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Spatial Distribution of Illegal Landfills in Poland

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Abstract:

Purpose: *This study aims to assess and forecast the spatial distribution of illegal landfills at the county level in Poland in the years 2010-2023.*
Design/Methodology/Approach: *We address the need for a more refined spatial understanding of the factors driving the distribution of illegal landfills in Poland from 2010 to 2023 by identifying spatial determinants and high-risk areas using spatial econometric models. We employed Spatial Lag Model [SLM], Spatial Error Model [SEM], and Spatial Lag of X [SLX] to assess impacts of socio-economic and environmental factors (e.g., population density, construction activity, forest cover, waste management costs) on landfill distribution. Local Indicators of Spatial Association (LISA) were used to detect spatial clusters and outliers.*
Findings: *The SLX model with forest cover and construction variables demonstrated the strongest global spatial fit (I Moran's = 0.09543, p = 0.00181), while a classical linear model (LM) with only construction activity identified the highest number of local clusters (244 High–High and 136 Low–Low units).*
Practical implications: *Illegal landfills pose a significant threat to environmental sustainability and public health worldwide, and despite growing research, there is still a lack of analyses of the spatial distribution of illegal waste sites to inform policy. In Poland in 2022 and 2023 despite the removal of thousands of such sites annually, over 2,000 illegal landfills still exist.*
Originality/Value: *The existence of spatial autocorrelation indicates that illegal waste dump distribution mainly depends on local conditions and the situation in neighboring districts. It provides evidence for the need to develop more effective policies to prevent the formation of such landfills.*

Keywords: *Illegal landfills, spatial econometrics, environmental sustainability, Moran's I statistic, clusters, high-risk areas.*

JEL codes: *Q53, Q51, Q58, R12, R14.*

Paper type: *Research paper.*

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1. Introduction

Illegal landfills, also known as waste dumps, are a serious social and environmental problem in Poland and worldwide. According to data from the Polish Central Statistical Office (GUS), 10,714 illegal landfills were closed in Poland in 2022, from which about 25,000 tonnes of municipal waste were collected.

However, at the end of that year, there were still 2,217 uncleaned landfills (Główny Urząd Statystyczny, 2023). A similar situation continued the following year - in 2023 when 9,804 illegal landfills were closed, 63.7 thousand tonnes of waste were collected, and 2,154 active illegal landfills were recorded (Sobolak, 2024).

It should be mentioned that the described phenomenon has intensified in recent years - the number of reported cases of illegal landfills in Poland increased from 5,340 in 2018 to 9,006 in 2020 (Komenda Główna Policji, 2021). It is estimated that around 25% of all waste globally is not collected. Another 39% is managed in uncontrolled conditions - illegal dumping or open burning (Kaza *et al.,* 2018).

Such illegal waste management leads to serious consequences such as environmental pollution, public health threats, and economic and sustainable development damage. According to the United Nations Environment Programme (UNEP), as much as 60-90% of the world's electronic waste (around 41 million tons per year) is illegally exported or stored outside the official system (Rucevska, 2015).

For example, African and Asian countries such as Ghana, Nigeria, India, and Vietnam have become hubs for global streams of abandoned electronic waste, undermining sustainable development efforts and taking away valuable raw materials that could be recovered in a circular economy (Srivastav *et al.,* 2023). The problem also concerns Europe. For example, in Romania, over 15,000 illegal landfills were identified in 2024; in Slovakia, almost 11,800; and in Albania, around 9,000 (Statista Research Department, 2025).

Developed countries with extensive waste management systems are still unable to cope with this problem - in England, local authorities had to deal with 1.13 million cases of fly-tipping in 2020/21, which was a 16% increase compared to the previous year (Defra Press Office, 2021). The scale of the phenomenon in question entails serious environmental and health consequences.

Illegal landfills are often located in secluded places - in forests, wastelands, by roads, or rivers. As a result, harmful substances penetrate the soil and groundwater, poisoning local ecosystems (Malinowski *et al.,* 2015). The waste decomposition products from illegal landfills may contain heavy metals, toxic organic compounds, or pathogenic microorganisms that contaminate surface and underground waters and the soil near the landfill (Białowąs *et al.,* 2015). The World Health Organization (WHO) points out improper waste management – including open burning or abandonment – hurts human health. This includes drinking water and food contamination and direct exposure of communities to hazardous substances.

