Per capita housing	-0.1548***	(0.0142)	-0.0701***	(0.0232)	-	
W*Metropolitan area	0.0084	(0.0273)	-0.0957***	(0.0285)	-	
W*Employment rate	-0.1129**	(0.0451)	-0.0448	(0.0746)	-	
W*Per capita GDP	-0.1010***	(0.0204)	0.0337	(0.0314)	-	
W*Per capita enterprises	-0.0407*	(0.0185)	0.0350	(0.0244)	-	
W*IQI	0.0566	(0.0663)	0.1044	(0.0892)	-	
ρ	0.6846***	(0.0096)	–	–	**0.1570***	**(.0155)**
λ	–	–	0.7013***	(0.0095)	**0.6284***	**(.0139)**
Number of observations	7,998		7,998		7,998	
Log likelihood	329.4344		392.7165		220.6833	
AIC	-620.87		-747.43		-417.37	
Adjusted R-squared	–		–		–	

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table A6 Direct, indirect and total effects of spatial models using *k*-nearest neighbour (knn) matrix, row-standardized

	SDM	SDEM	SAC
Direct effects	-0.0001***	-0.0001***	-0.0002***
Elevation above sea	0.5171***	0.5153***	0.5176***
Population density	0.1539***	0.1527***	0.1517***
Per capita homes	-0.0667***	-0.0526**	-0.1040***
Metropolitan area	0.1242***	0.1206***	0.1239***
Employment rate	0.1675***	0.1116***	0.1091***
GDP per capita	0.1115***	0.1137***	0.1031***
Per capita enterprises	-0.0569	-0.0297	0.0696*
IQI			
Indirect effects	-0.0004***	-0.0003***	-0.00003***
Elevation above sea	0.0395***	0.0573***	0.0935***
Population density	-0.1274***	-0.0701***	0.0274***
Per capita homes	-0.0959**	-0.0957***	-0.0188***
Metropolitan area	-0.0717	-0.0448	0.0224***
Employment rate	0.0354	0.0337	0.0197***
GDP per capita	0.0918**	0.0350	0.0186***
Per capita enterprises	0.0455	0.1044	0.0126*
IQI			
Total effects	-0.0005***	-0.0004***	-0.0002***
Elevation above Sea	0.5566***	0.5726***	0.6111***
Population density	0.0265	0.0826***	0.1791***
Per capita homes	-0.1626***	-0.1483***	-0.1228***
Metropolitan area	0.0525	0.0758	0.1463***
Employment rate	0.2029***	0.1453***	0.1288***
GDP per capita	0.2033***	0.1487***	0.1217***
Per capita enterprises	-0.0114	0.0747	0.0822*
IQI			

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Contribution statements Gennaro Punzo conceived and designed the analysis, wrote the paper, verified the analytical method, developed the theoretical framework. Rosalia Castellano supervised the project. Emma Bruno collected the data, carried out the experiment, derived the models and analysed the data. All authors read and approved the final manuscript.

Funding No funds, grants, or other support was received.

Open access funding provided by Università Parthenope di Napoli within the CRUI-CARE Agreement.

Declarations

Competing interests All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

References

Aguiar APD, Câmara G, Escada MIS (2007) Spatial statistical analysis of land-use determinants in the Brazilian Amazonia: Exploring intra-regional heterogeneity. Ecol Model 209(2–4):169–188

Aldieri L, Vinci CP(2020) Climate change and knowledge spillovers for cleaner production: New insights. Journal of Cleaner Production271

Anselin L (1988) Model validation in spatial econometrics: a review and evaluation of alternative approaches. Int Reg Sci Rev 11(3):279–316

Anselin L (2001) In: Baltagi BH, Baltagi BH (eds) Spatial econometrics. A companion to theoretical econometrics, vol 1. Blackwell, Oxford

Anselin L (2003) Spatial externalities, spatial multipliers, and spatial econometrics. Int Reg Sci Rev 26(2):153–166

Anselin L, Bera AK, Florax R, Yoon MJ (1996) Simple diagnostic tests for spatial dependence. Reg Sci Urban Econ 26(1):77–104

Anselin L, Lozano-Gracia N (2008) Errors in variables and spatial effects in hedonic house price models of ambient air quality. Empirical Economics 34(1):5–34

Ay JS, Chakir R, Le Gallo J (2017) Aggregated versus individual land-use models: modeling spatial autocorrelation to increase predictive accuracy. Environ Model Assess 22(2):129–145

