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Land Management and Utilization
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Anthropogenic Drivers of Land Take—A Panel Spatial Durban Error Model Analysis for Bavarian Municipalities

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Received: 21 December 2025; **Revised:** 18 February 2026; **Accepted:** 29 February 2026; **Published:** 27 March 2026

Abstract: This study examines the anthropogenic determinants of land take using a spatially extended STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework applied to panel data from 1,600 municipalities in Bavaria, Germany, covering the period from 2014–2022. A Spatial Durbin Error Model is employed to account for spatial dependence and spillover effects across neighboring municipalities. Moreover, literature defines affluence typically as income or GDP per capita indicating the level of affluence of private households or regions. In contrast, the results of this paper demonstrate that (also) public affluence is a suitable indicator for explaining land take. The results show that population and public affluence exert positive local effects on land take, while urban density significantly restrains land take. Moreover, a non-linear Environmental Kuznets Curve relationship for public affluence is observed, which materializes also through spatial spillover effects. Building permissions emerge as a key policy-related driver, generating positive indirect effects that propagate land consumption across adjacent municipalities. These findings highlight that land take is not only shaped by local conditions but evolves as a spatially interconnected process driven by fiscal capacity and planning decisions. The study underscores the need for coordinated, multi-regional land-use policies and highlights the analytical value of small-scale spatial STIRPAT applications in capturing environmentally relevant development dynamics.

Keywords: Land Take; Regional; STIRPAT; Spatial

1. Introduction

Land take is defined as the conversion of natural and semi-natural areas (e.g., agricultural land) into artificial land used for industry, housing and infrastructure [1]. It normally goes hand in hand with soil sealing, defined as the permanent covering of the soil surface by impermeable materials such as concrete and asphalt and therefore puts enormous pressure on habitats and soil functions including water infiltration, carbon storage, nutrient cycling, and biodiversity habitat provision. Beyond ecological degradation, land take (or in particular soil sealing) exacerbates urban heat island effects, increases flood risks, and diminishes the overall resilience of landscapes to climate change impacts. The phenomenon of land take is closely tied to urban sprawl, exacerbating inefficient land use patterns, increasing resource consumption, and magnifying ecological footprints.

Given these multifaceted consequences, limiting land take has become a policy priority of the EU, manifested for example in the Commission's soil strategy aiming at no net land take (NNLT) by 2050 [2].

In line with this target, land take in Germany must be reduced to net zero by 2050, mainly by higher compactness of cities, more efficient land uses outside the cities and a stronger focus on renaturation. However, despite some remarkable success between the years 2000 and 2015, where land take could have been reduced by about 50% [3], figures are now stagnating at about 58 ha of land a day.

The drivers behind this process are complex and often intertwined, ranging from demographic pressures and economic growth to governance frameworks and policy incentives. Understanding these drivers is crucial for designing effective mitigation strategies. However, the literature still faces challenges in capturing the localized, temporal, and spatial heterogeneity of land take, particularly at administrative levels where land use decisions are often made. Germany, however, offers a compelling observational unit due to its strong tradition of local self-government, where municipalities wield substantial authority over land use planning, building permits, and local infrastructure development.

We take advantage of this fact and employ a STIRPAT model (Stochastic Impacts by Regression on Population, Affluence, and Technology) to analyze main human anthropogenic drivers of land take caused by human activities at the level of municipalities. While the STIRPAT framework has been widely applied to investigate factors driving CO_2 emissions or air pollution its use in soil sealing research remains limited. Even fewer studies incorporate spatial dependencies that arise naturally in geographically contiguous units, where spillover effects and spatial autocorrelation can influence land take dynamics.

This paper contributes to filling these gaps by applying a modified STIRPAT model within a spatial panel data framework to analyze the anthropogenic drivers of land take across more than 1,600 Bavarian municipalities over the period 2014 to 2022. The study incorporates key variables including population, public affluence, building permits, and urban density to capture demographic, economic, policy, and structural influences. It also explicitly accounts for spatial dependencies, recognizing the interconnected nature of municipal decision-making and land use patterns.

For this purpose, the remainder of the paper is organized as follows. Section 2 discusses the drivers of soil sealing in the literature and reviews the empirical findings in this context. Section 3 presents the STIRPAT model specification and shows the scarce application in the STIRPAT community so far. Section 4 describes the data and presents the empirical application with results. Section 5 discusses the results and finally, the paper closes with concluding remarks and brief policy implications in Section 6.

2. Drivers of Land Take

A growing body of literature investigates the underlying drivers of land take, using different methodological and disciplinary approaches.

To begin with, Colsaet et al. [4] present a review of 193 qualitative and quantitative studies published between 1990 and 2016 in this field of research. The authors categorize drivers into four thematic groups: socio-economic drivers, policies and institutions, geographical constraints and path dependency or neighboring effects. Their findings highlight the dominance of economic and population growth as determinants of soil sealing. Moreover, studies show that infrastructure and transport can be important factors. Finally, neighboring effects should be considered, and the effects of public policies need more research attention.