This leads to the multiplication of vectors of infectious diseases, such as mosquitoes and rats (Al-Khatib *et al.,* 2014). Abandoned tires filled with rainwater are an ideal breeding ground for mosquitoes that carry diseases. This translates into their hatching even 100 times faster than in natural conditions (Bukova *et al.,* 2016).

Epidemiological studies show that communities living near illegal waste dumps are more likely to suffer from cancer and respiratory diseases. For example, in the Campania region in Italy, an increased incidence of stomach, liver, lung, and kidney cancer was recorded. This is caused by exposure to pollution from numerous illegal dumps and waste burning in the so-called ”Land of Fires” (Marfe *et al.,* 2020). As a result, this phenomenon hinders the achievement of the Sustainable Development Goals (Fazzo *et al.,* 2023). As the UNODC report notes, illegal dumping and waste trade is a growing global problem that harms the environment and health and undermines the achievement of the 2030 Agenda (Ichipi and Senekane, 2023).

2. Literature Review

The phenomenon of illegal landfills has attracted the attention of researchers from many fields for decades – from environmental sciences through economics to sociology, public health, law, and computer science. Its complex complexity is very often emphasized. Powerful connections with social, economic, and spatial factors are also described. Environmental studies indicate the harmful impact of illegal landfills on ecosystems. Cases of soil and groundwater contamination around illegal industrial and municipal waste dumps were described already in the 1990s (Du *et al.,* 2021).

Environmental analyses show that such landfills contain a mixture of municipal, construction, and hazardous waste, which leads to the emission of heavy metals, toxic organic compounds, and pathogens (Białowąs *et al.,* 2015; Al-Khatib *et al.,* 2014). Białowąs *et al.* (2015) detected high concentrations of lead, cadmium, and zinc in soil samples collected near illegal landfills in Poland.

Al-Khatib *et al.* (2014) indicated the deterioration of surface water quality in Palestine. Bukova *et al.* (2016) described Russia’s land cover disturbances, habitat degradation, and biodiversity loss. Italian studies from the ”Terra dei Fuochi” region document frequent spontaneous combustion in illegal landfills, which causes increased emissions of dioxins and PM particles (Marfe *et al.,* 2020). Methane emissions from the decomposition of organic waste from such sites also contribute to climate change (Kaza *et al.,* 2018). Illegal landfills are a source of threats to public health.

The WHO classifies uncontrolled waste dumping and incineration as developing countries’ most serious risk factors (Ahmad *et al.,* 2025). Epidemiological studies show a significant correlation between living near illegal landfills and the occurrence of cancer and respiratory and reproductive disorders. Fazzo *et al.* (2023) proved an increase in cancer and heart disease mortality in the Campania region in Italy. Ichipi and Senekane (2023) studied districts in Lagos (Nigeria) where an increase in cholera and malaria cases and numerous injuries to children were observed. It is confirmed (Ahmad *et al.,* 2025) that illegal dumps are more often located in areas inhabited by poorer or minority populations.

Ichinose and Yamamoto (2011) proved that an increase in fees for legal waste disposal translates into an increase in illegal dumps. Lakhan (2024) showed that the further away the legal collection points are located, the more frequent waste abandonment. Respondents from rural areas are often reluctant to transport waste more than 15 minutes from their homes (Al-Khatib *et al.,* 2014). Zahrah *et al.* (2024) indicated that in Indonesian provinces, up to 47% of plastic waste is openly burned or thrown directly into the environment due to the lack of a regular waste collection system.

Jorge (2025) found that increasing population density in urban areas, puts immense pressure on waste disposal systems. In turn, the research by Baraldi *et al.* (2024) indicates significant gender differences in the practices of illegal waste dumping. Many countries are taking legislative and enforcement actions. Starting in 2021, illegal dumping of hazardous waste in Poland is punishable by up to 12 years in prison (Ozdoba, 2023). In the European Union, Directive (EU) 2024/1203 imposes the obligation to penalize environmental crimes (Mentsola and Lahbib, 2024).

