



Identification of conflict zones based on land cover (LC) changes using advanced GIS software tools

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Abstract. The aim of this study was to identify areas at risk of land cover (LC) changes using the case study of the Sokółka municipality, utilizing advanced spatial analysis tools available in the GIS environment. The MOLUSCE module (Modules for Land Use Change Evaluation), operating within QGIS software, enables integrated analysis of spatial data using Artificial Neural Networks (ANN) and Cellular Automata (CA). The analysis encompassed data from the years 2014–2023, derived from the BDOT10k and Digital Terrain Model databases, which allowed for the identification of areas at risk of changes that could cause spatial conflicts. Model validation demonstrated high effectiveness (Kappa coefficient of 0.97), confirming its suitability for predictive analyses. A total of 223.42 ha of land was identified as particularly vulnerable to land cover changes, located mainly in the central part of the municipality – at the interface of industrial areas, water reservoirs, and raw material extraction sites. The obtained results confirm the effectiveness of the applied tools and methods and emphasize the need to implement an informed spatial policy that accounts for the potential occurrence of spatial conflicts and the necessity of protecting areas of high environmental value.

Keywords: land use transformation, GIS, MOLUSCE, land use conflicts.

Introduction

Geographical space should be analyzed as a coupled human-environment system, in which interactions between natural and anthropogenic processes result in complex and often unpredictable outcomes (Turner et al., 2007). Contemporary Land Use and Land Cover (LULC) changes occur amidst increasing development pressure, intensified urbanization, globalization, and highly dynamic socio-economic processes (Lambin et al., 2003; Lambin & Meyfroidt, 2011; Seto et al., 2012). Consequently, spatial transformations increasingly manifest as rapid, non-linear changes whose trajectories cannot be precisely predicted (Wu, 2013). These phenomena pose a particular challenge in areas of high environmental value, where an imbalance between investment pressure and ecological functions may lead to the emergence of spatial conflicts.

Therefore, one of the key challenges in contemporary land cover research is the identification of areas particularly susceptible to unpredictable transformations, as it is in these zones that tensions arising from competition for space most frequently emerge (Cieślak, 2019). These conflicts intensify particularly where diverse forms of land use – e.g., industrial, agricultural, and high natural value areas – intersect, generating pressure to alter development trajectories and causing environmental degradation (Hansen et al., 2012).

In this context, the analysis of land cover change dynamics becomes a vital diagnostic tool. LC changes reflect the landscape's response to environmental, economic, and social drivers, and their observed instability may indicate areas particularly susceptible to future transformations (Cieślak et al., 2017; Cieślak, 2018). Monitoring changes using remote sensing data and GIS, which enables a comprehensive and long-term assessment of transformation trends, is crucial for identifying locations with elevated conflict potential (Antrop, 2004; Yadav & Singh, 2024).

The advancement of simulation methods, including models based on Artificial Neural Networks (ANN) and Cellular Automata (CA), allows for increasingly precise identification of areas exhibiting persistent uncertainty regarding the direction of change (Hakim et al., 2019; Gharaibeh et al., 2020). These models, integrating environmental and anthropogenic data, enable the identification of locations where current processes are unstable and may lead to future conflicts, even though precise transformations remain difficult to predict (Turner et al., 2007).

The thesis of this paper posits that the analysis of land cover change dynamics can serve as a valuable source of information regarding the localization of spatially unstable areas – specifically those exhibiting recurrent transformation uncertainty, which may become future hotspots of spatial conflicts.

The aim of this study is to identify spatially unstable areas within the Sokółka municipality that may constitute potential sources of spatial conflicts. The analysis was conducted based on BDOT10k data and the Digital Terrain Model (DTM), utilizing advanced simulation tools within the GIS environment, which enabled the identification of zones at elevated risk of spatial transformation.

Literature Review

Changes in land use (LU) and land cover (LC) are a key symptom of changes in the functioning of the environment, both in its natural and anthropogenic components (Cieślak, 2019). Monitoring these changes is crucial for assessing imbalances between these components and for recognizing potential risks arising from spatial conflicts related to these imbalances (United Nations, 2022).

Changes in land use almost always lead to changes in land cover (Pick, 2005). For instance, clearing a forest (land cover) for crops (land use) causes a change in land cover from forest to agricultural (Malede et al., 2023; Tadele et al., 2025). This relationship can be reversed. Changes in land cover, resulting from natural disasters, for example, can affect the possibilities and methods of land use, and therefore the way it is used (Gubila et al., 2024).

This relationship is of great importance for sustainable development and manifests itself in many of its aspects (Hansen et al., 2012). It is particularly evident in the environmental dimension where changes in soil and in water quality – resulting, for example, from the conversion of forests to arable land – significantly affect the physicochemical properties of the soil (Neris et al., 2012; Hasan et al., 2020; Gubila et al., 2024). These phenomena undoubtedly have a direct negative impact on biodiversity and ecosystem functioning and contribute to an increase in natural hazards through increased susceptibility to soil erosion, landslides and floods (Birhanu et al., 2024).

LULC changes also translate into socio-economic factors. The strong expansion of built-up and industrial areas at the expense of agricultural and forest land has serious implications for food production, natural resources and climate, but also for increased infrastructure development and the expansion of commercial crops (Meyer & Turner, 1994; Barthel et al., 2019; Cieślak, 2019; Ishiyama et al., 2021; Afuye et al., 2024). It also significantly affects local economies and livelihoods (Cieślak et al., 2019). LULC transformation processes therefore cause serious changes in social structures in terms of employment, migration, lifestyle, and quality of life (Weith et al., 2021).

Understanding how different land uses affect soil, water, biodiversity, and ecosystems is fundamental to developing land management strategy (Ishiyama et al., 2021) and helps identify key processes leading to environmental pressures (Leuven & Poudevigne, 2002; Weith et al., 2021).

Modern geospatial technologies, such as Remote Sensing (RS) and Geographic Information Systems (GIS), have become indispensable tools for monitoring LC dynamics. They enable the large-scale acquisition of high-quality classification data, serving as the foundation for developing precise simulations and predictions (Nyeko, 2012; Biłozor & Cieślak, 2021; Kazak et al., 2022). Remote sensing provides data on land cover and its changes over time through satellite and aerial images. Various sensors (e.g. electro-optical, radar, laser, radiometers) are used for passive or active data collection (Pick, 2005; Hansen et al., 2012; Butt et al., 2015; Koranteng et al., 2023). Multispectral images (MSI) from satellite or airborne platforms have significantly improved our understanding of the Earth's surface and human activities on it (Chen et al., 2015; Lim et al., 2024). At regional and local scales, time series of Landsat or ASTER data are used to present the basic land cover and its changes (Netzband & Stefanov, 2004). LC is also studied based on radar and LIDAR data, which at local scale can provide data on vegetation structure and habitat distribution patterns (Laonamsai et al., 2023). Furthermore, very high-resolution satellite images (e.g. IKONOS and QuickBird) enable direct detection of even individual trees and aspects of vegetation structure (Ouma & Tateishi, 2008; Pu & Landry, 2012). Consequently, raster data are commonly used for classification of areas and terrain features such as soil, terrain or vegetation (Moharram & Sundaram, 2023) as well as for land cover changes resulting from planned human activities, but also from phenomena such as fires or floods (Alquraishi & Kumar, 2013; Acuña-Alonso et al., 2022).