Behnisch et al. [5] investigate the drivers of soil sealing of German municipalities for 2006 and 2012 by using satellite data. The study finds population growth and housing demand as key factors, as well as infrastructure density. Their findings highlight the spatial heterogeneity of land take, showing that even municipalities with declining populations can experience sealing due to legacy planning decisions and infrastructure expansion.

Next, Naumann et al. [6] investigate land use developments between 2000 and 2010 for European cities based on interviews (e.g., Milan, Vienna or Regensburg) and emphasize the complexity of land take dynamics driven by urbanization, infrastructural expansion, fragmented governance, and weak enforcement of spatial planning laws. Thus, they advocate for integrated land use governance and policy instruments like urban growth boundaries and specific compensation mechanisms.

Getzner et al. [7] use about 2,100 Austrian municipal-level data for the period from 2001 to 2019 for a panel regression analysis to explore socio-economic, political, and fiscal drivers of land use decisions. The study emphasizes the role of Austria's fiscal equalization system, which incentivizes municipalities to expand settlement areas to increase shared revenues from population and business growth. The analysis also reveals spatial spillovers regarding land consumption. Ge et al. [8] also find significant spillover effects when analyzing the relationship between land use and carbon emissions of 107 Chinese cities from 2003 to 2021. Luge et al. [9] find that land use structure efficiency has a positive spatial spillover effect across China by analyzing 282 Chinese cities from the period 2012 to 2021.

Bimonte and Stabile [10] analyze Italian regions from 2001 to 2012 by applying a panel regression approach to examine the relationship between economic development, corruption, and soil sealing. The regional analysis shows an inverted-U shaped relationship between GDP per capita and soil sealing, implying that regions with wealthier population may eventually adopt more sustainable land use practices. However, the inclusion of corruption indicators reveals that poor governance weakens the potential environmental benefits of affluence. In addition, Borruso et al. [11] find that Italy is in the decreasing phase of the Environmental Kuznets Curve (EKC) by analyzing the relationship between GDP per capita and land consumption of Italian provinces between 2015 and 2021.

Finally, Lohwasser et al. [12] analyze German districts between 2000 and 2020, linking demographic and economic determinants to local land transformation and air pollution. The study shows that while population and affluence significantly drive land take, the effect is moderated by its underlying urban form. For example, compact cities may mitigate environmental pressures compared to sprawling regions. By quantifying these dynamics in a multivariate, regionally differentiated model, the study applies the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework in this context.

Notably most studies identifying affluence as a potential driver of land take, generally refer to the wealth of the population rather than the municipalities' financial resources. One exception is an empirical study by Larsen and Hertwich [13] on municipal carbon footprints that analyzes potential impacts of available public funds for 429 Norwegian municipalities. Accordingly, local carbon footprints clearly increase with available funds, which could be explained by higher public spending in CO_2 intensive sectors (e.g., the building sector). A similar assumption could be made for land take, as rich municipalities can spend much more money on extended transport infrastructure, commercial space or residential area. At the same time, rich municipalities' land use management might be more restrictive to protect inner city green spaces and the surrounding nature, which clearly adds to quality of life.

All in all, the existing literature analyzes many potential influencing factors of land take. However, most studies do not analyze factors at the administrative level where the decisions on land use are made. Moreover, variables directly based on the decision-making units like public affluence are not considered so far. This paper addresses these gaps by focusing on the administrative level at which land use decisions occur, explicitly incorporating municipal fiscal capacity and spatial spillovers within a spatial panel framework.

3. Spatial Enlargement of the STIRPAT Framework

There exist plenty of studies using the STIRPAT framework in order to identify human drivers of environmental outcomes. Although it is important to consider spatial dependencies when analyzing environmental phenomena that exhibit geographic spillovers and localized interactions, only a few STIRPAT studies consider the spatial dimension.

Huang et al. [14] study $PM_{2.5}$ concentration factors in 31 Chinese provinces over the period 1998 to 2012. Liu and Nie [15] examine the food nitrogen footprint drivers across 30 Chinese provinces from 2000 to 2018. Li and Li [16] investigate the relationship between CO_2 emissions and economic growth across 30 Chinese provinces from 2016 to 2020. You and Lv [17] explore globalization effects on CO_2 emissions across 83 countries between 1985 and 2013. McGee et al. [18] analyze the impact of technology on CO_2 emissions for 173 countries at a single point in time. Last, Montero et al. [19] analyze drivers of NO_x concentration for 179 municipalities in the Madrid region between 2000 and 2009.

All studies focus on large spatial units—countries or sizable (Chinese) provinces—except for Montero et al. [19], who analyze a relatively small number of municipalities in Spain. Thus, there exists a gap in STIRPAT studies dealing with real small-scale spatial units over time.

The STIRPAT model has been widely employed across diverse research contexts to quantitatively assess human-induced environmental impacts. STIRPAT models are used to explain various environmental outcomes like CO_2-emissions, air pollution or energy consumption (see Vélez-Henao et al. [20] for an overview).

This methodological framework offers a powerful and adaptable approach for disentangling the contributions of demographic, economic, and technological factors to environmental change. Land take constitutes a critical indicator of environmental degradation. It is, therefore, noteworthy and somewhat unexpected that the application of the STIRPAT model to investigate land take dynamics remains scarce in existing literature.