D'Amato *et al.* (2018) showed that an increase in the number of inspections and the effectiveness of their enforcement leads to a reduction in the scale of the phenomenon. However, a parallel phenomenon of relocation of landfills to regions with weaker supervision occurs. Positive incentives also prove effective. Ichinose *et al.* (2011) documented that increasing the number of intermediate waste treatment facilities decreases the number of illegal dumping incidents.

Wang *et al.* (2021) confirmed that the comprehensive implementation effect of the guidance-incentive-mandatory policy as a combined policy is more effective than using only single one. Research from Hong Kong shows that low environmental awareness of citizens will reduce the effectiveness of current environmental policies (Ma *et al.,* 2023). In Poland, tools for combating illegal landfills include mobile applications (”mObywatel”, ”Zgłoś interwencję”), which allow citizens to report the locations of abandoned waste. Thanks to them, approximately 350 illegal landfills were removed in 2021-2023 (Główny Inspektorat Ochrony Środowiska (GIOŚ), 2023).

Modern technologies enable more effective detection and forecasting of the locations of illegal landfills. Gómez Maturano *et al.* (2024) used satellite images and machine learning to automatically detect landfills in Mexico, achieving high accuracy. Marrocco *et al.* (2024) used drones with cameras and deep learning algorithms in suburban areas in Italy to identify hidden micro-landfills.

Using spatial regression models in combination with GIS allows predictions of where illegal landfills may be created. For example, Syafrudin *et al.* (2023) showed that the highest risk occurs in mountainous, peripheral, and sparsely populated areas. Such data are helpful in planning prevention and locating new collection points.

This study aims to assess and forecast the spatial distribution of illegal landfills at the county level in Poland in the years 2010–2023. The analysis uses several quantitative variables of a socio-economic and environmental nature, such as population density, the amount of municipal waste per capita, average income, unemployment rate, waste collection, management costs, and the number of legal waste collection points.

3. Research Objective

This study aims to determine whether there is spatial differentiation in the number of municipal waste landfills in Poland at the county level in 2010 and 2023. The study considers environmental, demographic, and infrastructural factors, such as population density, the number of residential buildings, and pollutant emissions. The study will use spatial econometric models with spatial effects (SLX, SEM, SLM) and geographically weighted regression (GWR).

This approach will allow for capturing the local variability of regression parameters. Moran's global statistics and local LISA indices were used to examine the presence and strength of spatial autocorrelation. This will allow for determining the distribution of waste landfills that show significant spatial clusters. The analysis aims to check which models best describe the data and how the number and distribution of waste landfills changed between 2010 and 2023.

4. Research Methodology

To account for spatial dependencies in regional data, four classical models of spatial econometrics were applied: SLM (Spatial Lag Model), SEM (Spatial Error Model), SLX (Spatial Lag of X), and GWR (Geographically Weighted Regression). Each model represents a different type of spatial structure and is based on distinct theoretical assumptions. Before presenting the results of spatial analyses, it should be noted that only those models that showed statistically significant spatial autocorrelation were included in further interpretation. A detailed description of the applied approaches is presented below.

a) SLM Model

The SLM model extends the classical linear regression model by including a spatial autoregressive component in the dependent variable:

$$y = \rho W y + X\beta + \varepsilon \qquad \text{(Equation 1)}$$

The spatial weights matrix W (e.g., standardized binary or distance-based) represents the relationships between spatial units. The parameter ρ measures the strength of spatial autocorrelation in the dependent variable.

The model must be estimated using Maximum Likelihood Estimation (MLE), as ordinary least squares (OLS) would yield biased and inefficient results due to the endogeneity of the Wy term. The error term ε captures unobserved influences on the dependent variable that are not explained by the spatial lag or the covariates in X. It is typically assumed to be normally distributed with mean zero and constant variance. After transformation, the model can be expressed as:

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \quad \text{(Equation 2)}$$

which highlights the presence of direct and indirect (spillover) effects. Marginal effects are divided into direct effects (impact of local variables), indirect effects (influence of neighbouring units), and total effects (their sum).

