STANOVNIŠTVO, 2025, 00(0), 1–20
Original research paper

Submitted: 12 Jul 2025 | Revised: 01 Oct 2025 | Accepted: 02 Oct 2025
https://doi.org/10.59954/stnv.712
UDC 314.18:911.375:528.9:519.23(497.11)
First Online: 13 Nov 2025

Building-Level Binary Dasymetric Mapping and Spatial-Statistical Analysis of Population Change in Rural Serbia

Ivan Potić [1]

ABSTRACT

This study primarily implements a building-level Binary Dasymetric Mapping (BDM) framework to analyse population change between 2011 and 2022 in Barje Čiflik, a rural settlement in southeastern Serbia experiencing long-term depopulation. It extends the analysis with spatial and classical statistical methods. High-resolution ancillary data—including manually digitised building footprints, the number of storeys, and building function, all field-verified with abandoned dwellings identified during survey work—were integrated with census counts to allocate population using volume-based weighting.
Population estimates were assigned to each residential building to derive indicators of absolute and relative change, as well as density variation. The analysis combines spatial statistics (Global Moran's I and Getis–Ord Gi*) with classical statistical techniques (Ordinary Least Squares regression, Spearman's rank correlation, and LOWESS smoothing) to detect clustering, structural correlates, and spatial patterns of demographic change.
Results show that depopulation is spatially clustered, particularly in peripheral areas of the village, and that larger and multi-storey dwellings are more prone to decline. While density change was modest and statistically dispersed, the study highlights nuanced household-level transformations that remain obscured in aggregated data. The findings demonstrate that integrating BDM with statistical analysis provides a replicable and cost-effective tool for fine-scale demographic research in rural environments with limited data availability, thereby supporting methodological development and spatial planning.

KEYWORDS

population change, dasymetric mapping, building-level disaggregation, rural depopulation, spatial statistics

[1] *Institute of Social Sciences, Belgrade, Serbia*

Correspondence:
Ivan Potić,
Institute of Social Sciences, Centre for Demographic Research, 45 Kraljice Natalije, 11000 Belgrade, Serbia

Email:
ipotic@idn.org.rs

1 INTRODUCTION

Accurate, spatially detailed population data are essential for demographic analysis, urban planning, and risk assessment, particularly in rural areas facing depopulation. Conventional choropleth maps, which aggregate population counts into administrative units, often obscure critical local variations and introduce spatial artefacts due to the modifiable areal unit problem (MAUP) (Mennis 2009; Mennis and Hultgren 2006; Zandbergen 2011). Dasymetric mapping techniques overcome these limitations by redistributing population data to more precise spatial units using ancillary datasets that reflect potential residential capacity (Baynes, Neale, and Hultgren 2022; Mennis and Hultgren 2006).

Among the established approaches, binary dasymetric mapping (BDM) remains a practical method in data-scarce contexts due to its low data requirements and transparency. It assumes a uniform distribution of population within residential zones while excluding uninhabited areas based on ancillary land use or building data (Cartagena-Colón, Mattei, and Wang 2022; Mennis and Hultgren 2006). Although this assumption introduces potential errors in heterogeneous areas, recent studies have shown that integrating high-resolution ancillary data, such as building footprints, floor counts, and land use classifications, can significantly enhance the accuracy of population allocation (Pirowski and Szypuła 2024; Zandbergen 2011).

Beyond simple allocation, combining dasymetric mapping with spatial statistical analysis enables a more profound insight into demographic processes at fine spatial scales. Methods such as Moran's I, OLS regression, and hotspot analysis allow the identification of spatial patterns, clusters, and correlates of population change, which are particularly relevant in rural environments. Recent studies have widely adopted these approaches to refine demographic modelling and support targeted spatial interventions (Baynes, Neale, and Hultgren 2022; Chen 2021; Wooditch et al. 2021).

Despite growing methodological advances, studies that explore building-level population change over time remain limited, particularly in rural contexts. A recent study by Pajares et al. (2021) demonstrated the feasibility of combining top-down dasymetric disaggregation with bottom-up population estimation at the building level, using flexible, open-source tools adapted to data availability. However, such frameworks have yet to be fully implemented in rural settlements with declining populations, where the precision of allocation and spatial analysis of demographic dynamics are crucial.

Wan et al. (2023) also explored the use of landscape metrics as ancillary data in dasymetric mapping. Their research revealed that landscape metrics, which quantify spatial patterns of land use and land cover, often outperform traditional ancillary datasets in predicting population distribution. By incorporating these metrics, the study achieved higher accuracy in population estimations across diverse geographic contexts, emphasising the value of innovative ancillary data sources in dasymetric mapping.

These recent studies collectively demonstrate the ongoing evolution and refinement of dasymetric mapping techniques. The integration of high-resolution ancillary datasets, whether through detailed building information or advanced landscape metrics, continues to

https://doi.org/10.59954/stnv.712

enhance the accuracy and applicability of population distribution models, particularly in areas where traditional data sources may be limited or outdated.

In Serbia, dasymetric mapping has been increasingly utilised to enhance the spatial resolution of population data, particularly for applications in risk analysis and spatial planning. Researchers have developed national- and regional-level population models using soil sealing degrees, digital elevation models, and various GIS techniques, producing gridded outputs with substantially higher spatial fidelity than conventional choropleth maps (Krunić, Bajat, and Kilibarda 2015). Further studies have applied dasymetric mapping techniques to analyse demographic processes and their spatial manifestations. For instance, Krunic et al. (2018) employed dasymetric methods to examine the spatial aspects of demographic processes in Serbia, highlighting the importance of integrating statistical and spatial data for effective urban and regional planning. Additionally, Bajat et al. (2011) utilised dasymetric mapping to model population change indices in Southern Serbia from 1961 to 2027, demonstrating the influence of environmental factors on population dynamics. In urban contexts, dasymetric modelling using soil-sealing data and building-height information has been demonstrated in Belgrade, where census data from 2002 and 2011 were allocated to finer spatial units through detailed urban ancillary inputs (Bajat et al. 2013). Gajić, Krunić, and Protić (2021) proposed a classification framework for rural areas in Serbia, integrating multivariate analysis and GIS tools to delineate rural and urban areas, thereby facilitating targeted spatial planning and policy development.

This study advances methodological approaches by implementing a temporally comparative, building-level BDM framework to analyse the demographic change in Barje Čiflik, a rural settlement in southeastern Serbia undergoing long-term depopulation. Detailed ancillary data—derived from field surveys, satellite imagery, and volumetric attributes—were integrated with the census counts from 2011 and 2022 to enable volume-preserving population disaggregation at the scale of individual buildings. Beyond disaggregation, the study combines spatial statistics (Global Moran's I and Getis–Ord Gi*) with classical statistical methods (Ordinary Least Squares regression, Spearman's rank correlation, and LOWESS smoothing), providing a comprehensive examination of spatial clustering and structural correlates of change. The findings demonstrate that this multi-method framework enhances the spatial precision of population modelling and offers a replicable, data-efficient tool for capturing micro-scale demographic dynamics, with direct implications for rural planning and demographic policy in data-scarce contexts.

2 MATERIALS AND METHODS

2.1 AREA OF INTEREST

The study area is Barje Čiflik, located in the Pirot Municipality in southeastern Serbia. The administrative boundary of the settlement covers an area of 9.014 km², while the populated area occupies 0.39 km² (Figure 1).