Therefore, this study applies a spatially extended STIRPAT framework for 1,600 Bavarian municipalities between 2014 and 2023. This local-based approach is particularly appropriate for Germany, where municipal authorities have autonomy in land use decisions and thus make them the most relevant spatial units for analysis.

By integrating spatial panel regression within the STIRPAT model, this study not only demonstrates the adequacy of STIRPAT for land take analysis but also reveals the added value of working with small administrative units. This approach improves the understanding of spatial dependencies, spillover effects, and local policy impacts that can typically not be identified in analyses at higher aggregation levels.

Starting with the familiar, Ehrlich and Holdren [21] suggest a conceptual framework for calculating factors that contribute to environmental impacts. The so-called IPAT approach assumes that environmental impacts (I) are the product of population (P), affluence (A) and technology (T) [21,22]:

$$I = P \cdot A \cdot T. \tag{1}$$

Some time later, Dietz and Rosa [23] suggest to transform the IPAT equation into the so-called STIRPAT model that explains STochastic Impacts on the environment by Regression on Population, Affluence and Technology and provides the framework for empirical analysis. This development is due to the demand for estimating driving factors stochastically. The STIRPAT model can be expressed as follows:

$$I_{i,t} = c_t \cdot P_{i,t}^{\alpha} \cdot A_{i,t}^{\beta} \cdot T_{i,t}^{\gamma} \cdot e_{i,t}, \tag{2}$$

where $I_{i,t}$ is the environmental impact of country i at time t, $P_{i,t}$ is population, $A_{i,t}$ is affluence, $T_{i,t}$ is technology, c_t is the constant and $e_{i,t}$ is the residual error term. α, β and γ are the environmental outcome elasticities with respect to population, affluence or technology, respectively. The logarithmic form of Equation (2) dampens the skewed distribution of the variables and gives a tractable regression equation. So, the model is set up according to Equation (3):

$$\ln I_{i,t} = \ln c_t + \alpha \cdot \ln P_{i,t} + \beta \cdot \ln A_{i,t} + \gamma \cdot \ln T_{i,t} + \ln e_{i,t}, \tag{3}$$

By following most STIRPAT studies technology ($T_{i,t}$) is assumed to be part of the error term and caught up by time-fixed effects.

In addition, neighboring regions may exert an (additional) impulse through changes in (their) explanatory variables or due to other non-specified variables captured in the residuals. This especially holds for local trends such as land use, where decisions are made at the municipality level and municipalities in turn are exchanging with each other (e.g., official networks or natural exchange). Accordingly, the spatial panel model could be defined as a spatial Durbin model (SDM) (Equation (4a)) or spatial Durbin error model (SDEM) (Equation (4b)):

$$y = \rho W y + X\beta + WX\gamma + \varepsilon \tag{4a}$$

$$y = X\beta + WX\gamma + u, u = \lambda W u + \varepsilon \tag{4b}$$

where y is the vector of the dependent variables (impact I) for n municipalities, X the $n \times k$ matrix of explanatory variables, β the vector of elasticities, W the weight matrix (representing the spatial interaction effects of the dependent variable with the dependent variable in neighboring municipalities), ρ the spatial autoregressive coefficient (measuring the effect of the spatial correlation between one municipality and other neighboring municipalities), γ the exogenous spatial lag parameter, u denotes errors, ε residuals and λ is the parameter reflecting spatial correlation among errors.

4. Empirical Application

4.1. Data Description

For the empirical application, a balanced cross-regional panel dataset of 1,600 Bavarian municipalities between 2014 and 2022 is analyzed. Our dependent variable is land take, defined by the sum of residential buildings, transport as well as industrial and commercial area.

Turning to the explanatory variables, land take can first be assumed to rise with population, defined as increases in total number of residents. Obviously, the soil of the settlement and transport area is not completely sealed. In Germany, the share of sealed soil of the settlement and transport area is estimated at least to be about 45% [24]. Nevertheless, the settlement and transport area is the most intensive form of soil sealing with respect to other forms of land use. The second classical driver in the STIRPAT framework is affluence, which can be conceptualized in different ways depending on the context. While affluence is often measured as private affluence, commonly proxied by gross domestic product (GDP) per capita, we emphasize public affluence, defined here as the available public budget per capita. This distinction is crucial in the context of land use change because decisions regarding land allocation and development are predominantly made at the municipal level by public authorities rather than private households.

To operationalize public affluence, we utilize sales tax revenues per capita as an indicator of municipal financial capacity. This measurement captures the fiscal resources available to local governments, which directly influence their ability to invest in infrastructure, settlement expansion, and other land-intensive activities. This approach aligns with Larsen and Hertwich [13], who argue that wealthier municipalities are better positioned to expand built environments to accommodate population growth and economic development, thereby driving land take. Furthermore, Diezmartínez and Short Gianotti [25] highlight the role of public spending in shaping environmental policies. The incorporation of public affluence thus enhances the explanatory power of the STIRPAT framework in understanding land take within the complex socio-political context of municipal governance.

However, the relationship between public affluence and land take is potentially non-linear, reflecting the Environmental Kuznets Curve (EKC) hypothesis within the governance context. Specifically, municipalities with very high public affluence may prioritize environmental conservation and sustainable land management, leading to a deceleration or reversal of land take trends over time. This dynamic suggests that after a certain public income threshold, increased affluence fosters investments in environmental quality, green space preservation, and stricter land use regulations, which could mitigate land conversion.