The SLM model is used when there is strong justification for spatial diffusion processes, e.g., in the analysis of real estate prices, pollution levels, or unemployment.

b) SEM Model

The SEM model assumes that spatial dependence occurs not in the dependent variable but in the error term. The model takes the form:

$$y = X\beta + u \quad \text{(Equation 3)}$$

where $u = \lambda W u + \varepsilon$ (Equation 4)

The parameter λ represents the spatial autocorrelation in the error terms. The solution leads to:

$$y = X\beta + (I - \lambda W)^{(-1)} \varepsilon \quad \text{(Equation 5)}$$

indicating that the disturbances are spatially correlated. SEM is appropriate when omitted variables follow a spatial distribution, and their absence induces autocorrelation in the residuals. SEM is also estimated using MLE, and model diagnostics are based on residual analysis and the I Moran's statistic. SEM does not model spillover effects explicitly but corrects for spatial dependence in the error structure.

c) SLX Model

The SLX model augments the classical linear model by including spatially lagged explanatory variables:

$y = X\beta + WX\theta + \varepsilon$ (Equation 6)

The coefficients θ capture the influence of the average values of explanatory variables in neighbouring units on the dependent variable in a given region. The model does not incorporate spatial dependence in y or the residuals, allowing for standard OLS estimation. SLX is useful in situations where local phenomena are shaped by the spatial context of the explanatory variables, e.g., the impact of educational investment in neighbouring municipalities on local education outcomes.

d) GWR Model

Geographically Weighted Regression (GWR) was developed in response to the finding that a regression model estimated over the entire area of interest may not adequately address local variations. The simple principle on which it is based consists on estimating local models by least squares, each observation being weighted by a decreasing function of its distance to the estimation point.

Combining these local models makes it possible to build a global model with specific properties. GWR can be used, with the help of associated cartographic representations, to identify where local coefficients deviate the most from the overall coefficients, to build tests to assess whether the phenomenon is non-stationary and to characterise non-stationary.

$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{K} \beta_k(u_i, v_i)\, x_{ik} + \varepsilon_i$ (Equation 7)

Estimation is performed via a local weighted regression, where each observation is assigned, a weight based on distance (e.g., using a Gaussian kernel):

$w_{ij} = c\exp\left(\frac{-d_{ij}^2}{2b^2}\right)$ (Equation 8)

The bandwidth parameter b determines the degree of smoothing and the number of observations influencing local coefficient estimation. Both fixed and adaptive kernels may be used.

The distance term d_{ij} represents the spatial distance between observation i (where the model is estimated) and observation j (whose data may influence the local estimate). This distance is typically calculated using Euclidean or great-circle measures, depending on the coordinate system and scale of the data.

GWR allows for the analysis of local coefficient variation, mapping of parameter values, and testing of the significance of spatial heterogeneity. It is particularly useful when variable relationships differ across geographic space.

e) Local Indicators of Spatial Association

Local Indicators of Spatial Association (LISA) enable the identification of areas with statistically significant local spatial dependence. Each spatial unit is assigned a statistic that measures whether it is surrounded by neighbours with similar (or dissimilar) values of a given variable. The most commonly used measure is the local I_i Moran's:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_j w_{ij} \left(x_j - \bar{x}\right) \qquad \text{(Equation 9)}$$

The value of I_i indicates the strength and direction of local spatial autocorrelation around location i. This measure helps determine whether a specific location is surrounded by similar or dissimilar values, and thus whether it is part of a local cluster or an outlier.

These statistics allow for the identification and classification of spatial clusters and spatial outliers, based on the sign of I_i and the value of the standardized deviation z_i:

- High–High (HH): $I_i > 0, z_i > 0$ — the unit and its neighbors all have high values; indicates a positive spatial cluster of high values.
- Low–Low (LL): $I_i > 0, z_i < 0$— the unit and its neighbors all have low values; indicates a positive spatial cluster of low values.
- High–Low (HL): $I_i < 0, z_i >$— the unit has a high value but is surrounded by low values; indicates a spatial outlier.
- Low–High (LH: $I_i < 0, z_i < 0$ — the unit has a low value, but is surrounded by high values, also a spatial outlier.