The selection of Barje Čiflik as the case study location was motivated by clear long-term depopulation trends observed at the municipal and settlement levels. Between 1948 and 2022,

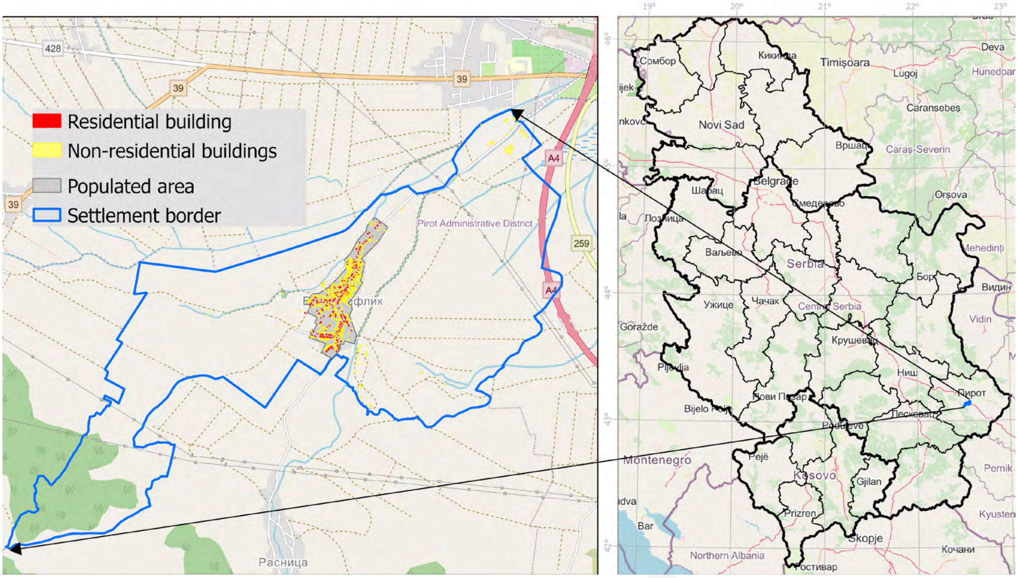

Figure 1 Study Area.
Source: OpenStreetMap Contributors (2017), adapted by Author

the population of the Pirot Municipality decreased by nearly 30%, while the broader Pirot District lost more than a half of its inhabitants. Within this regional context, Barje Čiflik exemplifies a rural settlement experiencing continuous demographic decline, with its population reduced by 38% over the past seven decades. The pace of decline accelerated after 2002, when the settlement experienced a sharper loss of residents (Table 1). Such demographic dynamics make Barje Čiflik a representative and analytically valuable example of rural depopulation in southeastern Serbia, offering insight into spatial patterns of demographic change at the micro-scale.

2.2 METHODOLOGY

The methodological approach of this study integrates BDM with advanced spatial and statistical analyses to assess temporal population change at the building level. The workflow encompasses four main phases: data preparation (including census data compilation, spatial data acquisition, and field verification), population allocation to individual buildings, temporal

Table 1 Historical population trends for the City of Pirot and the village of Barje Čiflik (1948–2022).

	1948	1953	1961	1971	1981	1991	2002	2011	2022
Pirot District	160,285	157,360	145,789	136,008	127,427	116,926	105,654	92,479	76,700
Pirot Municipality	70,049	69,210	68,073	69,285	69,653	67,658	63,791	57,928	49,601
Barje Čiflik	820	790	775	765	782	788	693	594	507

Source: Statistical Office of the Republic of Serbia (2024)

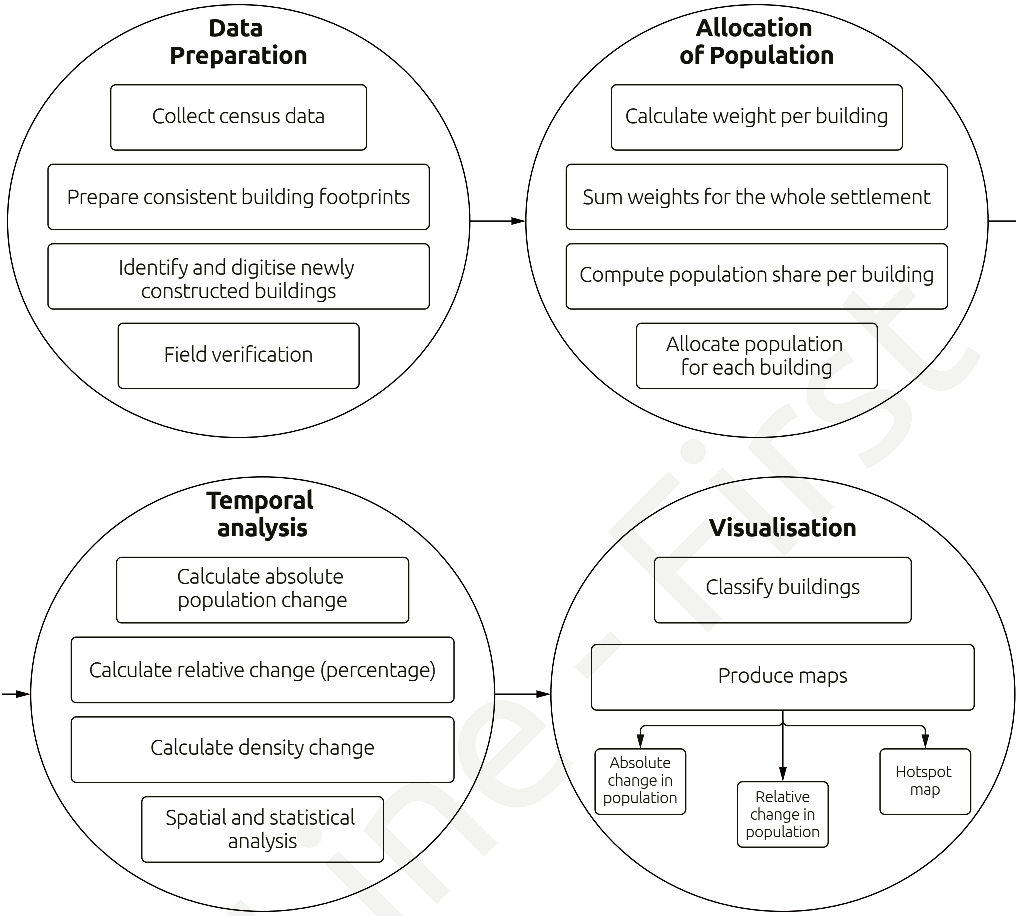

Figure 2 Workflow diagram for building-level dasymetric mapping and statistical analysis of population change

and spatial-statistical analysis of demographic indicators, and cartographic visualisation (Figure 2).

The data collection and spatial data compilation were performed using QGIS version 3.14 (QGIS Development Team 2024) and Google Earth Pro version 7.3 (Google 2020), while all statistical and spatial analyses were conducted in Python version 3.12 (Van Rossum and Drake 2009). The final cartographic visualisation and map layouts were produced in QGIS.

2.2.1 Data Collection

Population data were sourced from the Statistical Office of the Republic of Serbia and represented official census figures for 2011 and 2022 (Statistical Office of the Republic of Serbia 2024). Building footprints were digitised using QGIS and historical imagery from Google Earth Pro, dated November 2013 and July 2023, complemented by OpenStreetMap data (OpenStreetMap Contributors 2017). The field surveys, conducted in May 2025, were carried out to verify the number of storeys, and identify abandoned or demolished residential buildings.