A wide range of models based on modern research techniques is employed to track and predict LC changes (Kumari et al., 2022). Among the most popular and frequently applied are integrated Cellular Automata and Markov Chain (CA-Markov) models (Aliani et al., 2019; Aldileemi et al., 2023). This approach represents one of the most efficient and widespread hybrid models for LC simulation (Mosleh, 2025). As a statistical model, it utilizes past and current information to predict the future state of the system. While widely accepted for the quantitative estimation of changes, it predicts the correct magnitude but fails to account for the spatial distribution or direction of changes. For this reason, incorporating CA into the model has become crucial, as it enables the determination of the modeling direction. CA simulates the spatial evolution of LC by determining the state of a pixel based on its initial state, neighborhood effects, and transition rules. The integration of CA with MCM creates a robust tool for describing the spatiotemporal dynamics of LC (Mathewos et al., 2022). Another popular approach for tracking and predicting LC changes involves methods based on Artificial Neural Networks (ANN) or their hybrids

(Saputra & Lee, 2019; Aftab et al., 2024). Models such as CA-ANN (Cellular Automata-Artificial Neural Network) integrate cellular automata with artificial neural networks, most commonly the Multi-Layer Perceptron (MLP). In this approach, the neural network learns complex, non-linear relationships between driving factors and historical LC changes to determine the transition probability for each cell (Das & Prasad, 2025).

Deep Learning (DL) models and Time Series approaches, such as Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN), are also employed in LC predicting. Deep learning techniques, particularly Recurrent Neural Networks (RNN), are increasingly valued for their ability to model complex, non-linear, and temporal dependencies in satellite data, which is crucial for studying dynamic urban environments (Kerins et al., 2021; Naik et al., 2024). Their extension with Long Short-Term Memory (LSTM) allows for the consideration of long-term dependencies in LC time-series data, significantly enhancing their performance (Rousset et al., 2021). Another notable approach in LC prediction is the application of the Patch-Generating Land Use Simulation (PLUS) model (Mutale & Qiang, 2024). It is a versatile model that has demonstrated effectiveness in accurately simulating scattered LC patterns and urban expansion dynamics. The PLUS model combines a land expansion analysis strategy to overcome limitations such as the inability to simulate the interaction and evolution of open spaces and urban areas under various policy scenarios. Furthermore, research indicates that the PLUS model effectively simulates LC and landscape patterns (Liang et al., 2021; Lu et al., 2022).

The utilization of the aforementioned methods and their hybrid variants is becoming increasingly prevalent, facilitated by the application of specialized GIS software (Majidi Nezhad et al., 2025). This software significantly simplifies and accelerates analysis processes through built-in tools based on the methodologies discussed earlier. A prime example of such a tool is the MOLUSCE (Modules for Land Use Change Evaluation) plugin within Quantum GIS (QGIS), designed for analyzing dynamics and predicting future Land Cover (LC) change scenarios. The operation of MOLUSCE is based on the Cellular Automata (CA) method combined with Artificial Neural Network (ANN) architecture, frequently referred to as CA-ANN or MLP-ANN (Multi-layer Perceptron Artificial Neural Networks) (Bramantio et al., 2024). MOLUSCE has been employed, among others, to analyze changes and predict future land use in the Parangtritis Sand Dunes in the Bantul Regency, Special Region of Yogyakarta, Indonesia. This area is threatened by degradation due to settlement, tourism, and agriculture; the aim of the study was to analyze the dynamics and future land cover (Bramantio et al., 2024). Other examples of this model's application include examining the impact of anthropogenic factors – such as population growth, industrialization, and the associated demand for real estate – on LC changes, as well as predicting these changes for the Jagdalpur sub-region in the Bastar district of Chhattisgarh, India (Jain, 2024). Similar studies have been conducted to monitor, assess, and predict LC changes (including deforestation and agricultural expansion) in the Ouessè municipality in the Republic of Benin (N'Danikou et al., 2025); as well as in the areas of Gdańsk, Gdynia, and Sopot and neighboring counties in Poland (Dawid & Bielecka, 2022). The model was also utilized to predict soil erosion associated with LC changes for Oplenac, a wine-producing area in Serbia (Perović et al., 2018). Further examples include the use of this model for investigating and predicting changes related to urban sprawl and ecological land quality, for instance, in the Chiba Prefecture, Japan (Yadav & Singh, 2024).

The cited examples of MOLUSCE plugin applications are characterized by a high degree of reliability. Model validation is a crucial stage for assessing a model's credibility and predictive accuracy (Whiting et al., 2023). This process is conducted after the completion of the simulation but prior to generating the final long-term prediction (Van Vliet et al., 2016). It involves comparing the predicted land cover results for a simulated year with the actual (interpreted) LC data for the same reference year (Jayasinghe et al., 2021). The simulation performance is evaluated using two primary metrics: Overall Accuracy and the Kappa coefficient, the latter being a key indicator expressing the agreement between two categorical datasets (predicted and actual) (Foody, 2020).

Research and prediction of land cover (LC) changes are pivotal for sustainable development, yet they remain subject to numerous significant limitations. Models employed in such analyses often oversimplify complex landscape systems, failing to adequately capture overlapping forms of land cover and use (Rutledge et al., 2012). Their accuracy is further compromised by the necessity of extensive data processing and the scarcity of detailed cartographic information in many regions (Roy & Roy, 2010). These challenges are exacerbated by the dynamic and irregular nature of LC changes, which are heavily driven by human activity and are difficult to model precisely (Dharani & Sreenivasulu, 2021; Wang et al., 2022). Such limitations also stem from high requirements regarding data quality and quantity, issues with satellite imagery resolution, the high variability of land cover classes, and difficulties in obtaining appropriate training sets for machine learning methods (MohanRajan et al., 2020).

Additional barriers arise regarding model scalability; many models struggle to transfer results across distinct spatial and temporal conditions (Mooney et al., 2020). In certain regions, particularly those with limited observational data availability, such as high-latitude areas, modeling becomes even less reliable. Even advanced predictive models achieve only moderate performance, especially in areas characterized by high transformation dynamics and significant landscape heterogeneity. Intensive urbanization further complicates the pattern of changes, generating rapid and unpredictable transformations that lead to environmental degradation (Opelele Omeno et al., 2021). Collectively, these factors render LC prediction a highly complex task, fraught with numerous uncertainties. Nevertheless, it remains highly valuable for detecting areas exhibiting increased change dynamics and, consequently, those prone to various forms of spatial conflicts.

