ISBN 978-9941-36-434-1, ISSN 3088-4349, Tbilisi, Georgia, November 6-8, 2025

MODELING AS A TOOL FOR PREDICTING URBAN DEVELOPMENT: THE CASE OF BREST, REPUBLIC OF BELARUS

***Shchasnaya I., **Krupskaya M.**

**Belarusian state University, Belarus, Minsk*
***UE "BELNIIPGRADOSTROITELSTVA", Belarus, Minsk*
irina.schastnaya@gmail.com

Abstract. *The work considers the application of a two-layer SD-ANN-CA model for exploring trends in land use and land cover (LULC) and making LULC prediction for 2030 and 2035 for the city of Brest as a case study. Within the framework of the study a set of input data is identified, the features of the used model are emphasised and a workflow for its use is defined.*

Key Words: *modelling, prediction, land use, planning constraints, urban planning*

Introduction

The land use and land cover (LULC) prediction is of great importance for urban planning, especially in multifunctional cities, where planners must not only consider a wide range of factors – most notably spatial, temporal, and socio-economic influences on urban development – but also place emphasis on maintaining the quality of the environment. In today's context, modeling provides the most reliable approach for producing such comprehensive predictions [1].

In recent years, LULC models have advanced significantly – from the earliest quantitative approaches, which merely projected land-use demand and broad LULC trends, to modern spatial methods that simulate and reconstruct the spatial structure of land use [2]. Commonly used quantitative approaches include system dynamics (SD), grey models (GMs), Markov models, and artificial neural networks (ANN). Common spatial approaches include the Conversion of Land Use and its Effects model (CLUE), the Dynamic Land System model (DLS), cellular automata (CA), and multi-agent systems (MAS). Among these, CA models stand out for their dynamic evolution mechanisms and their capacity for fine-scale, high-resolution analysis, which has been extensively applied over the past decades [3, 4].

Unlike many studies that focus only on individual districts or a single type of land use, the approach discussed here adopts a more comprehensive perspective. The modeling is conducted at the scale of a major regional city and incorporates an extensive set of land-use categories. Although the model is not fully exhaustive, its elaboration is sufficient for city-level analysis, as it treats the entire urban area as a single system and integrates dynamic indicators of its development over the period 2015–2025.

Study area, material and methods

The city of Brest, which is one of the regional centres of the Republic of Belarus (population ~340 thousand people, area 146 km²), was chosen as the object of the study as a representative example of a large city with a complex and multifunctional land use structure. Its territory is marked by sharp zoning contrasts: industrial and residential districts are concentrated in the east and northeast, while the western and southern parts preserve the natural landscapes of the Polesian Lowland, including forests and wetlands. Of particular importance for modeling is the extensive network of green spaces and the riparian ecosystems of the Mukhavets and Bug rivers, which form the city's ecological framework and serve as one of the key limiting factors for spatial development. This combination of urbanized areas and valuable natural complexes makes Brest a suitable case for applying LULC prediction methods at the city scale.

This study requires two types of data: spatial and numerical (Table 1). To ensure proper model operation, spatial data must be standardized, and vector data converted into raster format. The coordinate system is unified using Pulkovo 1942/CS63 zone C1 (EPSG:3351) through the raster projection tool. The pixel size for all spatial data is set to 30 m using the resampling tool. The number of rows and columns in the raster data is standardized using the "Clip" tool. To ensure compatibility between QGIS and MATLAB, the raster format is additionally converted to ASCII-GRID format.

The data for the study are from open sources: raster images of Sentinel-2 mission, vector data of OpenStreetMap and official statistical indicators published by the National Statistical Committee of the Republic of Belarus.

Table 1. Set and specification of the input data.

Data type	Data	Time period	Description	Format / Resolution
Spatial Data	Remote sensing imagery	2015 2020 2025	Three input datasets representing land-use conditions (processed remote sensing data)	Raster, 10 m
	Digital Elevation Model (DEM)	2025	Surface elevation data obtained from DEM analysis; used as a model constraint	Raster, 30 m
	Road network	2025	Constraint for the model	Shapefile (lines)
	Water bodies	2025	Constraint for the model	Shapefile (polygons)
	Residential areas	2025	Constraint for the model	Shapefile (polygons)
	Administrative boundaries	2025	Delimitation of the modeling area	Shapefile (polygons)
	Protected areas	2025	Constraint set for the model (protected areas, green spaces, riparian buffers)	Shapefile (polygons)
Numerical Data	Demographic data	2015-2025	Input for the SD model: urban and rural population, population growth rates	PDF
	Industrial output	2015-2025	SD model: value added of primary, secondary, and tertiary sectors, along with their growth rates	PDF
	Agricultural output	2015-2025	SD model: production volumes, per capita consumption levels	PDF
	Urban development data	2015-2025	SD model: urbanization level, residential area, housing demand, land allocation by categories	PDF

The acquisition of land-use data involves image mosaicking, clipping, calibration, and supervised classification in QGIS. For the purposes of this study, the territory of Brest is categorized into six land-use types: cropland, forest, grassland, water bodies, built-up areas, and other land. Processing of DEM data for slope and elevation is conducted using 3D analysis tools, while Euclidean distances for road networks, water bodies, and settlements are calculated through spatial analysis tools.