All spatial data were processed within the QGIS 3.14 environment. Digitised vector layers were saved in shapefile (.shp) format, and attribute tables—including census and building metadata—were stored as comma-separated values (.csv) files. The coordinate reference system EPSG:32634 (UTM Zone 34N) was applied to all spatial layers to maintain projection consistency throughout the analysis.

Despite field verification, classifying uninhabited structures may contain uncertainties, particularly in intermittently occupied or seasonally used dwellings. These limitations reflect common challenges in verifying building status in rural areas and underscore the importance of supplementary validation sources, such as cadastral data, utility records, or community-based reporting, for improving future population allocation accuracy.

2.2.2 Population Allocation

The population allocation to individual buildings followed a multi-step procedure based on the BDM method, as introduced by Mennis and Hultgren (2006). First, a weighting factor was calculated for each residential building by multiplying its ground floor area by the number of storeys, as verified during fieldwork. This factor served as a proxy for potential residential capacity and has been widely adopted in previous studies using building-based dasymetric models (Pirowski and Szypuła 2024; Zandbergen 2011). All calculations and proportional allocations were implemented in Python using the Pandas (The pandas development team 2024) and NumPy libraries, enabling reproducible and transparent processing of census and building data.

Geometric attributes were calculated to support the dasymetric allocation. The ground floor area of each building was derived from polygon geometry using GeoPandas (Jordahl et al. 2020), while the distance from the settlement centre was computed by identifying the average centroid of all buildings and measuring the Euclidean distance of each object to that point using Shapely (Gillies et al. 2024). These spatial metrics served as explanatory variables in subsequent statistical models, thereby enhancing the spatial disaggregation framework.

Subsequently, the total weight was summed across all residential buildings within the settlement to establish a reference value for proportional distribution. Each building's population share was then determined by dividing its weight by the total settlement weight, following the principle of volume-preserving spatial disaggregation (Baynes, Neale, and Hultgren 2022).

Based on this share, population counts from the 2011 and 2022 censuses were proportionally allocated to each building, generating building-level population estimates for both periods. This disaggregated data formed the basis for further temporal and spatial analyses, consistent with dasymetric allocation approaches that have been proven effective in both urban and rural contexts (Cartagena-Colón, Mattei, and Wang 2022).

2.2.3 Temporal, Spatial, and Statistical Analysis

Temporal and spatial statistical analysis were conducted to comprehensively evaluate demographic change at the building level between 2011 and 2022.

Following the proportional allocation of census population to individual residential buildings, a suite of derived indicators was computed for each building to capture spatial and temporal dynamics:

a) Absolute population change (Δpop), defined as the difference in the estimated population between 2022 and 2011, was calculated for each building. This metric provides a direct measure of demographic increase or decline, and is often used as a baseline for identifying spatial clusters of change (Mennis and Hultgren 2006; Zandbergen 2011);

b) Relative population change (Δ%) was computed as the percentage change relative to the 2011 baseline, with conditional logic applied to prevent division by zero for the buildings with zero initial population. The calculation was performed according to Equation 1:

$$\Delta\% = \left(\frac{\Delta pop}{pop_{2011}}\right) \times 100 \tag{1}$$

Conditional logic was implemented to avoid division by zero, a standard approach in dasymetric modelling, where some buildings may have a baseline value of zero (Cartagena-Colón, Mattei, and Wang 2022);

c) Population density metrics were calculated for both years by dividing the estimated population by the building footprint area, yielding density 2011 and density 2022 attributes. The change in population density (Δdens) was subsequently derived as the difference between these two values.

A combination of spatial-statistical and classical statistical procedures was applied to the building-level indicators.

Spatial autocorrelation was assessed using **Global Moran's I statistic** to determine whether patterns of population change or density change exhibited significant clustering, dispersion, or randomness at the local scale (Chen 2021). The analyses were performed using the Python Spatial Analysis Library's (PySAL) submodule Exploratory Spatial Data Analysis (esda) (Rey et al. 2015).

Hotspot analysis using the Getis–Ord Gi* statistic was applied to Δpop and Δdens. For Δpop, the Gi* test was used in an exploratory manner to provide a visual representation of potential localised clusters of depopulation, serving primarily as a complementary cartographic tool. For Δdens, the Gi* analysis was implemented as a formal statistical procedure to identify significant local clusters of intensification (hotspots) or decline (coldspots). The Getis–Ord Gi* is a spatial statistic that evaluates each feature in the context of its neighbouring features, detecting clusters where high or low values are spatially concentrated (Ord and Getis 1995; Rey et al. 2015). The analyses were performed using the esda library in Python and verified in QGIS.

The Gi* value for each feature is calculated as follows in Equation 2:

$$G_i^* = \frac{\sum_j w_{i,j} x_j - \bar{X}\sum_j w_{i,j}}{S\sqrt{\left[\frac{n\sum_j w_{i,j}^2 x_j - \left(\sum_j w_{i,j}\right)^2}{n-1}\right]}} \tag{2}$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between features i and j, $\bar{X}$ is the mean of all attribute values, S is the standard deviation, and n is the total number of features (Ord and Getis 1995).

In addition to spatial statistics, classical statistical methods were employed.

Ordinary Least Squares (OLS) regression was employed to identify building-level factors influencing population change, incorporating variables such as building area, number of floors, and distance from the settlement centre. The OLS provides a global model that estimates the relationship between the dependent variable and one or more independent variables, offering insights into the factors that contribute to population dynamics (Wooditch et al. 2021). Model fitting and diagnostics were performed in Python using the statsmodels package (Seabold and Perktold 2010).

Spearman's rank correlation coefficient was calculated to examine the association between population change and distance from the settlement centre. This non-parametric measure is suitable for assessing the strength and direction of monotonic relationships between ranked variables (Lloyd 2010; Sheskin 2020). It was used to test whether the buildings located further from the settlement centre experienced different patterns of population change compared to those closer to the centre. The analysis was implemented using Python's scipy library (Virtanen et al. 2020).

2.2.4 Visualisation

The visualisation phase encompassed the cartographic and statistical representation of the population dynamics at the building level between 2011 and 2022. Multiple map layers and plots were generated to facilitate the spatial interpretation of the demographic change and its correlates:

- An Absolute Population Change Map illustrates the net change in the population per building, highlighting spatially differentiated patterns of growth and decline.
- The Relative Population Change Map presents the percentage change in the population for each building, normalising demographic shifts relative to the 2011 baseline.
- An Exploratory Hotspot Analysis of Δpop, based on the Getis–Ord Gi* statistic, provides a complementary visualisation of potential localised clusters of depopulation.
- The Spatial Residual Map displays the standardised residuals from the Ordinary Least Squares (OLS) regression model, enabling the detection of over- or under-predicted values for building-level population change.
- A Scatter Plot with LOWESS Curve visualises the relationship between the absolute population change and distance from the settlement centre, incorporating a locally weighted regression to capture potential non-linear spatial trends.
- Population Density Maps depict the spatial distribution of the building-level population density for 2011 and 2022 and the resulting Δdens, thereby identifying the zones of residential intensification and decline.
- A Hotspot Analysis of Δdens, performed using the Getis–Ord Gi* statistic, identifies the statistically significant clusters of density increase (hotspots) and decrease (coldspots), offering further insight into localised demographic reconfiguration.