To enhance the effectiveness of LC modeling, it is imperative to integrate remote sensing methods, GIS, and advanced machine learning techniques. The advancement of high-resolution satellite imagery and comprehensive spatial databases constitutes the key to increasing both the accuracy and utility of predictions. Naturally, the results of research conducted using remote sensing and broadly understood GIS, in addition to the appropriate methodological assumptions, depend to a large extent on the accuracy and reliability of the data. However, it is indisputable that remote sensing provides large-scale, current, and archival data on land cover, when integrated and analyzed in a GIS environment, enable comprehensive research on the dynamics of changes in land use and cover. This is crucial for understanding environmental processes, spatial planning, and sustainable development (Cieślak, 2019).

Data and methods

Research area

The urban-rural municipality of Sokółka, located in the eastern part of the Podlaskie Voivodeship, was selected as the study area due to the high complexity of its natural environment and the landscape's significant susceptibility to anthropogenic changes (Drzewiecka, 2021). This area is part of the post-glacial Sokółka Hills, characterized by diverse topography and varied hydrological and elevation conditions (Zaleszkiewicz et al., 2021). Geomorphological diversity coexists here with a mosaic land cover structure comprising the Knyszyn Forest complex, agricultural land, wetlands, and fragments of the Sokółka Hills Protected Landscape Area, all of which contribute to the region's high environmental value (Kondracki, 2009).

The municipality comprises the city of Sokółka and 68 villages organized into 55 village councils; it covers an area of over 300 km² and has a population of approximately 23,000 (Sokółka Municipality, 2024). In recent years, the area has witnessed intensified infrastructural and construction investments, increased transport accessibility, and the development of residential and economic functions. This growth stems, among others, from its location along major road and rail routes connecting Warsaw with Grodno, Vilnius, and Riga (Local Action Group Tatar Trail, 2008). At the same time, the region remains susceptible to spatial conflicts due to its proximity to the state border and high natural value areas, as well as the impact of the migration crisis, which has slowed certain investment processes in recent years (Municipal Office of Sokółka, 2017).

The selection of Sokółka as the study area is justified by the increasing transformation pressure typical of peripheral municipalities in north-eastern Poland, where agricultural intensification, dispersed settlement, and alterations in hydrological regimes lead to the escalation of functional conflicts and the risk of landscape degradation (Kocur-Bera & Lyjak, 2021; Ślawska, 2024). Simultaneously, the lack of comprehensive studies regarding long-term land cover changes for this municipality, which underscores the significance of the conducted analysis for both identifying local spatial processes and supporting planning policy and conservation measures.

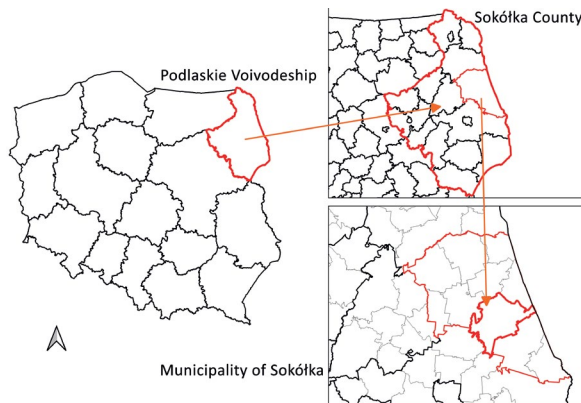


Fig. 1. Location of the research area in relation to the Polish voivodeships and the counties of the Podlaskie voivodeship

Research methods

The research objective required the collection of spatial data, the examination of relationships variables, and the determination of historical LC change trends, which served as the basis for building a predictive model of these changes. To achieve this aim, the MOLUSCE (Modules for Land Use Change Evaluation) tool was utilized, which supported at each of the designated stages of work. It is an advanced utility operating within QGIS software, used to analyze and predict changes in land use and cover (Kumari & Roy, 2025). The implemented algorithms allow for conducting, among others, correlation analyses, transition potential modeling, as well as simulations of future spatial changes (Dhiman et al., 2022). It enables the determination of areas at risk of change and the prediction of their future dynamics (Hakim et al., 2019). The assessment of LC transition potential is based variables such as distance from roads, buildings, or terrain characteristics (Pontius & Malanson, 2005).

The MOLUSCE tool includes an Artificial Neural Network (ANN) algorithm, which is an innovative approach to land-cover and land-use change modeling, enabling the identification of relationships between variables. ANNs are widely used in the prediction of dynamic spatial changes. The use of artificial neural networks in combination with geospatial data provides high-precision change models (Ahmad et al., 2022). This method has been used, among others, to predict landscape changes in mountainous regions where terrain diversity is very high (Fischer & Lindenmayer, 2007). ANNs also show potential in integrating socio-economic data with spatial data, which can support a more holistic approach to spatial management (Hakim et al., 2019). The workflow designed using MOLUSCE was divided into several stages, which are presented in Figure 2.

1. Data collection	2. Data analysis	3. Training a predictive model	4. Simulation of LU/LC changes	5. Evaluation of results
1.1. Land cover data from BDOT10k: 2014; 2017; 2020; 2023 1.2. Layers of land cover change factors • DTM: terrain	2.1. Converting vector data to raster data 2.2. Determination of statistics of transformations of utility classes • Correlation of change factors 2.3. Determining the change matrix • BDOT10k LC 2014-2017 • BDOT10k LC 2017-2020 • BDOT10k LC 2020-2023	3.1. Selection of the transition potential modelling method • Neural networks (ANN) 3.2. Training a model with three-year change interval data – the learning curve	• Calculation of land use spatial certainty • Generating a new map using cellular automata simulation based on a trained model	• Model validation based on the comparison of spatial certainty maps from three time intervals • Identification of areas at risk of spatial changes

Fig. 2. Steps of working with the Modules for Land Use Change Evaluation – MOLUSCE tool

- Data collection

This stage involved the selection of data to be implemented within the proposed analytical procedure. The modeling was based on land cover information derived from the PT (*Pokrycie Terenu – Land Cover*) layer of the BDOT10k database, available across multiple temporal cross-sections. Based on these data, changes were calculated between consecutive periods, i.e., 2014-2017, 2017-2020, and 2020-2023, while simultaneously incorporating additional spatial data in the form of a Digital Terrain Model (DTM).

The data used for the analysis were obtained from available database services, namely BDOT10k and DTM. BDOT10k data were downloaded in shapefile format and rasterized for the analysis. All data used in the analysis are provided in the Appendix.