To capture this non-linear relationship and potential EKC effects empirically, we include a squared term of public affluence in the model. This specification allows us to test the hypothesis that the impact of public affluence on land take changes direction at higher levels of municipal wealth, reflecting a transition from expansion-driven land use to environmentally conscious land preservation.

Another variable directly representing a municipal characteristic is building permissions (measured by the number of building permissions issued of one municipality compared to all building permissions of all municipalities for a specific year). The variable is supposed to indicate a municipalities openness regarding building projects.

Finally, land take is assumed to slow down with increasing urban density. This is simply due to the fact that high density areas are characterized by an already high share of built-up areas and scarce unsealed land. This is in contrast to cities' peripheries, where shares of unsealed land are high and land take is driven by low density suburban development (EC. Urban Sprawl in Europe).

With regard to the spatial enlargement of the model, the weighting matrix is defined as inverse distance matrix, i.e., the matrix represents the reciprocal of the distance between spatial units with closer units having higher weights. The matrix based on inverse distances seems to be preferred over a contiguity matrix (i.e., direct neighbors are considered with respect to shared borders) on municipality level due to the independency of short intermunicipal distances on shared borders or communal networks at district (across municipalities) levels (so the neighboring effect does not "stop" after the second border; nevertheless, the contiguity matrix is also used for robustness reasons).

Table 1 presents a descriptive overview of all variables which all stem from the Bavarian Statistical Office [26].

Table 1. Summary statistics.

Variables	Units	Mean	Standard Deviation	Minimum	Maximum
Land take (settlement and transport area)	total ha	212.60	158.79	34.20	1,411.49
Population	total number	5,214.12	5,447.49	587	61,440
Public affluence (sales tax per inhabitant)	€/capita	48.22	72.25	2.87	1,260.04
Building permissions	% of building permissions (from all municipalities)	0.00050	0.00050	0.000033	0.0079
Density	inhabitants/ha	1.90	2.49	0.12	31.51

4.2. Model Setup and Results

Starting with the Moran test for spatial autocorrelation, findings indicate a spatial dependency among residuals. Furthermore, the Breusch-Pagan test shows that there is spatial heterogeneity in the residuals (**Table 2**). Thus, following regression Equation (4b), the SDEM is estimated. The SDEM is used due to the dependency among residuals and the assumption that the explanatory variables influence the explained variable in one region and another region. Concretely, we explain land take (y) by population, public affluence, public affluence squared, building permission and population density (X). Moreover, land take is explained by the development of these factors in neighboring regions.

Table 2. Moran (Chi^2) and Breusch-Pagan (BP) test statistics.

Year	Chi^2/BP	Year	Chi^2/BP	Year	Chi^2/BP
2014	437.96***/6.89***	2017	443.24***/6.76***	2020	434.45***/7.89***
2015	437.78***/7.34***	2018	446.95***/6.97***	2021	426.39***/7.48***
2016	443.48***/6.35***	2019	435.66***/8.43***	2022	431.26***/6.99***

Note: *** $p < 0.01$.

The SDEM is estimated with both, random- and fixed-effects as well as two types of matrices (i.e., inverse distance and contiguity) to control for the robustness of results (**Table 3**). Note, that the postestimation test statistics are inconclusive regarding a decision for the fixed- or random-effects model. For example, Pseudo R^2 and Wald Chi^2 test statistics indicate that the random-effects model is preferred over the fixed-effects model. However, focusing on the Hausman test statistic, BIC/AIC criteria or log likelihood indicates that the fixed-effects would be preferred over the random-effects model.

Table 3. Impacts on land take (SDEM Model).

Land Take (Total)	(1) Fixed-Effects	(2) Random-Effects	(3) Fixed-Effects	(4) Random-Effects
Population	0.33***	0.84***	0.34***	0.81***
	(0.02)	(0.01)	(0.02)	(0.01)
Public Affluence	0.01***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Public Affluence squared	−0.01	−0.01*	−0.02**	−0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Building permission	0.01	0.01***	0.01*	0.01***
	(0.01)	(0.01)	(0.01)	(0.01)
Urban density	−0.17***	−0.34***	−0.17***	−0.37***
	(0.02)	(0.01)	(0.02)	(0.01)
Constant	No constant	−1.53***	No constant	−1.59***
		(0.09)		(0.08)
W times population	0.08	−0.04	−0.01	0.02***
	(0.96)	(0.04)	(0.07)	(0.01)
W times public affluence	0.92***	0.42***	0.01	−0.01
	(0.14)	(0.16)	(0.01)	(0.01)
W times public affluence squared	−0.11***	−0.06***	−0.01	0.01
	(0.02)	(0.02)	(0.01)	(0.01)
W times building permission	0.02**	0.07***	0.01	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
W times urban density	−0.13	−0.07	0.03	0.44***
	(0.91)	(0.08)	(0.07)	(0.01)
λ	4.62***	3.38***	0.44***	0.44***
	(0.05)	(0.01)	(0.01)	(0.01)
Type of matrix W	Inverse distance	Inverse distance	contiguity	Contiguity
Pseudo R^2	0.22	0.90	0.56	0.89
AIC Criterion	−63,188.91	−58,896.24	−63,365.90	−59,004.66
BIC Criterion	−63,037.41	−58,729.59	−63,214.40	−58,838.01
Wald Chi^2	157,034.90***	71,055.80***	6,098.77***	13,792.43***
Log likelihood	31,614.45	29,470.12	31,702.95	29,524.33
Hausmann Chi^2	2,331.63***	2,331.63***	845.82***	845.82***

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Standard errors in parentheses; Year fixed-effects are included; All variables logarithmized; Number of communities: 1,600; Number of Observations: 14,400.