All maps were created using QGIS 3, employing consistent classification schemes and symbology to ensure visual comparability. Python-based visualisations were implemented using Matplotlib (Hunter 2007) and Seaborn (Waskom 2021) libraries, facilitating static mapping and exploratory data analysis. The resulting visual outputs are critical for interpreting demographic shifts and formulating spatial policy.

3 RESULTS

In 2022, the total area covered by buildings was 62,716.78 m², comprising 889 structures. Residential buildings accounted for 17,084.76 m², with no observed spatial changes during the study period, and included 211 structures. Non-residential buildings increased slightly from 659 (44,093.91 m²) in 2011 to 678 (45,632.02 m²) in 2022.

A significant population loss was recorded at the building level for 55 of the 211 residential buildings, each losing one inhabitant. Relative population change varied, with one building showing a 100% decrease, while most buildings (156) experienced stagnation. The spatial distribution of the population change revealed depopulation clusters, predominantly in the settlement's peripheral areas. The maps of absolute and relative changes (Figure 3 and Figure 4) effectively highlighted these spatial patterns.

The spatial autocorrelation of the building-level population change between 2011 and 2022 was assessed using Global Moran's I statistic. For Δpop, Moran's I value was 0.1953, with a z-score of 6.62 and a p-value of 0.0010. These values indicate a statistically significant positive spatial autocorrelation, suggesting

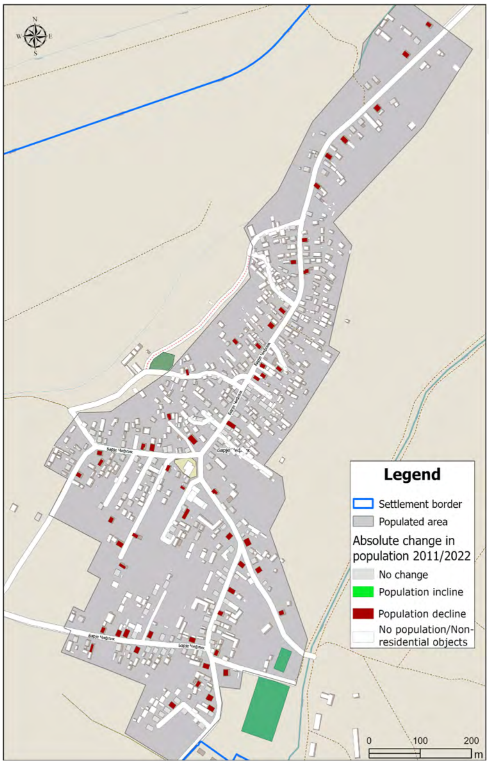

Figure 3 Absolute population change at the building level between 2011 and 2022

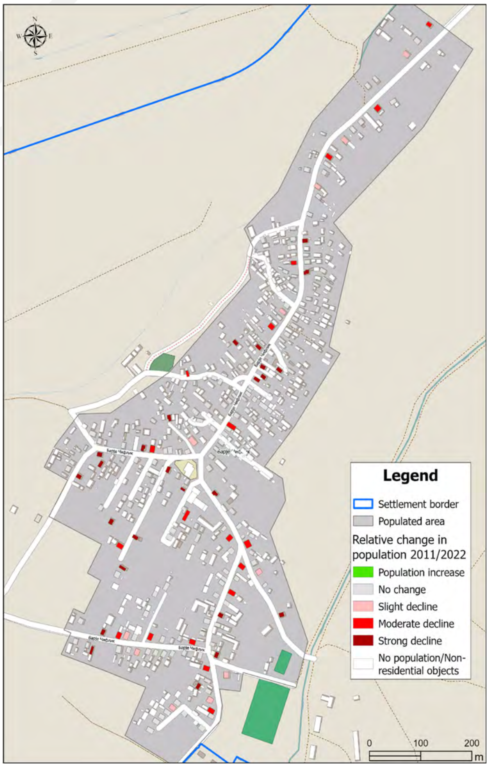

Figure 4 Relative population change per building (2011–2022)

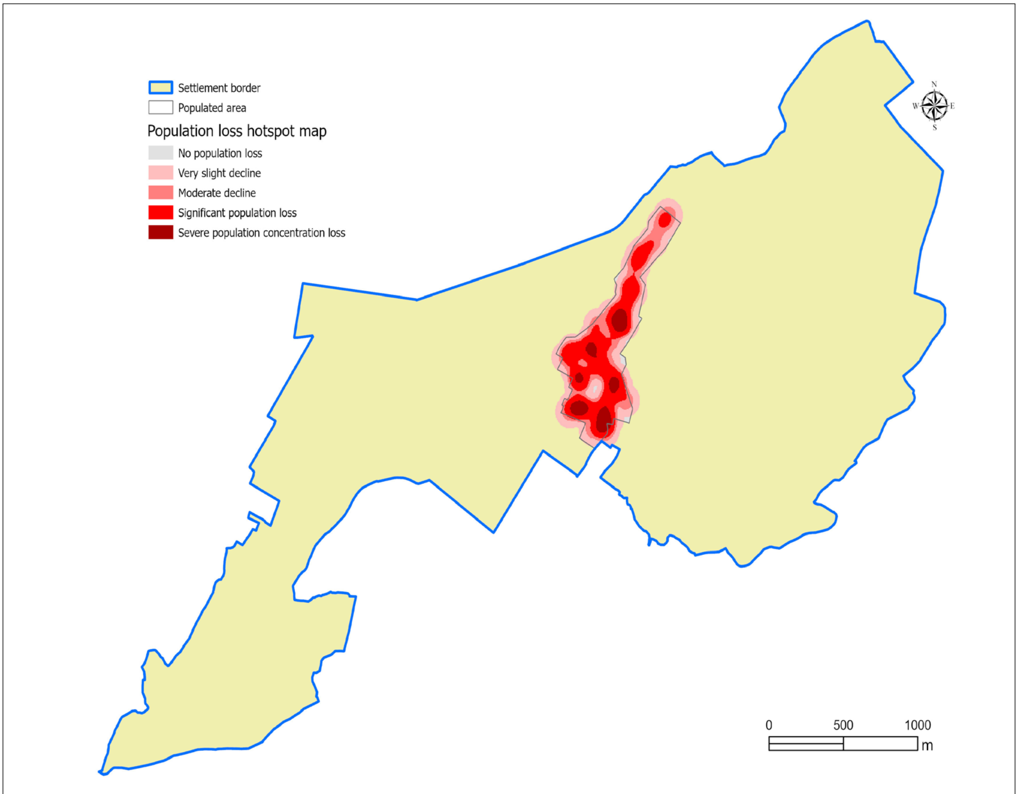

Figure 5 Hotspot map of building-level population decline (2011–2022)

that buildings experiencing similar magnitudes of population change tend to cluster spatially. Likewise, the change in population density per building (Δdens) exhibited a Moran's I value of 0.1301, with a z-score of 4.22 and a p-value of 0.0020, reflecting significant spatial clustering. These results demonstrate that absolute and relative (density-based) demographic shifts were not randomly distributed, but spatially structured within the study area.

In addition to the global measure of spatial autocorrelation, an exploratory hotspot analysis using the Getis–Ord Gi* statistic was applied to Δpop. This analysis served as a complementary visualisation, highlighting localised clusters of depopulation at the building level.

The results (Figure 5) illustrate the areas where population loss appeared spatially concentrated, complementing Moran's I findings of significant spatial autocorrelation.

Ordinary Least Squares (OLS) regression was conducted to identify the factors influencing building-level population change between 2011 and 2022 (Figure 6).