The Database of Topographic Objects (BDOT10k) is an official, large-scale spatial dataset created and updated by the Geodetic and Cartographic Service in Poland. It constitutes the primary national reference database at a scale of 1:10,000 and includes detailed information regarding topographic objects, land development elements, infrastructure, and land cover. Its thematic scope encompasses 286 object types grouped into 57 classes and 9 object class categories. The analysis focused on the PT (*Pokrycie Terenu* – Land Cover) category, which consists of 12 object classes:

- **PTWP** – Inland waters – Class code 1;
- **PTZB** – Urban development – Class code 2;
- **PTLZ** – Forests – Class code 3;
- **PTRK** – Shrubs – Class code 4;
- **PTUT** – Permanent cultivation – Class code 5;
- **PTTR** – Arable land – Class code 6;
- **PTKM** – Roads – Class code 7;
- **PTGN** – Wasteland – Class code 8;
- **PTPL** – Square – Class code 9;
- **PTSO** – Landfills – Class code 10;
- **PTWZ** – Excavation area – Class code 11;
- **PTNZ** – Remaining undeveloped land – Class code 12.

Each class is further divided into land cover subclasses, totaling 35 distinct types. BDOT10k data are acquired using aerial photogrammetry, high-resolution orthophotos, field measurements, and integration with other national registers (e.g., PRG, GESUT, EGIB). The database is characterized by high geometric accuracy: the standard object positioning accuracy is 1.5 m, while for objects difficult to identify, an accuracy threshold of 5 m is permissible. These parameters make the database suitable for detailed spatial analyses at the municipal and local levels.

BDOT10k data for the territory of Poland are available from the website of the Head Office of Geodesy and Cartography (GUGiK). The data used for this research are presented in Figure 3.

Another source of information within the GUGiK resources is the Digital Terrain Model, which provides a digital representation of the terrain surface. In studies on land cover (LC) changes, the DTM is a key source of spatial data. It depicts the absolute elevation of surface points, excluding elements such as trees or buildings. The DTM is particularly useful in spatial analyses where topography plays a crucial role, such as assessing the availability of land for investment, identifying flood areas or other natural hazards. The Digital Terrain Model used in spatial analyses in Poland is available in several variants, differing in terms of the reference system and resolution. These include, among others, PL-KRON86-NH with a 1.0 m resolution, and PL-EVRF2007-NH, available both with a grid size of 1.0 m or smaller and as a 5.0 m resolution variant. In this study, the PL-EVRF2007-NH DTM with a grid resolution of 1.00 m or less was employed, enabling a precise representation of elevation conditions within the municipality. The detailed parameters, sources, and characteristics of the DTM used are presented in the Appendix. In this study, data from the Digital Terrain Model were used to determine the impact of terrain on land use transformation and served as a significant variable in the artificial neural network model. The data are presented in Figure 4.

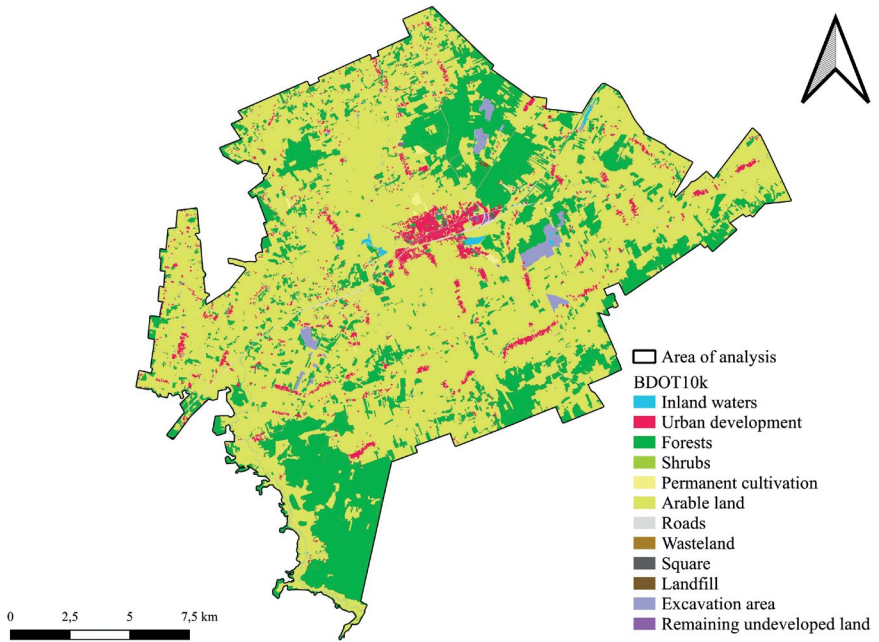


Fig. 3. Land cover classes in the Sokółka municipality in 2014 based on the Database of Topographic Objects (BDOT10k)

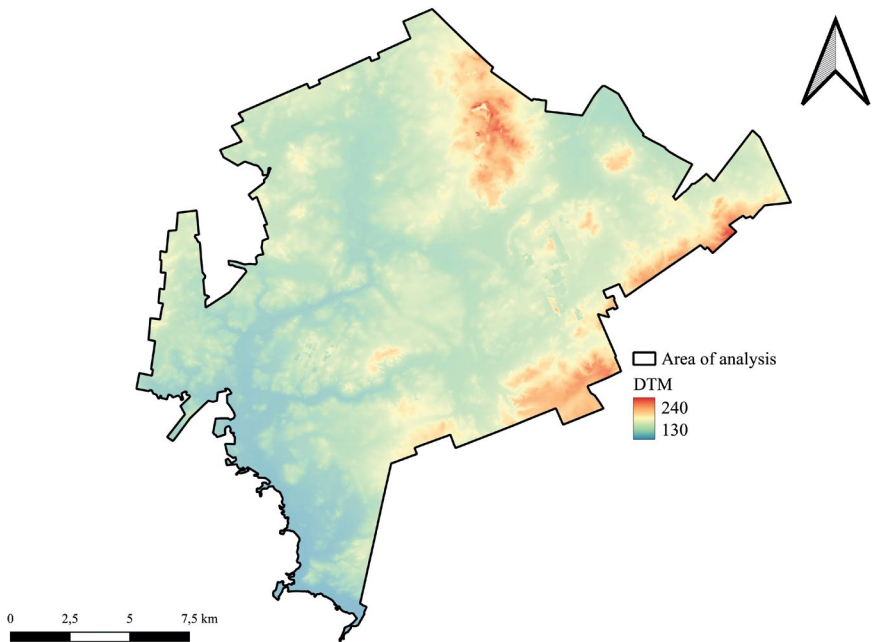


Fig. 4. Digital Terrain Model (DTM) of the Sokółka municipality.