The findings confirm that land take positively and significantly relates to a region's growth in population and public affluence. This holds for the results based on the inverse distance (**Table 3**), columns (1) and (2)) as well as based on the contiguity matrix (**Table 3**), columns (3) and (4)).

Furthermore, we observe a positive impact of building permissions, which is only insignificant in the fixed-effects model when the inverse distance matrix is used. Similarly, we find a negative and significant impact of public affluence squared for all models but for the fixed-effects model with the inverse matrix. Note that the EKC dynamic and thus the role of public affluence on land take is also confirmed when public affluence is defined as income tax (instead of sales tax) revenues (see **Appendix A**, **Table A1**).

In contrast, urban density negatively (and significantly) affects land take in both models and both types of matrices.

Further, the positive and significant coefficients for λ strengthens the assumption of positive spillover effects. Reflecting the spatial correlation among errors, the results indicate that the spatial interdependence in terms of land take goes beyond the drivers observed by the model.

Due to spillover and feedback effects between neighboring regions, the coefficients for the explanatory variables based on the estimation of Equation (4b) do not directly reflect the marginal effects of the explanatory variables on land take due to its spillover effects. Any factor may not only affect the region itself but also its neighbors and their neighbors (including potential feedback effects on the region itself). Therefore, most studies differentiate between direct, indirect and total effects for an adequate interpretation of the explanatory variables [27].

To begin with, direct effects largely coincide with the respective coefficient estimates associated with land take. In addition, it includes feedback effects that originate in region i, run through the other municipalities and come back to the region itself. Indirect effect, in contrast, reflects all spillover effects on land take originating from all other regions. Finally, total effects are defined as the sum of direct and indirect effects. The results, given by **Table 4**, confirm the positive direct impacts of population and public affluence as well as the negative impact of urban density (i.e., coefficients based on both, fixed- and random effects model, are significant). Furthermore, we observe positive and significant indirect effects on land take from increasing public affluence and building permissions in other regions. Moreover, indirect effects of squared public affluence are significant and negative confirming the EKC theory in this context. So, after passing a specific threshold, rising affluence in neighboring municipalities leads to less land take (also) in the considered region. Positive indirect effects related to population and negative spillovers of urban density are not significant. Note that there are similar results of the direct, indirect and total effects when the contiguity matrix is used for estimation (see **Table A2**).

Table 4. Direct, indirect and total effects (fixed-effects/random-effects) (based on inverse matrix) and SDEM.

Variable	(1) Direct Effects	(2) Indirect Effects	(3) Total Effects
Population	0.34***/0.84***	0.08/−0.04	0.42/0.79***
Public Affluence	0.02***/0.02***	0.90***/0.41***	0.91***/0.43***
Public Affluence squared	−0.01/−0.01*	−0.11***/−0.06***	−0.11***/−0.06***
Building permission	0.01/0.01***	0.02**/0.01***	0.02**/0.07***
Urban density	−0.17***/−0.34***	−0.13/−0.07	−0.30/−0.41***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; All variables logarithmized.

5. Discussion of Results

The findings indicate that increasing land take is positively related to population growth, economic development and building permissions. Moreover, they confirm that land take is very much a local topic, largely affected by municipal trends and political decision-making.

To begin with, public affluence shows positive impacts on land take and thus existing findings are confirmed. However, literature defines affluence typically as income or GDP per capita indicating the level of affluence of private households or regions. In contrast, the results of this paper demonstrate that (also) public affluence (i.e., revenue from sales tax) is a suitable indicator for explaining land take. Most likely, wealthier municipalities have higher financial capabilities, which in turn allows for more intensive land use decisions (development of residential, commercial and infrastructural area). Of course, land consumption due to private buildings also depends on private investments. Nevertheless, municipalities hold control over spatial planning and land use development must be consistent with the local zoning plan.

Interestingly, the findings show an ambiguous effect of public affluence on land take. The effect on land consumption turns negative at a specific level of public affluence. Thus, in line with the EKC hypothesis the relationship between affluence and environmental degradation follows an inverted U-shape. Once a municipality reaches a certain limit of wealth, decisions on land take may be taken more carefully as environmental issues may gain in importance versus (further) economic growth. While this effect is mostly discussed for the relationship between income and GHG emissions (e.g., Naveed et al., Bibi and Jamil [28,29]), related research on land take shows that the hypothesis is also valid for land take (e.g., Borruso et al. [11] for land take in Italian municipalities).