The model included building area, number of floors, and distance from the settlement centre as explanatory variables. The analysis revealed that both the number of floors and the building area were significantly and negatively associated with population change, indicating that larger and multi-storey buildings were more likely to experience a

Table 2 Ordinary Least Squares Regression Results for Building-Level Population Change (2011–2022)

Variable	β (coef)	Std. Err.	*t*	*p*	95% CI
Intercept	0.4374	0.011	40.795	0.000	0.416 – 0.459
area	–0.0050	0.0000986	–50.417	0.000	–0.005 – –0.005
floors	–0.3996	0.008	–51.654	0.000	–0.415 – –0.384
dist_center	0.0000115	0.0000149	0.772	0.441	–0.0000178 – 0.0000408

population decline. Distance from the settlement centre was not a statistically significant predictor. The model as a whole was highly important, with the included variables explaining nearly all of the variance in building-level population change (Table 2).

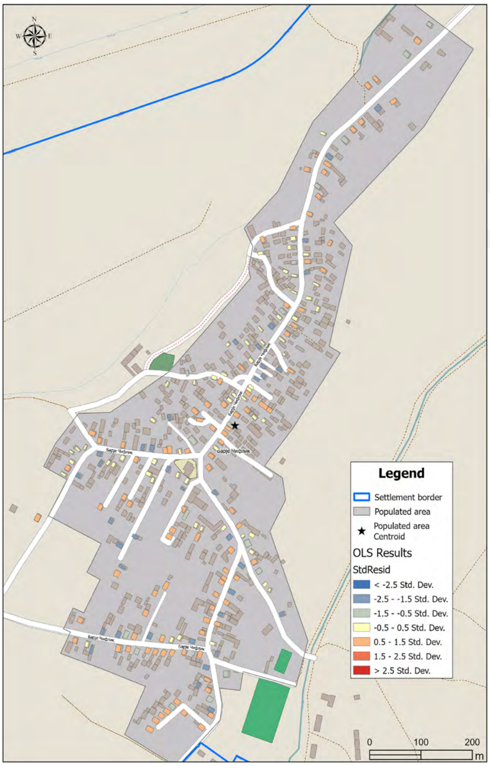

Figure 6 Spatial distribution of standardised residuals from the OLS regression model for building-level population change (2011–2022) in Barje Čiflik

The relationship between population change and distance from the settlement centre was assessed using Spearman's rank correlation coefficient. The analysis revealed a statistically significant negative association (rho = –0.273, $p < 0.001$), suggesting that the buildings located further from the settlement centre were more likely to experience population decline than those closer to the centre. The scatter plot (Figure 7) illustrates the relationship between the building-level population change (2011–2022) and the distance of each building from the settlement centre. Each point represents a residential building, while the red LOWESS curve provides a smoothed visualisation of the overall trend. The observed distribution reveals considerable variability; however, a gradual downward slope in the trend line suggests a negative relationship. This graphical pattern is consistent with Spearman's rank correlation analysis results, which indicated a statistically significant negative association (rho = –0.273, $p < 0.001$). These findings imply that the buildings located further from the settlement centre were more likely to experience a decline in population during the observed period.

The population density was computed exclusively for residential buildings, as non-residential structures do not accommodate a permanent population.

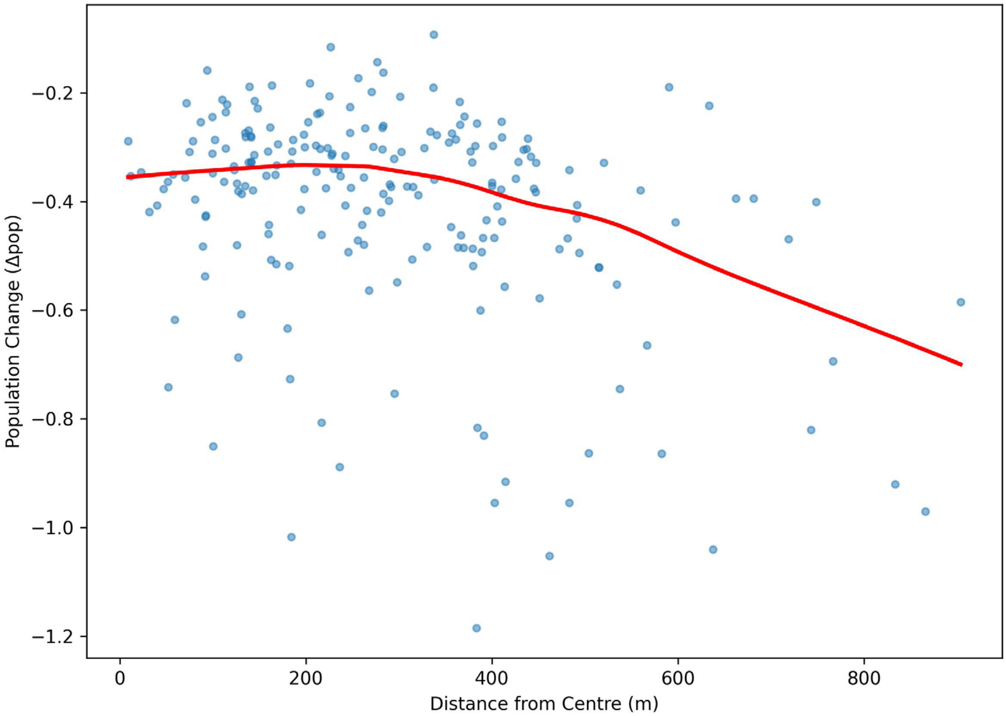

Figure 7 Scatter plot of absolute building-level population change (2011–2022) versus distance from the settlement centre. Each point represents a residential building, and the red curve shows a locally weighted regression (LOWESS) trend.

Since the number, footprint area, and number of storeys of the residential buildings remained unchanged between 2011 and 2022, all observed changes in population density per building are attributable solely to demographic dynamics, rather than to physical transformation or land use change (Figure 8). This allows for a focused analysis of population redistribution, depopulation, or intensification within the existing residential stock.

While the spatial distribution of Δdens illustrates potential areas of residential intensification or decline (Figure 8), additional statistical testing is required to determine whether these patterns exhibit significant spatial clustering. Therefore, a hotspot analysis using the Getis–Ord Gi* statistic was conducted.

The results indicate a complete absence of statistically significant spatial clusters: all residential buildings were classified as non-significant (Gi_Bin = 0), suggesting that the observed changes in density were randomly distributed and did not form spatially coherent patterns. This outcome is consistent with the narrow distribution of Δdens values (mean = –0.0032, median = 0), confirming that the demographic changes during the observed period were diffuse, rather than concentrated within specific residential zones.