- Land Cover Change Analysis

The next stage of the work involved the analysis of quantitative changes in land cover between specific time points. It was carried out for BDOT10k data for the years 2014 and 2017, in which 12 land use classes were defined. The *Area Changes* utility implemented in MOLUSCE enables the identification of land use classes that changed their area in the examined time period. The algorithm operates based on rasters and their individual cells, determined based on the map resolution. Subsequently, the percentage changes of the area of each land cover class were calculated. The results of these calculations are presented in Table 1.

Table 1. Summary of land use changes for 2014-2017

Class	area 2014	area 2017	Δ	2014	2017	Δ
	ha			%		
1 – Inland waters	95.96	104.35	8.39	0.31	0.33	0.03
2 – Urban development	1,080.85	1,081.36	0.51	3.44	3.45	0.00
3 – Forests	8,150.55	8,183.84	33.29	25.97	26.08	0.11
4 – Shrubs	21.31	35.07	13.75	0.07	0.11	0.04
5 – Permanent cultivation	99.63	102.76	3.12	0.32	0.33	0.01
6 – Arable land	21,356.33	21,279.62	-76.71	68.06	67.81	-0.24
7 – Roads	181.52	183.31	1.79	0.58	0.58	0.01
8 – Wasteland	1.72	1.72	0.00	0.01	0.01	0.00
9 – Square	31.38	23.06	-8.32	0.10	0.07	-0.03
10 – Landfills	5.78	5.87	0.09	0.02	0.02	0.00
11 – Excavation area	328.06	332.51	4.45	1.05	1.06	0.01
12 – Remaining undeveloped land	26.70	46.32	19.62	0.09	0.15	0.06

- Transition Potential Modeling Procedure

In this study, Transition Potential Modeling (TPM) was employed to assess the spatial stability of land cover. The drivers of these changes were analyzed and subsequently, a spatial model was developed to describe them both spatially and statistically. The Artificial Neural Network (ANN) method was used to build the model. This method is commonly used to create spatial models of land use and cover change probability (Gharaibeh et al., 2020; Ramdani et al., 2021; Souza et al., 2022). The transition potential value assigned to each raster cell determines the probability of transitioning from one LC class to another. The certainty of this change is given on a scale of 0 to 100. Additionally, each change factor is assigned weights, which are iteratively modeled to reduce the differences between actual and calculated changes. For this purpose, the *backpropagation algorithm* was used (Puig-Arnavat & Bruno, 2015), the aim of which is to minimize the mean square error of the changes. For the correct operation of the algorithm, it was necessary to determine the key parameters, which for this study were defined as presented in Figure 5.

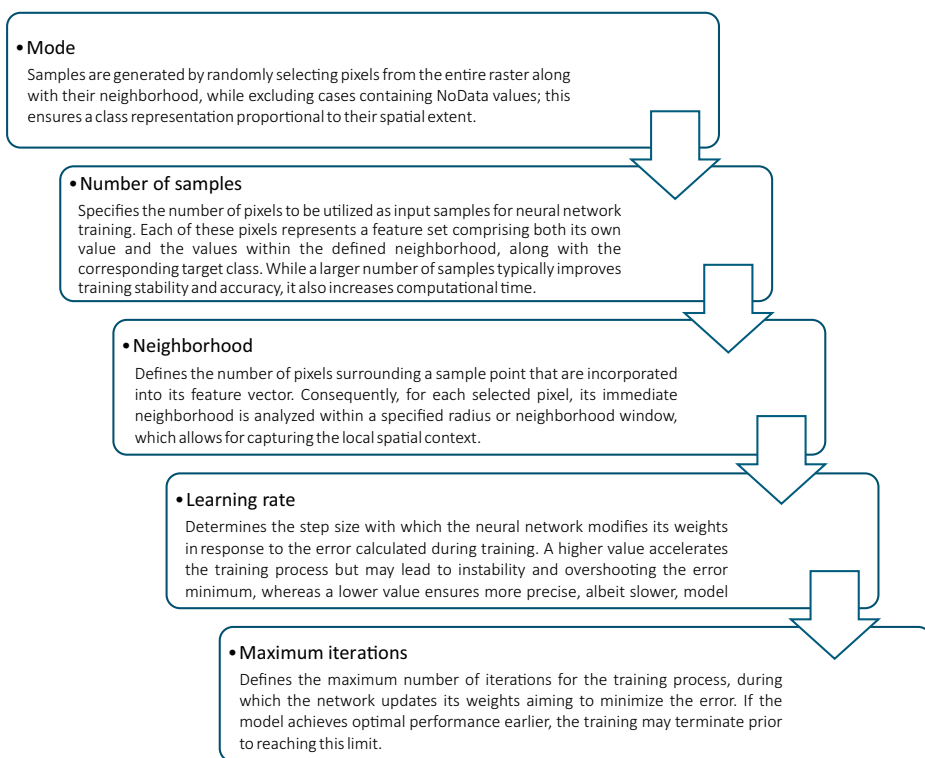


Fig. 5. Artificial Neural Networks (ANN) algorithm operating parameters

• Modeling LC risk areas

In the spatial analysis performed for the purpose to identify areas with a high risk of spatial instability Cellular Automata (CA) were used. This method is based on local interactions between cells in a spatial grid and transition rules determining the changes in the state of each cell over time. For each cell, the state of the neighborhood and the transition potential are checked. After reaching the maximum number of iterations, the tool generates a Certainty map, which reflects the level of confidence with which the model can determine the direction of spatial change. Cells with low certainty are interpreted as unstable or conflict-prone areas. The transition rules are based on the following function:

$$S_{t+1}(i,j) = f(S_t(i,j), N(S_t(i,j)), P_{i,j}) \tag{1}$$

Where:

$S_{t+1}(i,j)$ – state of cell (i,j) at time $t+1$,

$S_t(i,j)$ – state of cell (i,j) at time t ,

$N(S_t(i,j))$ – state of neighboring cells at time t ,

$P_{i,j}$ – cell transition potential (i,j) calculated based on the transition potential modeling.

In the process of determining this function, certainty function map is (value range 0-100) created:

- Validation of the LC prediction model

The validation process of the model results was conducted based on three consecutive time intervals derived from the BDOT10k data:

- 2014-2017;
- 2017-2020;
- 2020-2023.

For each of these periods, a Certainty raster was generated, constituting a key output component of the analysis. These Certainty maps reflect the degree of confidence with which the model can unequivocally classify cells as stable or unstable. High certainty values indicate stable areas, whereas low values denote conflict areas where the model registers ambiguity regarding the direction of change and signals an elevated risk of spatial transformation. In the model, these values are represented using a hybrid color scale:

- High values (80-100%) are marked with shades of dark and light blue, indicating stable areas where the model determines the absence of change with high certainty;
- Medium values (40-80%) are represented by transitional colors (greenish tones), reflecting moderate model certainty;
- Low values (0-10%), interpreted as conflict areas, are marked with distinct warm colors ranging from yellow to intense red.