LISA interpretation supports detailed local diagnostics of spatial heterogeneity and helps visualize spatial patterns of association. This makes it a powerful tool for identifying meaningful geographic structures, selecting appropriate spatial econometric models, and interpreting the results of spatial regressions such as GWR, SLX, or SEM. Additionally, LISA results can be mapped to highlight areas of statistically significant spatial clustering, which is particularly useful in regional analysis, epidemiology, environmental studies, and socioeconomic geography.

The selection of the appropriate model was based on diagnostic tests (I Moran's, LM tests), significance of spatial parameters, and comparison of information criteria (AIC).

f) Justification for the Selection of Explanatory Variables

The study examines how environmental, social, and infrastructural factors affect the location of illegal waste dumps.

• Forests – often chosen for dumping waste because they are hidden and difficult to control (Białowąs et al., 2015; Malinowski et al., 2015).
• Roads – more roads can facilitate waste disposal, but in cities, it encourages better supervision (Jorge, 2025; Zahrah et al., 2024)
• Emissions – high emissions are associated with industrial activities and may mean poor environmental supervision, encouraging illegal waste dumping (Kaza et al., 2018; Statista Research Department, 2025)
• Buildings – more buildings mean more waste. When there are no collection points, the risk of illegal waste dumps increases, (Al-Khatib et al., 2014; Zahrah et al., 2024).
• Population – more inhabitants mean more waste and greater social pressure and control, which may limit the phenomenon (Ahmad et al., 2025; Zahrah et al., 2024)

5. Results

The SLX and GWR models obtained the highest Moran's statistics values (e.g., 0.1285 in 2023 at $p<0.001$). The remaining combinations of variables that did not show significant spatial effects were omitted from the analysis of results. Therefore, only the models with the greatest spatial significance are presented in the next section.

Table 1. *Top 5 models by Moran's I statistic.*

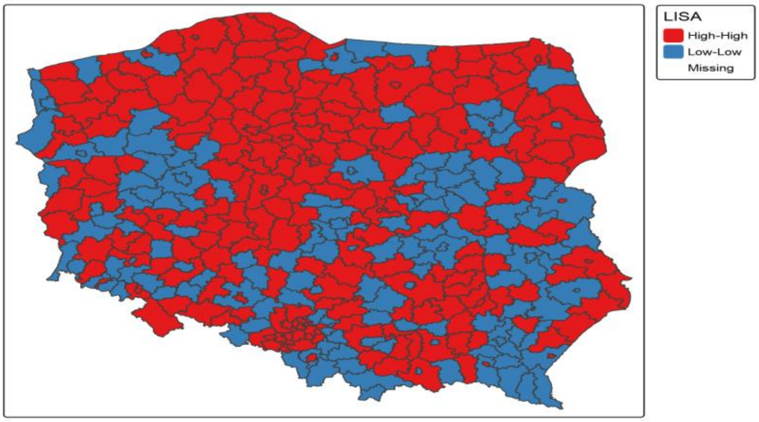
Model	Type	Year	Moran's I	p-value	Strength	Remarks
Road emission	SLX	2023	0.09543	0.00181	strong	highest correlation
Road emission	SLX	2023	0.08497	0.00456	strong	minimal alternative
emission_population	GWR	2010	0.10231	0.00112	strong	key demographic predictor
emission_population_construction	GWR	2010	0.10958	0.00087	strong	urban cluster model
forests_roads_emissions_construction	GWR	2023	0.12850	< 0.001	very strong	comprehensive urban structure

Source: *Own calculation.*

The use of local LISA spatial autocorrelation indices, which allowed us to interpret counties with significant local autocorrelation - both positive (High-High and Low-Low clusters) and negative (High-Low and Low-High). The results of the SLX and GWR models showed the greatest localization and interpretation ability. This allowed us to capture both regional neighbourhood dependencies and local heterogeneity of causal relationships.