https://doi.org/10.59954/stnv.712

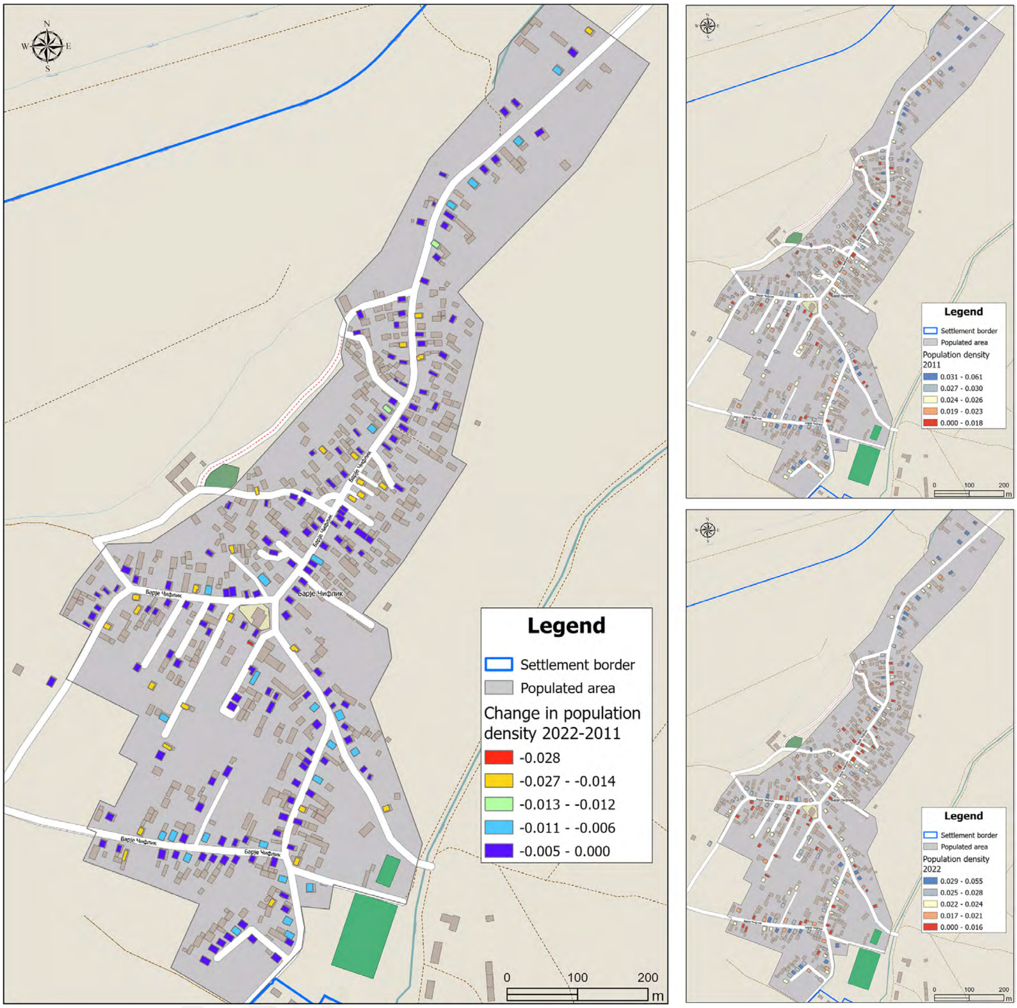

Figure 8 Spatial distribution of population density per building in 2011 and 2022, and change in density at the building level. The diverging colour scale highlights areas with the most significant intensification or decline in residential use.

4 DISCUSSION

The results of this study reveal a nuanced pattern of population change at the building level in Barje Čiflik between 2011 and 2022. While the overall number of residential buildings remained constant, 55 out of 211 exhibited a decrease in population, reflecting a partial manifestation of the broader depopulation process. The statistically significant positive spatial autocorrelation (Moran's I = 0.1953 for Δpop) suggests that population loss is not random but clustered, particularly in peripheral parts of the village. These findings align with the established rural depopulation patterns in southeastern Serbia, where demographic decline is spatially uneven and conditioned by location and infrastructure (Bajat et al. 2011; Krunić, Bajat, and Kilibarda 2015). The exploratory Gi hotspot analysis of absolute population change (Figure 5) provides additional visual confirmation of this pattern, highlighting localised clusters of depopulation at the building level in line with the significant spatial autocorrelation identified by Moran's I.

Nevertheless, the interpretation of these results requires caution. Based on floor area and number of storeys, the volumetric weighting factor provides a robust proxy for residential capacity; however, it assumes a consistent household size and occupancy across all structures. This assumption may oversimplify demographic behaviours, especially in rural contexts marked by seasonal migration, informal housing use, or partial abandonment. Additionally, the absence of statistically significant hot or cold spots in the Getis–Ord Gi* analysis for Δdens indicates that density shifts are diffuse and lack intense local concentration, potentially reflecting the slow, household-level character of demographic change in rural Serbia. While building volume may not perfectly capture household size in rural settings where occupancy is more uniform, it provides a transparent and field-verified proxy that enables systematic allocation at the building level in the absence of household microdata. This limitation is acknowledged but does not undermine the value of comparing relative spatial patterns of change. A central limitation of this research is that official census data are only available at the settlement level, with no disaggregation to individual households. The absence of household-level population counts and detailed dwelling structures necessitates an estimation procedure based on building volume as a proxy for these data. While this approach involves assumptions, it offers a replicable solution for micro-scale analysis in data-scarce environments. The demanding fieldwork required to verify storeys, functions, and occupancy further highlights the challenges of extending such analyses to larger settlements. In the future, advances in remote sensing and alternative ancillary datasets may offer more efficient ways to refine this methodology in contexts where input data remain limited.

Furthermore, only two census benchmarks (2011 and 2022) were used, which limits the temporal depth of the analysis, while socio-economic covariates were not included as contextual controls. The absence of statistically significant Gi* hotspots for Δdens suggests that demographic shifts were diffuse and weakly concentrated locally, consistent with the gradual, household-level character of rural depopulation in Serbia.

The results of the classical statistical analyses provide further insight. Contrary to expectations, larger and multi-storey buildings were more likely to experience population decline, suggesting prior overestimation of capacity or disproportionate outmigration from structurally dominant dwellings. The significance of building area and number of floors in the OLS model reflects their role in the allocation framework itself. Rather than serving as an independent validation, the regression results highlight the structural correlates embedded in the dasymetric logic, confirming that larger dwellings are disproportionately affected by population decline. Meanwhile, distance from the settlement centre was not a statistically significant predictor in the OLS model, despite the Spearman correlation indicating a modest negative

https://doi.org/10.59954/stnv.712

association. This discrepancy highlights the potential for non-linear or contextual factors—such as road access, land ownership, or family ties—to mediate the spatial logic of rural depopulation, which warrants deeper ethnographic or multivariate exploration. Where feasible, it would also be valuable to test the spatial autocorrelation of residuals (for example, applying Moran's I to OLS residuals) to evaluate potential spatial dependence not captured by the global regression model.

The methodological framework adopted in this study builds directly on the BDM approach developed by Mennis and Hultgren (2006) while expanding its temporal dimension and enhancing spatial resolution. The integration of ground-verified building data and volumetric attributes, combined with spatial statistical tools, distinguishes this study from earlier BDM applications based solely on land use/land cover overlays (Cartagena-Colón, Mattei, and Wang 2022; Zandbergen 2011). The focus on building-level disaggregation across two census years allows for a rare micro-scale temporal comparison in a rural context, addressing a gap noted by Pajares et al. (2021), who called for more implementations of flexible, open-source frameworks for historical disaggregation.

Concerning research in Serbia, this study offers a significant advancement over prior approaches. While Bajat et al. (2011) and Krunić, Bajat, and Kilibarda (2015) demonstrated the utility of dasymetric mapping for national and regional assessments, their models were based on gridded data with resolutions of 100 × 100 m or higher, relying primarily on soil sealing proxies. The present study departs from these raster-based frameworks by allocating the population at the level of individual buildings using volume-preserving disaggregation, thus achieving greater spatial specificity. Furthermore, applying spatial statistical methods (Global Moran's I, Getis–Ord Gi*) together with classical statistical techniques (OLS regression, Spearman correlation) contributes a more analytically rich interpretation of demographic processes than the models focused solely on spatial redistribution.