Barbier EB, Tesfaw A (2015) Explaining forest transitions: The role of governance. Ecol Econ 119:252–261

Bateman IJ, Jones AP, Lovett AA, Lake IR, Day BH (2002) Applying geographical information systems (GIS) to environmental and resource economics. Environ Resour Econ 22:219–269

Bimonte S, Stabile A (2017) Land consumption and income in Italy: a case of inverted EKC. Ecol Econ 131:36–43

Bradshaw TK, Muller B (1998) Impacts of Rapid Urban Growth on Farmland Conversion: Application of New Regional Land Use Policy Models and Geographical Information Systems 1. Rural Sociol 63(1):1–25

Briassoulis H (2019) *Analysis of Land Use Change: Theoretical and Modeling Approaches*. Scott Loveridge and Randall Jackson. WVU Research Repository

Burridge P, Elhorst JP, Zigova K (2016) Group interaction in research and the use of general nesting spatial models. Emerald Group Publishing Limited

Case AC, Rosen HS, Hines JR (1993) Budget spillovers and fiscal policy interdependence. J Public Econ 52(3):285–307

Chakir R, Le Gallo J (2013) Predicting land use allocation in France: A spatial panel data analysis. Ecol Econ 92:114–125

Cho M, Linneman P(1993) Interjurisdictional spillover effects of land use regulations.Journal of Housing Research,131–163

Ciccarelli C, Fenoaltea S (2013) Through the magnifying glass: provincial aspects of industrial growth in post-Unification Italy 1. The Economic History Review 66(1):57–85

Colsaet A, Laurans Y, Levrel H (2018) What drives land take and urban land expansion? A systematic review. Land Use Policy 79:339–349

De Sá SA, Palmer C, Di Falco S (2013) Dynamics of indirect land-use change: empirical evidence from Brazil. J Environ Econ Manag 65(3):377–393

Deng X, Huang J, Rozelle S, Uchida E (2010) Economic growth and the expansion of urban land in China. Urban Stud 47(4):813–843

Deng X, Huang J, Rozelle S, Zhang J, Li Z (2015) Impact of urbanization on cultivated land changes in China. Land Use Policy 45:1–7

Di Liberto A, Sideri M (2015) Past dominations, current institutions and the Italian regional economic performance. *European Journal of Political Economy* 38, 12–41 (2015)

Elhorst JP (2010) Applied spatial econometrics: raising the bar. Spat Economic Anal 5(1):9–28

European Committee of the Regions (2019) The impacts of metropolitan regions on their surrounding areas. Available at http://www.cor.europa.eu

European Environmental Agency (2017) Landscapes in transition. An account of 25 years of land cover change in Europe, vol 10. EEA Report

Feng Y, Yang Q, Hong Z, Cui L (2018) Modelling coastal land use change by incorporating spatial autocorrelation into cellular automata models. Geocarto Int 33(5):470–488

Ferris AE, Frank EG (2021) Labor market impacts of land protection: The Northern Spotted Owl. J Environ Econ Manag 109:102480

Fingleton B, Le Gallo J (2008) Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: finite sample properties. Papers in Regional Science 87(3):319–339

Fiorini L, Zullo F, Romano B (2017) Urban development of the coastal system of the Italian largest islands: Sicily and Sardinia. Ocean & Coastal Management 143:184–194

Galinato GI, Galinato SP (2013) The short-run and long-run effects of corruption control and political stability on forest cover. Ecol Econ 89:153–161

Getzner M, Kadi J (2020) Determinants of land consumption in Austria and the effects of spatial planning regulations. Eur Plan Stud 26(8):1095–1117

Guastella G, Pareglio S, Sckokai P (2017) A spatial econometric analysis of land use efficiency in large and small municipalities. Land Use Policy 63:288–297

Haines-Young R (2009) Land use and biodiversity relationships. Land Use Policy 26:S178–S186

Halleck Vega S, Elhorst JP (2015) The SLX model. J Reg Sci 55(3):339–363

Handavu F, Chirwa PW, Syampungani S (2019) Socio-economic factors influencing land-use and land-cover changes in the miombo woodlands of the Copperbelt province in Zambia. For Policy Econ 100:75–94

Huang C, Huang X, Peng C, Zhou Z, Teng M, Wang P (2019) Land use/cover change in the Three Gorges Reservoir area, China: Reconciling the land use conflicts between development and protection. CATENA 175:388–399