As part of the spatial analysis of illegal landfills in Poland, a number of maps illustrating the results of the GWR models and the LISA classification were used. The interpretation of these maps allows for a deeper understanding of the spatial variation in the number of landfills and the effectiveness of the models used. The GWR model and LISA (number of landfills population) showed strong High–High clusters in central and southern Poland, especially in urban areas. This means that population density was clearly correlated with the number of illegal landfills on a local scale. On the other hand, the Low–Low areas dominated on the northern outskirts of the country, which suggests a lower risk in areas with lower population density.

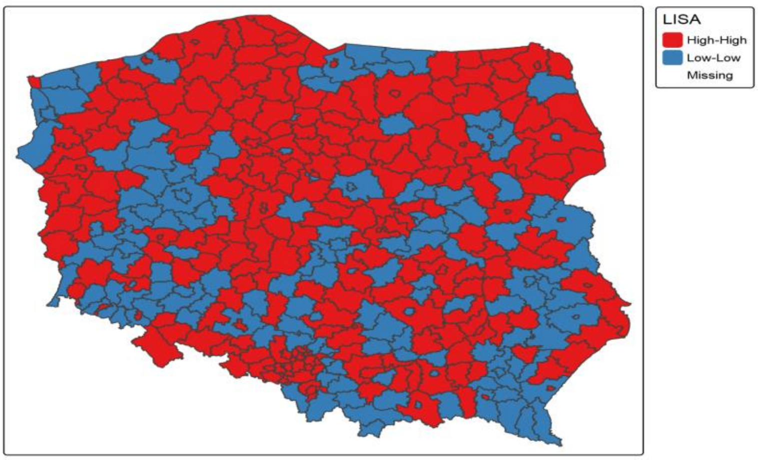
Figure 1. *Map of LISA SLX results for 2010*



Source: *Own elaboration.*

However, after including the "construction" variable in the GWR model for 2010 (number of landfills construction + population), the map showed an even stronger concentration of High-High clusters in urbanized regions such as Silesia, Warsaw or Tricity. The results of this model are consistent with the results of the previous model.

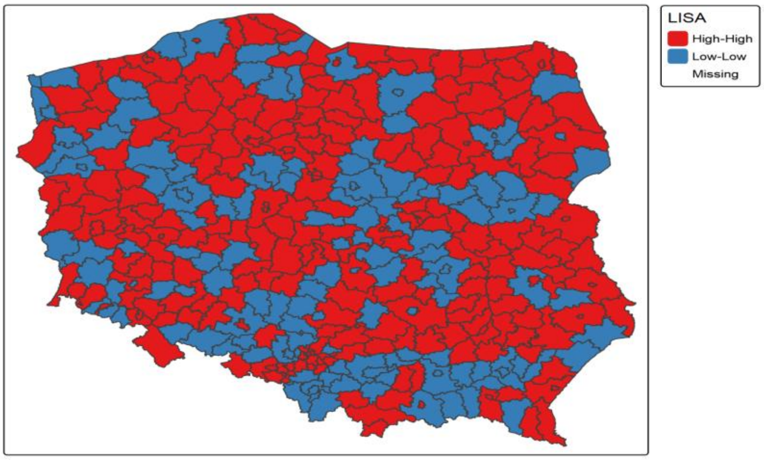
Figure 2. *Map of LISA GWR for 2010*



Source: *Own elaboration.*

However, according to the model presented on the LISA GWR map for 2023, it was possible to determine persistent and intensified High-High clusters in the center, south and north-east of the country. There are clear Low-Low clusters in the west and north-west.

Figure 3. *GWR LISA results for 2023*



Source: own elaboration

Among spatial models such as SLM sems SLX models, the results of the SLX model were estimated separately for the years 2010 and 2023. This model showed the most that the situation in the surrounding counties reflected the situation in each county.