The study by Pirowski and Szypuła (2024) provides a particularly relevant benchmark, as it demonstrates the efficacy of building volume in improving population allocation accuracy. However, their work is oriented towards urban settings with dense and diverse building stock. By contrast, the current research tests the same principle in a sparsely populated rural settlement, broadening the empirical applicability of the volume-based dasymetric allocation. Similarly, Wan et al. (2023) advocate for integrating landscape metrics into population disaggregation; yet, such metrics are less effective in low-density, morphologically homogeneous villages. In this context, building-level ancillary data—field-verified and temporally differentiated—remain the most effective tool for capturing subtle demographic dynamics.

Ultimately, this research provides a reproducible and resource-efficient methodology for fine-scale demographic analysis in rural environments where traditional data sources may be outdated or insufficient. The approach is well-suited for monitoring depopulation, guiding rural revitalisation policies, and providing input for targeted spatial planning. A methodological limitation concerns the interpretation of very small residential units. In dwellings with only one or two inhabitants, the departure or loss of a single individual formally results in a 100% decline. While this outcome is statistically correct, it may exaggerate the perceived magnitude of the change. This artefact is a common challenge of fine-scale dasymetric approaches and should be viewed as a statistical amplification rather than as a direct reflection of demographic processes.

These conclusions primarily reflect the studied local context and time frame; broader generalisations require further validation across diverse rural morphologies and socio-economic environments.

5 CONCLUSION

This study demonstrates the potential of temporally comparative, building-level BDM for analysing population change in rural settlements. By allocating the census data from 2011 and 2022 to individual residential buildings based on volumetric weighting factors, the research provides a high-resolution depiction of demographic dynamics in Barje Čiflik, southeastern Serbia. Integrating spatial methods (Global Moran's I, Getis–Ord Gi* hotspot analysis) with classical statistical techniques (OLS regression, Spearman correlation) offers additional insights into the spatial structure and determinants of population change.

The findings reveal that the population decline is spatially clustered, particularly in peripheral zones, and larger and multi-storey buildings are disproportionately affected. Although no significant density-based hotspots were identified, the observed trends suggest a diffuse and gradual pattern of rural depopulation. The results underscore the importance of integrating dasymetric mapping with spatial analysis for small-area demographic research, particularly in data-limited contexts.

Beyond methodological contributions, the study expands the applicability of BDM approaches to low-density rural contexts and highlights the importance of building-level ancillary data for capturing micro-scale demographic transformations.

This study also faced several limitations. One limitation of the analysis is that relative changes in small households may appear disproportionately large, as the loss of a single resident can represent a significant proportion of the entire population in that unit. This effect is inherent to micro-scale approaches and should be taken into account when interpreting the results. In addition, the classification of uninhabited or seasonally occupied houses, although field-verified, may involve uncertainties typical of rural contexts. These limitations should be considered when interpreting the results. The conclusions presented here are based on modelled building-level estimates rather than direct household counts. This approach reflects a trade-off between data availability and spatial precision. While it cannot fully capture household heterogeneity, it enables a fine-scale analysis of relative spatial patterns of change that would otherwise remain invisible. The most fundamental limitation arises from the availability of census data only at the aggregate settlement level, without disaggregation at the household level. This constraint necessitated a modelled allocation approach, which represents an estimation rather than direct measurement. Despite this, the integration of volumetric proxies and field verification enabled the generation of fine-scale insights that would otherwise remain inaccessible. This trade-off between precision and feasibility underscores both the contribution and

https://doi.org/10.59954/stnv.712

the challenge of applying building-level dasymetric methods in rural demographic research.

Future work should explore the integration of socio-economic indicators, dynamic housing characteristics, and alternative validation sources to refine population modelling further and support rural policy development. These conclusions primarily reflect the specific local and temporal context analysed here; broader generalisations require validation across diverse rural settings and socio-economic conditions.

ACKNOWLEDGMENTS

This paper was written as part of the 2025 Research Program of the Institute of Social Sciences with the support of the Ministry of Science, Technological Development and Innovation of the Republic of Serbia.

REFERENCES

Bajat, B., Hengl, T., Kilibarda, M., & Krunić, N. (2011). Mapping population change index in Southern Serbia (1961–2027) as a function of environmental factors. *Computers, Environment and Urban Systems*, *35*(1), 35–44. https://doi.org/10.1016/j.compenvurbsys.2010.09.005

Bajat, B., Krunić, N., Samardžić Petrović, M., & Kilibarda, M. (2013). Dasimetrično modeliranje dinamike prebivalstva na urbanih območjih. *Geodetski vestnik*, *57*(04), 777–792. https://doi.org/10.15292/geodetski-vestnik.2013.04.777-792

Baynes, J., Neale, A., & Hultgren, T. (2022). Improving intelligent dasymetric mapping population density estimates at 30 m resolution for the conterminous United States by excluding uninhabited areas. *Earth System Science Data*, *14*(6), 2833–2849. https://doi.org/10.5194/essd-14-2833-2022

Cartagena-Colón, M., Mattei, H., & Wang, C. (2022). Dasymetric Mapping of Population Using Land Cover Data in JBNERR, Puerto Rico during 1990–2010. *Land*, *11*(12), 2301. https://doi.org/10.3390/land11122301

Chen, Y. (2021). An analytical process of spatial autocorrelation functions based on Moran's index. *PLOS ONE*, *16*(4), e0249589. https://doi.org/10.1371/journal.pone.0249589

Gajić, A., Krunić, N., & Protić, B. (2021). Classification of Rural Areas in Serbia: Framework and Implications for Spatial Planning. *Sustainability*, *13*(4), 1596. https://doi.org/10.3390/su13041596

Gillies, S., van der Wel, C., Van den Bossche, J., Taves, M. W., Arnott, J., Ward, B. C., & others. (2024, July 13). Shapely. Zenodo. https://doi.org/10.5281/ZENODO.5597138

Google. (2020). Google Earth Pro 7.3.3.7786. *Geospatial Solutions*.

Harris, C. R., Millman, K. J., Van Der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hunter, J. D. (2007). Matplotlib: A 2D Graphics Environment. *Computing in Science & Engineering*, *9*(3), 90–95. https://doi.org/10.1109/MCSE.2007.55

Jordahl, K., Bossche, J. V. D., Fleischmann, M., Wasserman, J., McBride, J., Gerard, J., … Leblanc, F. (2020, July 15). geopandas/geopandas: v0.8.1. Zenodo. https://doi.org/10.5281/ZENODO.3946761

Krunić, N., Bajat, B., & Kilibarda, M. (2015). Dasymetric Mapping of Population Distribution in Serbia Based on Soil Sealing Degrees Layer. In K. Růžičková & T. Inspektor (Eds), *Surface Models for Geosciences* (137–149). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-18407-4_12

Krunic, N., Gajic, A., Srnic, D., & Tosic, D. (2018). Spatial aspects of demographic processes in Serbia. *Stanovnistvo*, *56*(2), 23–38. https://doi.org/10.2298/STNV1802023K

Lloyd, C. D. (2010). *Spatial data analysis: an introduction for GIS users*. Oxford: Oxford university press.