It is precisely this lower segment of the scale (0-10%) that serves as the basis for identifying zones at risk of transformation. On the maps, these areas stand out as the most contrasting elements, marked as red and yellow patches dispersed throughout the municipality's structure; this distinctiveness facilitates their unambiguous identification and subsequent spatial analysis. Since the primary objective of this study was not to predict future land cover changes but rather to identify areas characterized by entrenched instability, the validation process required an approach that enabled the assessment of the persistence of spatial uncertainty patterns.

In the first stage of validation, three independent Certainty maps were generated, each reflecting the spatial structure of change uncertainty for a specific time interval. Subsequently, a quantitative comparison was performed by calculating Pearson correlation coefficients (r) between all pairs of periods. The application of the Pearson correlation is justified by the nature of the analyzed data, as certainty values are continuous variables with a uniform range of 0-100, enabling the assessment of the strength of spatial dependence between the rasters. This analysis enables the determination of whether spatial uncertainty patterns are consistent over time, which constitutes a key indicator of the validity of the spatial stability modeling.

Correlation values exceeding 0.30 indicate that the changes registered by the model across consecutive time intervals are consistent, and that the identified conflict areas appear in similar locations in subsequent analyzed periods. Such consistency serves as key evidence that the applied method correctly identifies persistent spatial zones of instability. In the context of the adopted research objective, this validation approach is fully adequate and justified. It ensures that the obtained results rest on a solid statistical foundation and that the detected unstable areas are genuinely characterized by a recurrent susceptibility to change over time.

Results

The analysis of land use and land cover in the Sokółka municipality allowed for the identification of areas at risk of transformation. Using the input data, an analysis was carried out using an Artificial Neural Network (ANN). Its best result at the level of Kappa = 0.97, indicating a high compliance of the model with real data, was obtained with the following parameters, should be entered into the program:

1. Mode of operation (number of training samples) = 10,000,
2. Neighborhood = 1 pixel,
3. Learning rate = 0.001,
4. Maximum number of iterations = 300,
5. Hidden layers = 10,
6. Momentum = 0.001.

The graph (Fig. 6) shows the learning curve of the artificial neural network. The X -axis represents the number of iterations, while the Y -axis represents the error value. The green line shows the error on the training set, and the red line shows the error on the validation set. Δ Overall Accuracy indicates the difference between the model accuracy obtained between subsequent training iterations. The obtained value of 0.0001 is very small, indicating model stability and a marginal impact on the quality of analysis. The minimum value of the validation error (*Min Validation Overall Error*) was 0.0012. The low validation error confirms the effectiveness of the model in the process of identifying conflict areas. The Current Validation Kappa reflects the extent to which the neural network has captured 'change patterns' between consecutive periods; its value of 0.9741 indicates a high efficacy of the learning process.

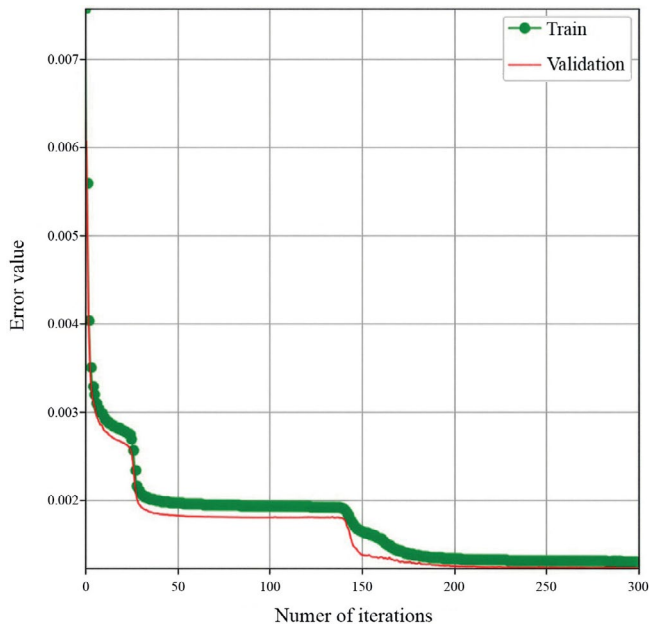


Fig. 6. ANN learning curve describing the accuracy of the model

Utilizing Cellular Automata (CA) based on three time intervals, spatial certainty models were generated. The results underwent validation to assess their significance and suitability for identifying potential conflict areas. The Pearson correlation method was employed, yielding the following values:

- $r = 0,74$ for the pair 2014-2017 and 2017-2020,
- $r = 0,47$ for the pair 2014-2017 and 2020-2023,
- $r = 0,45$ for the pair 2017-2020 and 2020-2023.

All values exceeded the significance threshold of $r = 0.30$, adopted as the minimum level indicating the existence of a statistically significant relationship between continuous variables. The highest correlation value (0.74) indicates a very strong spatial agreement between the first pair of Certainty maps, whereas values in the range of 0.45-0.47 represent moderate, yet distinct and statistically significant dependencies (Cohen, 1988). This implies that the spatial patterns of uncertainty do not emerge randomly; rather, they reflect recurring schemes of spatial behavior observed in the actual BDOT10k data.

The next result of the analysis was the generation of a map of transformation uncertainty (Fig. 7). It was generated using the *Certainty Function*. The map shows the distribution of the probability of land use transformations in the Sokółka municipality. The range of the result values is from 0 for uncertain areas to 100 for the most certain areas.

The blue and green shaded areas represent stable areas with a low probability of LC changes. The model shows high certainty of no future changes in these areas, indicating that the land use of these areas is stable. The areas marked in red are susceptible to change, particularly due to anthropogenic pressure. They interact with neighboring land use and may become areas of intensive change. In many places, they overlap with