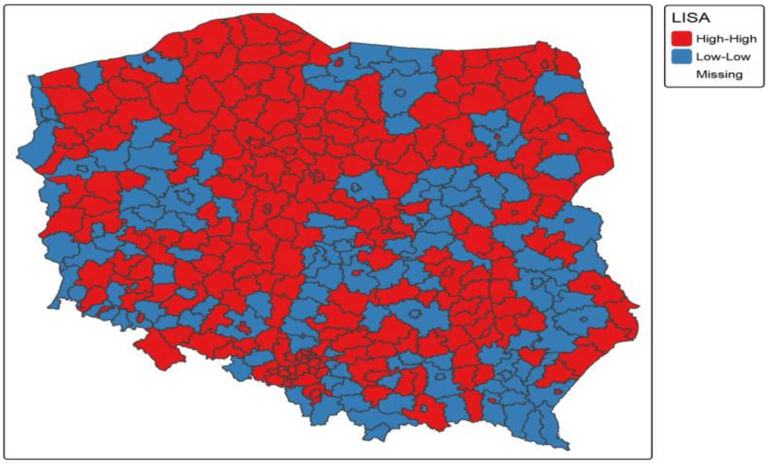
In 2010, the SLX model showed very clear clusters of the High–High (HH) type. These are counties in provinces such as Mazowieckie, Slaskie and part of Lodzkie province.

It should be noted that both the number of landfills and the values of the residuals of spatial explanatory variables were high - both locally and in the vicinity. On the other hand, clusters of the Low–Low (LL) type occurred in the north-east and in the border regions.

However, in 2023, the spatial distribution of HH clusters was further consolidated and expanded, especially in the Warsaw agglomeration, Silesia and the eastern part of the Malopolska province. There is a strong correspondence between HH areas in the SLX model and the distribution of actual cases of illegal landfills.

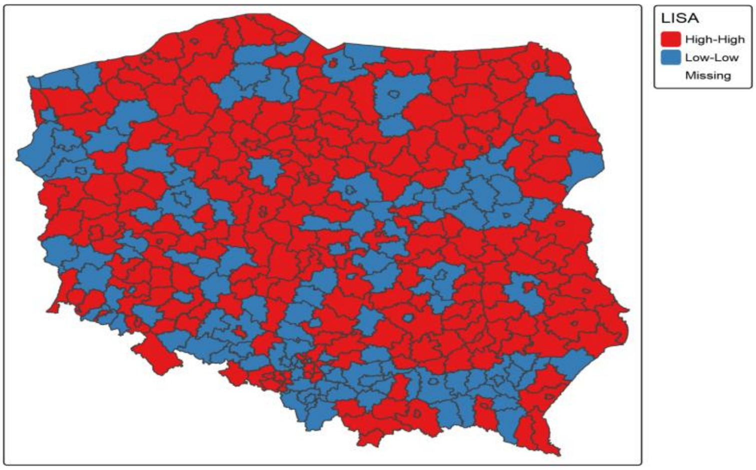
The increase in the number of LL clusters in the western and north-western regions (including Lubuskie, Western Pomerania) may indicate the effect of local improvement in waste management.

Figure 4. *LISA results of SLX residuals model 2010*



Source: *Own elaboration.*

Figure 5. *LISA results of SLX residuals model 2023*



Source: *Own elaboration.*

Comparing the results of the SLX and GWR models, it can be stated that they are convergent. Both models indicate similar result areas, such as urban agglomerations: Warsaw, Silesia and Lodz. Additionally, there is a permanent presence of High-High clusters in central and south-eastern Poland. This convergence concerns areas with the largest number of illegal landfills.

6. Conclusions

The study analysed the spatial distribution of illegal landfills in Poland in 2010 and 2023 using spatial econometric models: SLM, SEM, SLX and GWR. Local LISA spatial autocorrelation indices were also used. The aim of the analysis was to identify significant spatial clusters (HH and LL clusters) and to assess neighbourhood dependencies and local diversification of the causes of landfill creation.

The best results were obtained for the SLX and GWR models. The SLX model results showed general spatial patterns. It was also confirmed that the situation in neighbouring counties significantly affects the number of illegal landfills in a given unit. In turn, the GWR model allowed for capturing the differentiation of the strength of dependencies between variables (e.g. population, development) in individual locations.

Both models indicated the persistent presence of High-High clusters in large urban agglomerations such as Warsaw, Silesia and Lodz. In analyzed years 2010 and 2023, a clear deepening and expansion of these clusters was observed. The research results may suggest low effectiveness of preventive measures. On the other hand, Low-Low clusters appeared mainly in peripheral regions with low population density.

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