Hytönen J, Mäntysalo R, Peltonen L, Kanninen V, Niemi P, Simanainen M (2016) Defensive routines in land use policy steering in Finnish urban regions. Eur Urban Reg Stud 23(1):40–55

Irwin EG, Bockstael NE (2002) Interacting agents, spatial externalities and the evolution of residential land use patterns. J Econ Geogr 2(1):31–54

Ispra(2015) Il consumo di suolo in Italia. Rapporti 218/2015

ISPRA-SNPA (2018) Qualità dell'ambiente urbano – XIV Rapporto ISPRA Stato dell'Ambiente 82/18

Ji H, Tate MP (2021) Spillover effects of central cities on sustainability efforts in a metropolitan area. Policy Sci 54(1):95–121

Jiang L, Deng X, Seto KC (2013) The impact of urban expansion on agricultural land use intensity in China. Land Use Policy 35:33–39

Kaufmann D, Kraay A, Mastruzzi M (2011) The Worldwide Governance Indicators: Methodology and Analytical Issues. Hague J Rule Law 3:220–246

Kelejian HH, Robinson DP (1993) A suggested method of estimation for spatial interdependent models with autocorrelated errors, and an application to a county expenditure model. Papers in Regional Science 72:297–312

Kelejian HH, Prucha IR (1998) A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. J Real Estate Finance Econ 17(1):99–121

Kelejian HH, Prucha IR (2010) Spatial models with spatially lagged dependent variables and incomplete data. J Geogr Syst 12(3):241–257

Lee LF (2003) Best spatial two-stage least squares estimators for a spatial autoregressive model with autoregressive disturbances. Econom Rev 22:307–335

Lee LF (2007) GMM and 2SLS estimation of mixed regressive, spatial autoregressive models. J Econ 137(2):489–514

LeSage JP, Pace RK (2014) The biggest myth in spatial econometrics. Econometrics 2(4):217–249

LeSage J, Pace RK (2009) Introduction to spatial econometrics. Chapman and Hall/CRC

Manski CF (1993) Identification of endogenous social effects: The reflection problem. Rev Econ Stud 60(3):531–542

Mazzocchi C, Sali G, Corsi S (2013) Land use conversion in metropolitan areas and the permanence of agriculture: Sensitivity Index of Agricultural Land (SIAL), a tool for territorial analysis. Land Use Policy 35:155–162

Mellino S, Ulgiati S (2015) Mapping the evolution of impervious surfaces to investigate landscape metabolism: An Emergy–GIS monitoring application. Ecol Inf 26:50–59

Meyfroidt P (2016) Approaches and terminology for causal analysis in land systems science. J Land Use Sci 11(5):501–522

Meyfroidt P, Lambin EF, Erb KH, Hertel TW (2013) Globalization of land use: distant drivers of land change and geographic displacement of land use. Curr Opin Environ Sustain 5(5):438–444

Nifo A, Vecchione G (2014) Do institutions play a role in skilled migration? The case of Italy. Reg Stud 48(10):1628–1649

Overmars KP, De Koning GHJ, Veldkamp A (2003) Spatial autocorrelation in multi-scale land use models. Ecol Model 164(2–3):257–270

Overmars KP, Verburg PH (2005) Analysis of land use drivers at the watershed and household level: linking two paradigms at the Philippine forest fringe. Int J Geogr Inf Sci 19(2):125–152

Pileri P, Maggi M (2010) Sustainable planning? First results in land uptakes in rural, natural and protected areas: the Lombardia case study (Italy). J Land Use Sci 5(2):105–122

Polasky S, Costello C, McAusland C (2004) On trade, land-use, and biodiversity. J Environ Econ Manag 48(2):911–925

Punzo G, Castellano R, Bruno E (2022) Using geographically weighted regressions to explore spatial heterogeneity of land use influencing factors in Campania (Southern Italy). Land Use Policy 112:105853

Reed WR (2015) On the practice of lagging variables to avoid simultaneity. Oxf Bull Econ Stat 77(6):897–905

Rodríguez-Pose A (2013) Do institutions matter for regional development? Reg Stud 47(7):1034–1047

Romano B, Zullo F, Ciabò S, Fiorini L, Marucci A(2015) Geografie e modelli di 50 anni di consumo di suolo in Italia. Scienze e ricerche (n. 6), aprile. ISSN: 2283–5873