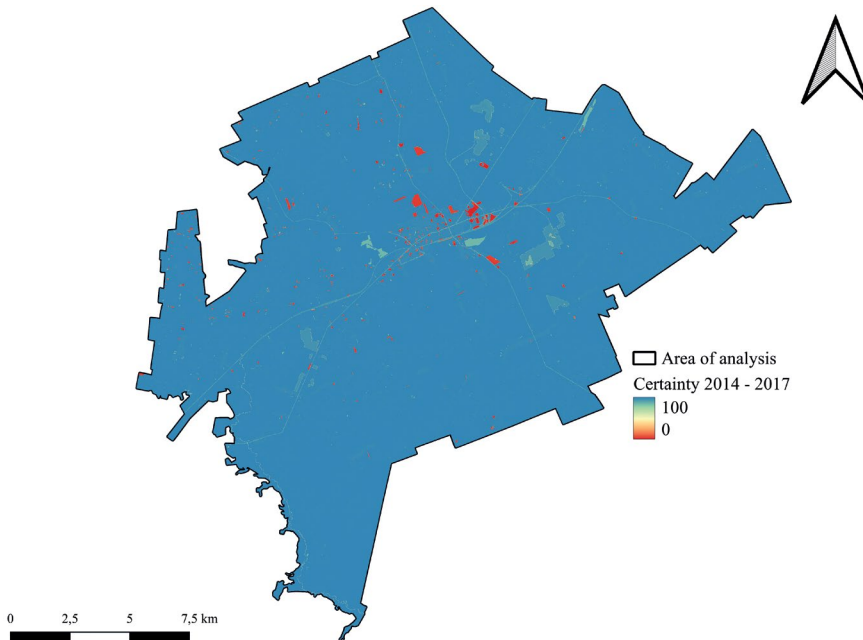
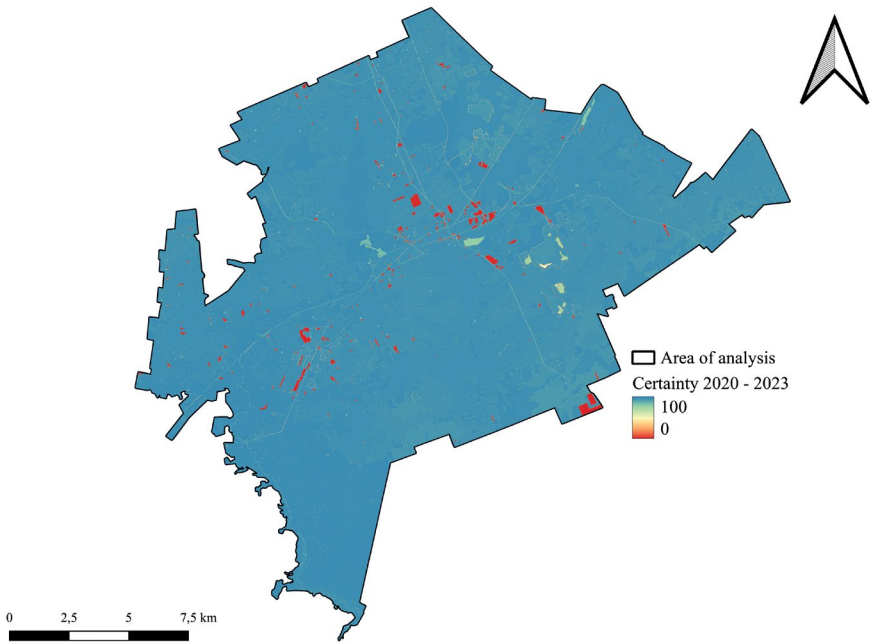
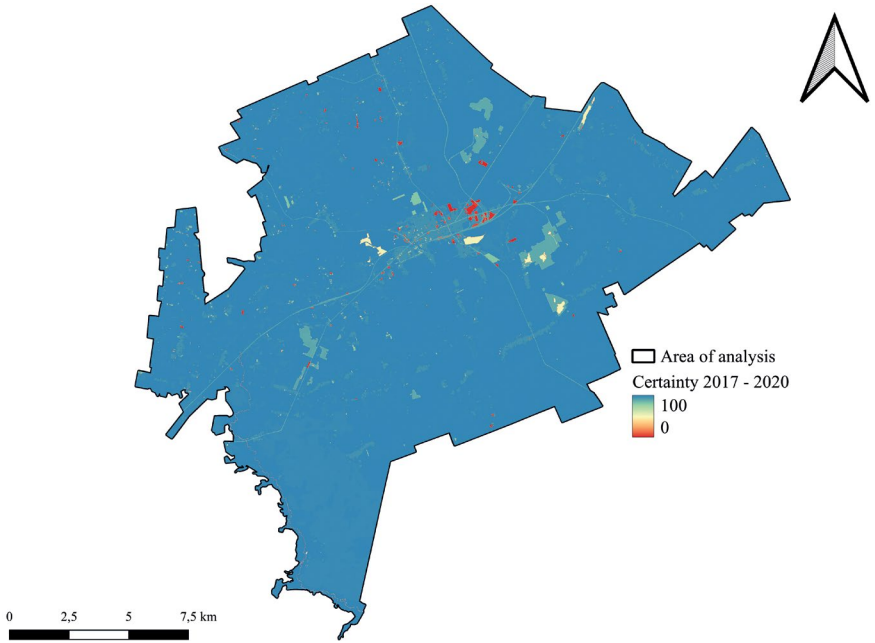


Fig. 7. Comparison of spatial uncertainty maps for the Sokółka municipality in three time intervals ↑→



areas subject to land use limitations and will require special attention in the planning processes undertaken. This is particularly relevant given the inability to precisely predict the specific nature of future changes in these zones.

In the next step, the analysis focused on areas with certainty values below 10%. The 10% threshold was assumed as a noticeable influence of variables that have a real potential for change (Pontius & Malanson, 2005). For each time interval, the resulting Certainty map was vectorized, and the surface area of zones formed by contiguous low-certainty cells was calculated. A significance threshold was defined as a minimum area of 1 ha, implying that only cell clusters of this size or larger were interpreted as areas of genuine spatial instability. In the subsequent step, the unstable areas identified for the three analyzed periods (2014-2017, 2017-2020, and 2020-2023) were overlaid to determine the spatial intersection of conflict zones. Finally, a buffer with a radius of 100 m was generated around these common areas, based on the premise that potential land use conflicts exert an impact on their immediate neighborhood (Kozak et al., 2014) and only then were the areas identified as being at risk of LC changes (Fig. 8). Consequently, these areas are interpreted as being the most susceptible to spatial conflicts.

Following spatial verification and surface area recalculation, it was determined that the total extent of zones at risk of change within the municipality amounted to 223.42 ha. The uncertainty areas, overlapping across time, indicate persistent hotspots of spatial instability within the 2014-2023 interval and constitute a valuable source of information regarding the location of land use conflicts during the analyzed period.