To examine land-use change across the six categories – cropland, forest, grassland, water bodies, built-up areas, and other land – a two-layer model is employed, integrating system dynamics (SD) and an artificial neural network–cellular automata (ANN-CA) framework [5].

The upper layer of the model defines constraints. These include meso-level drivers influencing land-use change and macro-level projections of demand for each land-use category. This component, developed through system dynamics, captures general principles: it identifies factors affecting land-use change, their key interrelations, and overall demand for each category. In effect, the upper layer communicates to the lower one how much land of each type will be required in the future.

The lower layer is designed to forecast and spatially allocate all six land-use categories under the imposed constraints. Within the ANN stage of the ANN-CA model, the neural network is trained on the factor relationships and feedbacks identified in the SD layer to establish transition rules for subsequent simulation by cellular automata. These rules parameterize the CA, which operates with consideration of micro-spatial constraints – namely, centers of land-use gravity, or areas around which changes are most likely to occur, derived using a gravity-transfer method. In this way, the lower layer determines the precise spatial distribution of land-use categories on the map.

Furthermore, the ANN-CA outputs are validated against the macro-level constraints: a forecast map is accepted only if the deviation between the areas of the four key categories (arable land, built-up land, forest, and grassland) as projected by the SD model and as simulated by ANN-CA does not exceed ±5%. The overall structure of the model is presented in Fig. 1.

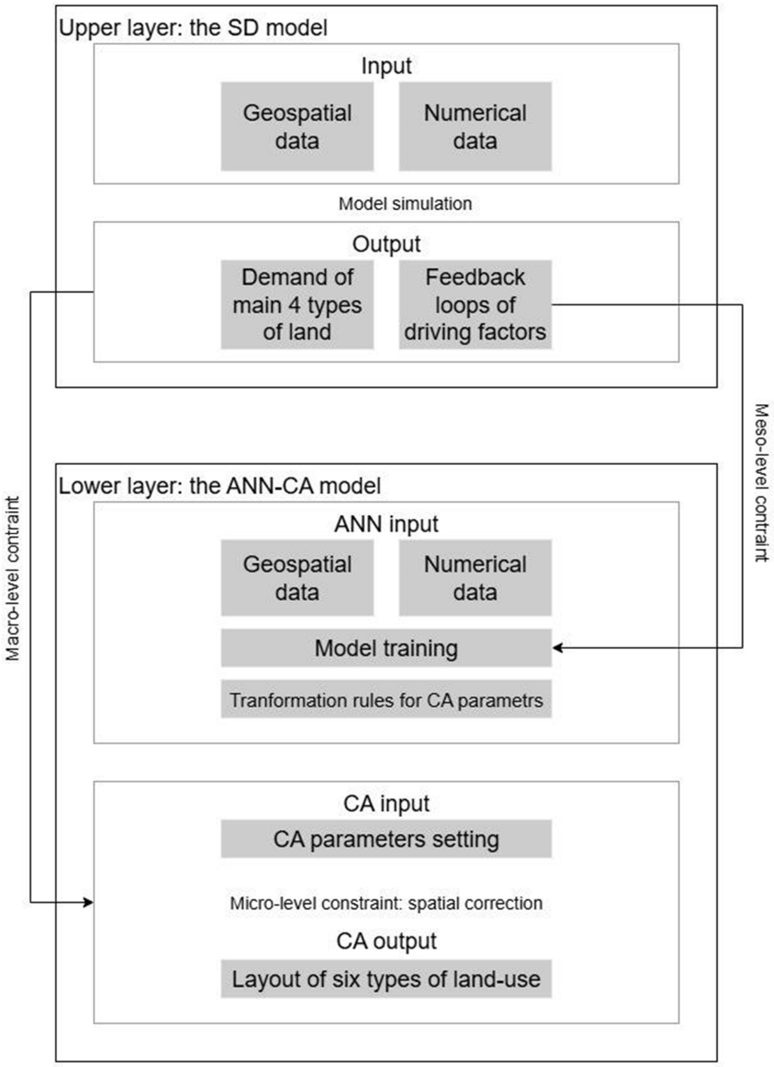

Fig. 1. Two-layer SD-ANN-CA model execution procedure.