Romano B, Zullo F (2014a) Land urbanization in Central Italy: 50 years of evolution. J Land Use Sci 9(2):143–164

Romano B, Zullo F (2014b) The urban transformation of Italy's Adriatic coastal strip: Fifty years of unsustainability. Land Use Policy 38:26–36

Romano B, Zullo F (2016) Half a century of urbanization in southern European lowlands: a study on the Po Valley (Northern Italy). Urban Res Pract 9(2):109–130

Salvati L, Carlucci M (2016) Patterns of sprawl: The socioeconomic and territorial profile of dispersed urban areas in Italy. Reg Stud 50(8):1346–1359

Salvati L, Perini L, Sabbi A, Bajocco S (2012) Climate aridity and land use changes: A regional-scale analysis. Geographical Res 50(2):193–203

Salvati L, Zambon I, Chelli FM, Serra P (2018) Do spatial patterns of urbanization and land consumption reflect different socioeconomic contexts in Europe? Sci Total Environ 625:722–730

Salvati L, Zitti M, Perini L (2016) Fifty years on: long-term patterns of land sensitivity to desertification in Italy. Land Degrad Dev 27(2):97–107

Savini F, Aalbers MB (2016) The de-contextualisation of land use planning through financialisation: Urban redevelopment in Milan. Eur Urban Reg Stud 23(4):878–894

Schneider LC, Pontius RG Jr (2001) Modeling land-use change in the Ipswich watershed, Massachusetts, USA. Agric Ecosyst Environ 85(1–3):83–94
Sciara GC (2020) Implementing regional smart growth without regional authority: The limits of information for nudging local land use. Cities 103:102661
Shu C, Xie H, Jiang J, Chen Q (2018) Is urban land development driven by economic development or fiscal revenue stimuli in China? Land Use Policy 77:107–115
Silveira P, Dentinho TP (2018) A spatial interaction model with land use and land value. Cities 78:60–66
Skonhoft A, Solem H (2001) Economic growth and land-use changes: the declining amount of wilderness land in Norway. Ecol Econ 37(2):289–301
Smiraglia D, Ceccarelli T, Bajocco S, Salvati L, Perini L (2016) Linking trajectories of land change, land degradation processes and ecosystem services. Environ Res 147:590–600
Staiger DO, Stock JH (1997) Instrumental variables regression with weak instruments. Econometrica 65:557–586
Stakhovych S, Bijmolt TH (2009) Specification of spatial models: A simulation study on weights matrices. Papers in Regional Science 88(2):389–408
Tellman B, Eakin H, Janssen MA, de Alba F, Turner II, B.L (2021) The role of institutional entrepreneurs and informal land transactions in Mexico City's urban expansion. World Dev 140:105374
Towe CA, Klaiber HA, Wrenn DH (2017) Not my problem: Growth spillovers from uncoordinated land use policy. Land Use Policy 67:679–689
Turner BL, Meyfroidt P, Kuemmerle T, Müller D, Chowdhury R, R (2020) Framing the search for a theory of land use. J Land Use Sci 15(4):489–508
United Nations – Economic and Social Council (2019) Special edition: progress towards the Sustainable Development Goals, E/2019/68 Economic and Social Council, https://undocs.org/en/E/2019/68
United Nations Environment Programme – UNEP (2012) GEO5: Global Environment Outlook - Environment for the Future We Want. Nairobi. Available from http://www.unep.org/geo/pdfs/geo5/GEO5_report_full_en.pdf
Verburg PH, Schot PP, Dijst MJ, Veldkamp A (2004a) Land use change modelling: current practice and research priorities. GeoJournal 61(4):309–324
Verburg PH, van Eck JRR, de Nijs TC, Dijst MJ, Schot P (2004b) Determinants of land-use change patterns in the Netherlands. Environ Plan 31(1):125–150
Wang J, Wu Q, Yan S, Guo G, Peng S (2020) China's local governments breaking the land use planning quota: A strategic interaction perspective. Land Use Policy 92:104434
Wolfersberger J, Delacote P, Garcia S (2015) An empirical analysis of forest transition and land-use change in developing countries. Ecol Econ 119:241–251
Wu Y, Shan J, Choguill CL (2021) Combining behavioral interventions with market forces in the implementation of land use planning in China: A theoretical framework embedded with nudge. Land Use Policy 108:105569
Zoppi C, Lai S (2015) Determinants of land take at the regional scale: A study concerning Sardinia (Italy). Environ Impact Assess Rev 55:1–10