Additionally, findings indicate that the decreasing effect of public affluence on land take is especially transmitted by indirect effects (**Table 4**, column (2)). One reason could be that a higher land consumption of neighboring areas can serve as a deterrent example for one's own area.

Further, the findings show that the share of building permissions of one municipality (compared with all other municipalities) positively affects land take. Obviously, the number of building permissions increases land take. But the variable can also be interpreted as the strictness of a municipality regarding the decisions on building permissions. The higher the share, the lower the strictness and the more permissive the decisions regarding building permissions are made. Further, the effect of buildings transmissions is also transmitted by indirect effects. Building permissions can act like a signal for development diffusion and thus increase land take in neighboring areas.

The results demonstrate significant spatial dependence in land take, thereby corroborating previous findings that factors such as public affluence, Environmental Kuznets Curve (EKC) effects, and building permission policies in one municipality exert measurable influences on the land take patterns of neighboring municipalities. This observation aligns with empirical evidence indicating that residential and commercial development is more likely to occur in municipalities adjacent to areas experiencing similar growth dynamics [30].

Several underlying mechanisms may explain why land take in one municipality affects that of neighboring jurisdictions, as indicated by the spatial dependence detected in the model's error terms. Among these are the presence of intermunicipal governance networks and collaborative authorities—such as intercommunal planning projects or district administrative bodies—which facilitate coordinated or mutually influential land use decisions across municipal boundaries. Additionally, more informal yet impactful factors such as the "visibility effect" may play a role, whereby land use changes in one municipality signal developmental trends or pressures to adjacent municipalities, influencing their strategic planning or investment decisions.

Notably, the negative coefficient on the squared term of public affluence (reflecting EKC dynamics) emerged predominantly through indirect spatial effects. This suggests that the EKC phenomenon for land take operates not only at the local scale but also propagates through spatial interactions, effectively generating regional "development restraint" signals. These signals appear to reduce land take in neighboring municipalities, indicating a diffusion of environmentally motivated behavioral or policy responses across adjacent areas.

This nuanced understanding of spatial spillovers underscores the importance of adopting a regional perspective when designing land use policies, as municipal land take decisions are interlinked and capable of producing cascading effects beyond their administrative borders.

We acknowledge that our model may be subject to omitted variable bias due to the exclusion of several potentially significant determinants of land take. While we have focused on key socio-economic, fiscal, and spatial variables at the municipal level, other factors known to influence land consumption and urban expansion were not incorporated. These include transport accessibility, industrial structure, zoning regulations, housing market dynamics, regional economic conditions, land availability, topographic constraints, the presence of protected or conservation areas, and commuting behavior.

Transport accessibility, for example, often plays a pivotal role in shaping development patterns by increasing the attractiveness and feasibility of land conversion in peripheral or previously less accessible locations. Industrial structure may influence land demand differently depending on the intensity and spatial requirements of economic activities. Zoning restrictions serve as direct regulatory instruments that can either limit or promote land take, while housing prices may proxy underlying residential demand pressures driving urban sprawl. Topography and the presence of protected natural areas set physical boundaries that limit land development, and commuting patterns reflect spatial interactions and demand for residential proximity to employment centers.

Our exclusion of these variables primarily results from data limitations and the deliberate scope of this study, which prioritizes a parsimonious modeling approach centered on municipal fiscal capacity and broad socio-economic drivers.

Future research is encouraged to address these gaps by incorporating multi-dimensional datasets and employing more granular spatial and regulatory information. Integrating these additional determinants can advance the understanding of the multifaceted and context-dependent drivers of land take, improving model robustness and policy relevance.

6. Conclusions

Land take is a primary driver of local biodiversity loss, weakened climate regulation, and soil erosion, with its patterns closely intertwined with trends in neighboring regions. Consequently, addressing land take at the municipal level makes a significant contribution to environmental policy. Utilizing the STIRPAT framework and the Spatial Durbin Error Model (SDEM), this study analyzes the anthropogenic drivers of land take across 1,600 municipalities in Bavaria, Germany, from 2014 to 2022. Unlike existing literature, this research incorporates the spatial dependence of small-scale municipalities where actual decision-making occurs. The findings reveal the presence of spatial dependence in land take within these small jurisdictions, demonstrating that factors influencing land take also exert significant spatial spillover effects.

By accounting for spatial dependence through inverse-distance and contiguity weighting, this study offers novel insights into how public affluence and building permission interact to drive land take across local jurisdictions. While positive impacts of population growth and negative effects of urban density on land take are largely attributable to inner region development, public affluence drives land take locally and in the form of spillovers from neighboring areas. Interestingly, the negative effect of the squared term of public affluence (confirming the EKC hypothesis) and the positive effect of building permission were also identified as spillover effects. This suggests that the EKC for land take manifests mainly through spatial transition effects, generating signals for regional development restraint that reduce land take in adjacent municipalities. Conversely, building permission acts as a signal for development diffusion, catalyzing land take in neighboring areas. Theoretically, this study underscores that the relationship between space-intensive environmental variables—such as land take—and policies like decisions on building permissions is a spatial phenomenon emerging through interactions between adjacent regions.