To compare forecast results with the actual state of land use and land cover, the following equations were employed to assess model accuracy:

$$OA = N_{inc}/N_{tot}\ OA = N_{inc}/N_{tot} \tag{1}$$

$$k = (P_a - P_e)/(P_i - P_e)\ k = (P_a - P_e)/(P_i - P_e) \tag{2}$$

Equation (1) calculates the proportion of misclassified pixels relative to the total number of pixels in the samples, where N_{inc} N_{inc} denotes the number of pixels incorrectly predicted by the model and N_{tot} N_{tot} the total number of pixels. Equation (2) is applied in evaluating CA simulations, where kk represents the kappa coefficient; Pa indicates actual accuracy; Pe the expected accuracy; Pi and the ideal accuracy (100%).

Moving to the next stage – specifying model constraints – it is important to note that LULC outcomes result from the interplay between anthropogenic and natural factors, which include political, institutional, economic, cultural, technological, and environmental drivers. In existing studies, two principal categories are generally considered: geographical (including natural) and socio-economic factors.

Spatial (geographical) drivers of land-use change are typically consistent across studies and include elevation, slope, distance to main roads, distance to water bodies, and distance to administrative centers. These factors are also incorporated in the considered model. Because spatial variables vary widely in scale and range (e.g., slopes from 0° to over 30°, road distances from 0 to 5,000 m), they are normalized to a 0–1 range. Normalization accelerates neural network training while preserving the original probability distribution.

In contrast, the proposed set of socio-economic drivers is broader and more diverse. In the model, the upper SD layer captures socio-economic trends for the period 2015–2025. When combined with spatial drivers, this enables the transfer of significant socio-economic dynamics into the ANN-CA learning process, thereby improving the capacity to identify land-use change patterns. Selected socio-economic indicators include demographic data, measures of industrial and agricultural output, and information on urban development.

Furthermore, the study extends traditional LULC analysis by incorporating constraint layers representing protected areas: protected areas, green spaces, and riparian buffers. A defining feature of this approach is the assignment of land-use categories within these zones as fixed and unchangeable, thereby safeguarding their ecological potential throughout the predicting horizon.

Conclusion

The study considered a method for predicting land use and land cover (LULC) change based on an integrated two-layer model that combines system dynamics for the quantitative assessment of land demand with an artificial neural network–cellular automata (ANN-CA) framework for spatial simulation.

Considered method encompasses the full research cycle: from data collection and preprocessing of spatial and statistical information, specification of constraints, and construction of a transition matrix, to calibration, presicting, and the evaluation of both predictive and spatial accuracy. A key feature of the approach is the integration of macro-level constraints derived from the system dynamics model, which ensures quantitative consistency of land allocation, as well as the application of ANN-CA, which captures local trends and spatial configurations of change.

The implementation of this method enables the generation of reproducible scenarios of land use development for 2030 and 2035, while also providing insights into the respective contributions of macro- and micro-level factors to territorial transformation. The study outcomes will have practical relevance for spatial planning, environmental management and sustainable regional development strategies.

References

1. Laurini R., Promises of Artificial Intelligence for Urban and Regional Planning and Policymaking. // In: Laurini R., Nijkamp P., Kourtit K., Bouzouina L. (eds). Knowledge Management for Regional Policymaking. Springer, Cham, 2022, pp. 3–20. https://doi.org/10.1007/978-3-031-15648-9_1
2. Li X., Gong P., Urban growth models: progress and perspective. // Science Bulletin, 61, 2016, pp. 1637–1650. https://doi.org/10.1007/s11434-016-1111-1
3. Wang R., Derdouri A., Murayama Y., Spatiotemporal Simulation of Future Land Use/Cover Change Scenarios in the Tokyo Metropolitan Area. // Sustainability, 10, 2018, 2056, pp. 1–18. https://doi.org/10.3390/su10062056
4. Liu X., Liang X., Li X., Xu X., Ou J., Chen Y., Li S., Wang S., Pei F., A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. // Landscape and Urban Planning, 168, 2017, pp. 94–116.
5. Zhao J., Zhu X., Zhang F., Gao L., A Two-Layer SD-ANN-CA Model Framework for Multi-Typed Land Use and Land Cover Change Prediction under Constraints: Case Study of Ya'an City Area, Western China. // Land, 13, 2024, 714, pp. 1–20. https:/doi.org/10.3390/land13050714