Mennis, J. (2009). Dasymetric Mapping for Estimating Population in Small Areas. *Geography Compass*, *3*(2), 727–745. https://doi.org/10.1111/j.1749-8198.2009.00220.x

Mennis, J., & Hultgren, T. (2006). Intelligent Dasymetric Mapping and Its Application to Areal Interpolation. *Cartography and Geographic Information Science*, *33*(3), 179–194. https://doi.org/10.1559/152304006779077309

OpenStreetMap Contributors. (2017). OpenStreetMap. *Planet dump retrieved from* https://planet.osm.org. https://www.openstreetmap.org

Ord, J. K., & Getis, A. (1995). Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*, *27*(4), 286–306. https://doi.org/10.1111/j.1538-4632.1995.tb00912.x

Pajares, E., Muñoz Nieto, R., Meng, L., & Wulfhorst, G. (2021). Population Disaggregation on the Building Level Based on Outdated Census Data. *ISPRS International Journal of Geo-Information*, *10*(10), 662. https://doi.org/10.3390/ijgi10100662

Pirowski, T., & Szypuła, B. (2024). Dasymetric Population Mapping Using Building Data. *Annals of the American Association of Geographers*, *114*(5), 1001–1019. https://doi.org/10.1080/24694452.2024.2313500

QGIS Development Team. (2024). QGIS Geographic Information System. *Open Source Geospatial Foundation Project*. Open Source Geospatial Foundation. http://qgis.org http://qgis.osgeo.org/ http://qgis.osgeo.org. Accessed 21 March 2024

Rey, S., Anselin, L., Li, X., Pahle, R., Laura, J., Li, W., & Koschinsky, J. (2015). Open Geospatial Analytics with PySAL. *ISPRS International Journal of Geo-Information*, *4*(2), 815–836. https://doi.org/10.3390/ijgi4020815

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and Statistical Modeling with Python (92–96). Paper presented at Python in Science Conference, Austin, Texas. https://doi.org/10.25080/Majora-92bf1922-011

Sheskin, D. J. (2020). *Handbook of Parametric and Nonparametric Statistical Procedures* (5th edn). Chapman and Hall/CRC. https://doi.org/10.1201/9780429186196

Statistical Office of the Republic of Serbia. (2024). Number of population in 1948, 1953, 1961, 1971, 1981, 1991, 2002, 2011 and 2022. Belgrade: SORS. https://data.stat.gov.rs/Home/Result/31010101?languageCode=en-US. Accessed 29 May 2025

The pandas development team. (2024, September 20). pandas-dev/pandas: Pandas. Zenodo. https://doi.org/10.5281/ZENODO.3509134

Van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace.

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., … Vázquez-Baeza, Y. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nature Methods*, *17*(3), 261–272. https://doi.org/10.1038/s41592-019-0686-2

Wan, H., Yoon, J., Srikrishnan, V., Daniel, B., & Judi, D. (2023). Landscape metrics regularly outperform other traditionally-used ancillary datasets in dasymetric mapping of population. *Computers, Environment and Urban Systems*, *99*, 101899. https://doi.org/10.1016/j.compenvurbsys.2022.101899

Waskom, M. (2021). seaborn: statistical data visualization. *Journal of Open Source Software*, *6*(60), 3021. https://doi.org/10.21105/joss.03021

Wooditch, A., Johnson, N. J., Solymosi, R., Medina Ariza, J., & Langton, S. (2021). Ordinary Least Squares Regression. In *A Beginner's Guide to Statistics for Criminology and Criminal Justice Using R* (245–268). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-50625-4_15

Zandbergen, P. A. (2011). Dasymetric Mapping Using High Resolution Address Point Datasets. *Transactions in GIS*, *15*(s1), 5–27. https://doi.org/10.1111/j.1467-9671.2011.01270.x

Data Availability Statement

The datasets generated and/or analysed during this study are available from the following link: https://doi.org/10.5281/zenodo.15870007

How to cite: Potić, I. (2025). Building-Level Binary Dasymetric Mapping and Spatial-Statistical Analysis of Population Change in Rural Serbia. *Stanovništvo*. https://doi.org/10.59954/stnv.712

Binarno dasimetrijsko mapiranje i prostorno-statistička analiza promene broja stanovnika na nivou objekata u ruralnoj Srbiji

PROŠIRENI SAŽETAK

Ovaj rad primarno primenjuje binarno dasimetrijsko mapiranje (BDM) na nivou objekata radi analize promena u broju stanovnika u seoskom naselju Barje Čiflik u jugoistočnoj Srbiji u periodu između dva popisa (2011–2022), dok analizu dodatno proširuje primenom prostornih i klasičnih statističkih metoda. Osnovni cilj istraživanja je razvoj metodološki pouzdanog i replikativnog pristupa koji omogućava preciznu procenu mikrodemografskih promena u uslovima ograničene dostupnosti podataka.

Stanovništvo je raspoređeno na pojedinačne stambene objekte primenom volumenskog indeksa – proizvoda prizemne površine i broja spratova – koji je verifikovan terenskim obilaskom, prilikom kojeg su identifikovani i napušteni objekti. Prostorni podaci su prikupljeni ručnim digitalizovanjem na osnovu satelitskih snimaka visoke rezolucije i OpenStreetMap slojeva, dok je obrada izvršena u QGIS okruženju uz primenu koordinatnog sistema WGS 84 / UTM zona 34N. Tabelarni podaci iz popisa stanovništva integrisani su sa prostornim slojevima radi alokacije stanovništva na nivou objekata.

Na osnovu tako dezagregiranih podataka izračunati su indikatori apsolutne i relativne promene broja stanovnika i promene gustine. Prostorne i klasične statističke metode – Global Moran's I, Getis–Ord Gi*, regresija običnih najmanjih kvadrata (OLS), Spirmanova korelacija i LOWESS analiza – primenjene su radi identifikacije obrazaca grupisanja, strukturnih faktora i prostornih tokova demografskih promena.

Rezultati pokazuju da je depopulacija prostorno grupisana, naročito u perifernim zonama naselja, dok su objekti veće površine i višespratnice češće beležili pad broja stanovnika. Uočene su i razlike u intenzitetu promena između centralnog jezgra i rubnih delova naselja, gde manji, prizemni objekti pokazuju veću stabilnost stanovništva. Promene gustine pokazuju visoku disperziju i nisku statističku povezanost, ali ukazuju na suptilne transformacije na nivou domaćinstava koje ostaju nevidljive u agregiranim podacima, naročito u slučajevima sezonskog boravka ili delimične napuštenosti objekata. Prostorna autokorelacija potvrđuje postojanje lokalnih žarišta demografskog opadanja, što naglašava potrebu za mikroanalitičkim pristupima u demografskom istraživanju ruralnih područja i ukazuje na značaj integrisanja prostornih i društvenih faktora u daljim analizama.

Istraživanje predstavlja metodološki doprinos u primeni BDM u ruralnim područjima sa ograničenim podacima, pri čemu se postiže visoka prostorna rezolucija i omogućava procena dinamike stanovništva na nivou objekta. Kombinacija detaljnih prostornih podataka, statističkih metoda i terenske verifikacije pokazuje da predloženi okvir pruža donekle ekonomičan, replikativan i naučno utemeljen model pogodan za praćenje depopulacije i podršku prostornom planiranju u okruženjima sa ograničenim podacima.

KLJUČNE REČI

promena broja stanovnika, dasimetrijsko mapiranje, dezagregacija na nivou objekata, depopulacija ruralnih prostora, prostorna statistika

https://doi.org/10.59954/stnv.712