Although these results should be interpreted within the specific context of the study area rather than as broad generalizations, they emphasize the necessity of multi-regional land take reduction policies. Land take is not determined solely by a municipality's internal demographic, economic, and political factors; this may be explained by close interrelations of municipalities due to urban sprawl, trade or daily commuting. Thus, the reduction of land consumption is difficult to achieve through isolated municipal actions.

Land take reduction should reflect on fostering the diffusion of environmental preferences across regions and strengthening land management. For instance, incentives could be provided when fiscal increases in core affluent areas are utilized for non-diffusive development, such as intensive (compact) development in peripheral neighborhoods. In Bavaria, there should be more exchange across the municipal buildings committees or even one common committee for each district could be established. Additionally, stricter building permission standards should be implemented to suppress additional land take between adjacent areas, spreading land restraint as a chain effect across the region. Finally, increasing the costs associated with building permission across adjacent areas could serve as a practical mechanism.

Author Contributions

Conceptualization, J.L. and A.S.; methodology, J.L.; software, J.L.; validation, J.L., S.C. and A.S.; formal analysis, J.L.; investigation, J.L.; resources, J.L.; data curation, J.L.; writing—original draft preparation, J.L.; writing—review and editing, J.L., S.C. and A.S.; visualization, J.L.; supervision, J.L.; project administration, J.L. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data are available upon request.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

The authors declare that no artificial intelligence (AI) tools were used in the preparation of this manuscript.

Appendix A

Table A1. Impacts on soil sealing (based on inverse distance matrix (*I*), public affluence is defined as income tax revenues).

Soil Sealing (Total)	(1) Fixed-Effects	(2) Random-Effects
Population	0.34***	0.88***
	(0.03)	(0.01)
Public Affluence	0.20***	0.31***
	(0.05)	(0.05)
Public Affluence squared	−0.02***	−0.02***
	(0.01)	(0.01)
Building permission	0.01	0.02***
	(0.01)	(0.01)
Urban density	−0.18***	−0.30***
	(0.02)	(0.01)
Constant	No constant	−3.20***
		(0.23)
I * population	0.47	0.06
	(1.02)	(0.10)
I * public affluence	3.14***	−0.12
	(0.95)	(0.18)
I * public affluence squared	−0.18***	0.01
	(0.06)	(0.02)
I * building permission	0.03*	0.05***
	(0.02)	(0.01)
I * urban density	0.01	−0.43***
	(0.94)	(0.10)
λ	3.62***	3.44***
	(0.05)	(0.01)
Pseudo R^2	0.01	0.91
AIC Criterion	−48,787.05	−45,312.84
BIC Criterion	−48,655.22	−45,166.36
Wald Chi^2	42,306.86***	46,568.92***
Log likelihood	24,411.52	22,676.42
Hausmann Chi^2	2,456.73***	2,456.73***

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Standard errors in parentheses; Year fixed-effects are included;

All variables logarithmized; Number of communities: 1,600; Number of observations: 11,200.

Table A2. Direct, indirect and total effects (fixed-effects) (based on contiguity matrix) and SDEM.

Variable	(1) Direct Effects	(2) Indirect Effects	(3) Total Effects
Population	0.34***/0.83***	−0.01/−0.06*	0.33***/0.78***
Public Affluence	0.02***/0.03***	0.01/0.49***	0.02*/0.52***
Public Affluence squared	−0.02**/−0.01***	−0.01/−0.07***	−0.01/−0.07***
Building permission	0.02**/0.01***	0.01/0.04***	0.02*/0.04***
Urban density	−0.17***/−0.35***	0.02/−0.30***	−0.14**/−0.64***

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; all variables logarithmized.

References

1. European Environment Agency. Net land take in cities and commuting zones in Europe. Available online: https://www.eea.europa.eu/en/analysis/indicators/net-land-take-in-cities?activeAccordion=ecdb3bcf-bbe9-4978-b5cf-0b136399d9f8 (accessed on 15 December 2025).
2. European Commission. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: EU Soil Strategy for 2030. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021DC0699 (accessed on 15 December 2025).
3. Umweltbundesamt. Built-up areas and soil sealing. Available online: https://www.umweltbundesamt.de/themen/boden-flaeche/bodenbelastungen/bebauung-versiegelung (accessed on 15 September 2025). (in German)
4. Colsaet, A.; Laurans, Y.; Levrel, H. What drives land take and urban land expansion? A systematic review. *Land Use Policy* **2018**, *79*, 339–349. [CrossRef]
5. Behnisch, M.; Poglitsch, H.; Krüger, T. Soil sealing and the complex bundle of influential factors: Germany as a case study. *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 132. [CrossRef]
6. Naumann, S.; Frelih-Larsen, A.; Prokop, G.; et al. Land Take and Soil Sealing—Drivers, Trends and Policy (Legal) Instruments: Insights from European Cities. In *International Yearbook of Soil Law and Policy 2018*; Ginzky, H., Dooley, E., Heuser, I., et al., Eds.; Springer: Cham, Switzerland, 2019; Volume 2018, pp. 83–112. [CrossRef]
7. Getzner, M.; Bröthaler, J.; Neuhuber, T.; et al. Socio-economic, political and fiscal drivers of unsustainable local land use decisions. *Land Use Policy* **2025**, *153*, 107537. [CrossRef]
8. Ge, K.; Wang, Y.; Liu, X.; et al. Spatial effects and influence mechanisms of urban land use green transition on urban carbon emissions. *Ecol. Indic.* **2025**, *172*, 113261. [CrossRef]
9. Luge, W.; Tianjiao, Z.; Tiyan, S. Spatial-temporal evolution and influencing factors of urban land use structure efficiency: Evidence from 282 cities in China. *J. Cleaner Prod.* **2025**, *500*, 145275. [CrossRef]
10. Bimonte, S.; Stabile, A. The effect of growth and corruption on soil sealing in Italy: A regional environmental Kuznets curve analysis. *Environ. Resource Econ.* **2019**, *74*, 1497–1518. [CrossRef]
11. Borruso, G.; Gallo, A.; Magris, F.; et al. Land take, land use and environmental issues. Is the Kuznets curve valid? The case of Italy. *Spatial Econ. Anal.* **2025**, 1–16. [CrossRef]
12. Lohwasser, J.; Bolognesi, T.; Schaffer, A. Impacts of population, affluence and urbanization on local air pollution and land transformation—A regional STIRPAT analysis for German districts. *Ecol. Econ.* **2025**, *227*, 108416. [CrossRef]
13. Larsen, H.N.; Hertwich, E.G. Identifying important characteristics of municipal carbon footprints. *Ecol. Econ.* **2010**, *70*, 60–66. [CrossRef]
14. Huang, W.; Wang, H.; Zhao, H.; et al. Temporal-spatial characteristics and key influencing factors of $PM_{2.5}$ concentrations in China based on STIRPAT model and Kuznets curve. *Environ. Eng. Manag. J.* **2019**, *18*. [CrossRef]
15. Liu, C.; Nie, G.H. Identifying the driving factors of food nitrogen footprint in China, 2000–2018: Econometric analysis of provincial spatial panel data by the STIRPAT model. *Sustainability* **2021**, *13*, 6147. [CrossRef]
16. Li, L.; Li, Y. The spatial relationship between CO_2 emissions and economic growth in the construction industry: Based on the Tapio decoupling model and STIRPAT model. *Sustainability* **2022**, *15*, 528. [CrossRef]
17. You, W.; Lv, Z. Spillover effects of economic globalization on CO_2 emissions: A spatial panel approach. *Energy Econ.* **2018**, *73*, 248–257. [CrossRef]
18. McGee, J.A.; Clement, M.T.; Besek, J.F. The impacts of technology: A re-evaluation of the STIRPAT model. *Environ. Sociol.* **2015**, *1*, 81–91. [CrossRef]
19. Montero, J.M.; Fernández-Avilés, G.; Laureti, T. A local spatial STIRPAT model for outdoor NO_x concentrations in the community of Madrid, Spain. *Mathematics* **2021**, *9*, 677. [CrossRef]
20. Vélez-Henao, J.A.; Vivanco, D.F.; Hernández-Riveros, J.A. Technological change and the rebound effect in the STIRPAT model: A critical view. *Energy Policy* **2019**, *129*, 1372–1381. [CrossRef]
21. Ehrlich, P.R.; Holdren, J.P. Impact of population growth: Complacency concerning this component of man's predicament is unjustified and counterproductive. *Science* **1971**, *171*, 1212–1217. [CrossRef]
22. Commoner, B.; Corr, M.; Stamler, P.J. The causes of pollution. *Environment* **1971**, *13*, 2–19. [CrossRef]
23. Dietz, T.; Rosa, E.A. Rethinking the environmental impacts of population, affluence and technology. *Hum. Ecol. Rev.* **1994**, *1*, 277–300.
24. Umweltbundesamt. Soil Sealing. Available online: https://www.umweltbundesamt.de/daten/flaeche-boden-land-oekosysteme/boden/bodenversiegelung#was-ist-bodenversiegelung (accessed on 12 November

2025). (in German)
25. Diezmartínez, C.V.; Short Gianotti, A.G. Municipal finance shapes urban climate action and justice. *Nat. Clim. Change* **2024**, *14*, 247–252. [CrossRef]
26. Bayerisches Landesamt für Statistik. The Database of the Bavarian State Office for Statistics. Available online: https://www.statistikdaten.bayern.de/genesis/online (accessed on 18 May 2025). (in German)
27. LeSage, J.; Pace, R.K. *Introduction to Spatial Econometrics*; Chapman and Hall/CRC: New York, NY, USA, 2009. [CrossRef]
28. Naveed, A.; Ahmad, N.; Aghdam, R.F.; et al. What have we learned from Environmental Kuznets Curve hypothesis? A citation-based systematic literature review and content analysis. *Energy Strategy Rev.* **2022**, *44*, 100946. [CrossRef]
29. Bibi, F.; Jamil, M. Testing environment Kuznets curve (EKC) hypothesis in different regions. *Environ. Sci. Pollut. Res.* **2021**, *28*, 13581–13594. [CrossRef]
30. Zhou, B.; Kockelman, K.M. Neighborhood impacts on land use change: A multinomial logit model of spatial relationships. *Ann. Reg. Sci.* **2008**, *42*, 321–340. [CrossRef]