The identified areas are located in the central strip of the analysis area. They stretch from the eastern to the western border of the municipality. The northern and southern

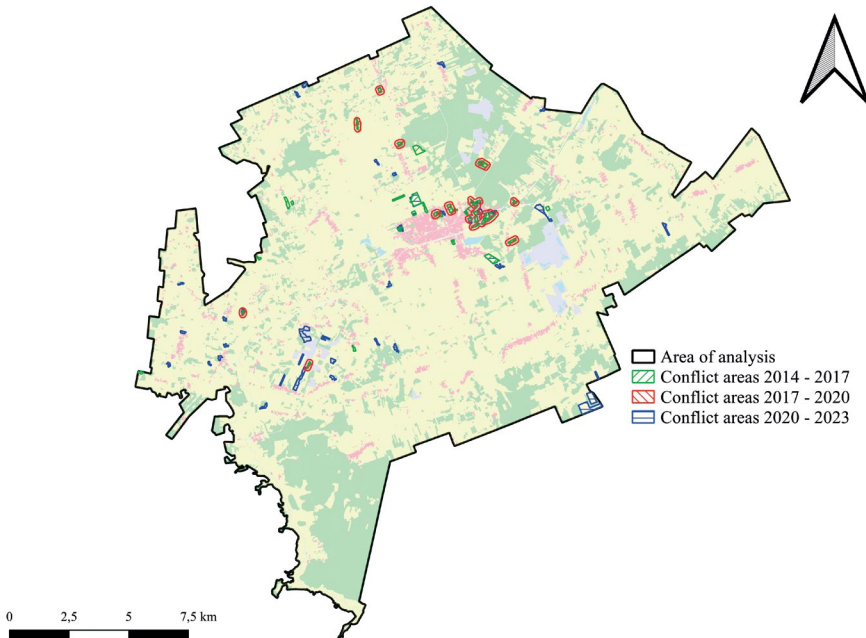


Fig. 8. Identification of unstable zones across three analyzed time intervals

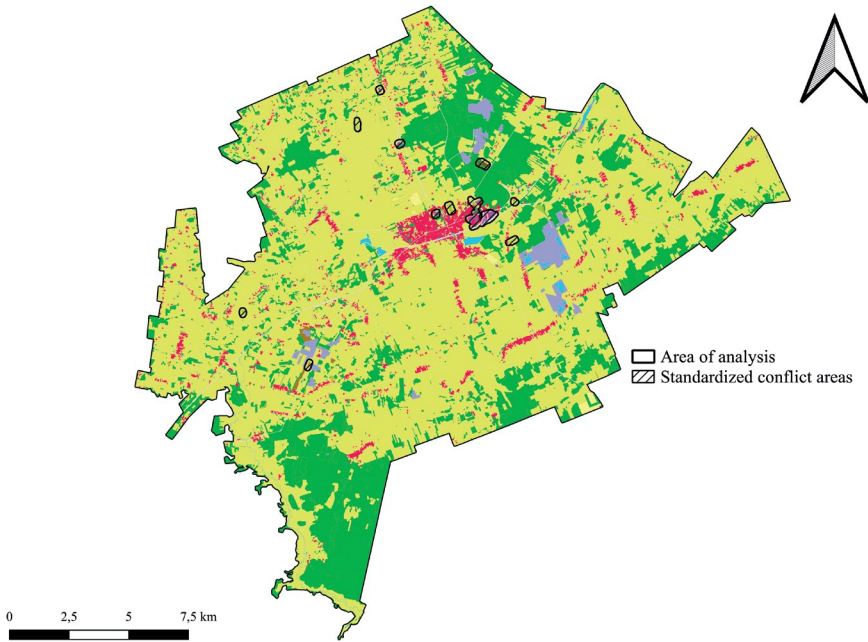


Fig. 9. Identification of unstable zones in the study area

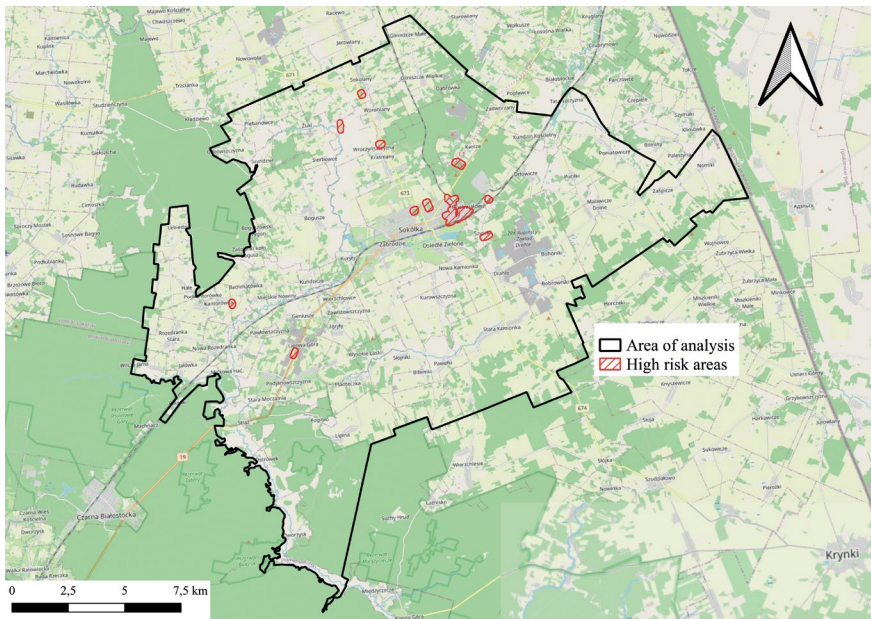


Fig. 10. Areas at risk of land use changes within the Sokółka municipality based on data from 2014-2023

parts are relatively less susceptible to transformation. Areas on the border of different forms of use are particularly at risk. Two areas are particularly notable due to their size. The first is the area of construction and road aggregate extraction located near the village of Lipowa Góra. The second area is located within the town of Sokółka. In this case, the risk of change is generated by the location of industrial areas, water reservoirs, and nearby gravel pit areas. In addition, areas adjacent to the village of Wroczyńszczyzna are also at risk of change. This area is characterized by the presence of a sawmill that sources raw materials from the surrounding lands. Conflicting interests of various social groups regarding the direction of land use in this space may contribute to the intensification of spatial conflicts.

The identified areas are places where different forms of land use meet, which usually intensifies anthropogenic pressure leading to more intensive land use. Concurrently with increasing urbanization and industrial use of the area (numerous mining areas), there may be fragmentation of the valuable natural landscape and loss of cultural identity may occur. Potential investments changing LC may cause not only conflicts in space but also conflicts over space.

Discussion and Summary

The analysis of land use and land cover in the Sokółka municipality revealed trends in spatial changes and the location of potential risks related to LC changes. Data obtained from BDOT10k and DTM proved to be an important source of information in the process of assessing and indicating these changes. The use of GIS tools to analyze these data significantly facilitated this process and allowed for the quick identification of problem areas that may be a source of spatial conflicts and disrupt the priorities of sustainable development in the studied area. The use of advanced modeling methods, such as Artificial Neural Networks (ANN) or Cellular Automata (CA), increases the reliability of the analysis results, which means that the described procedure may become useful in the process of implementing a proactive spatial policy.

The results of the analysis indicate that the problem areas are located mainly in the central part of the municipality, where land use diversity is high. The forms of use such as industrial areas, water reservoirs, or areas of mineral extraction are adjoin each other. These areas are particularly sensitive to anthropopressure and may be susceptible to spatial conflicts. The largest identified problem areas at risk of changes, i.e. open-pit areas near the village of Lipowa Góra and the industrial part of the city of Sokółka, require special attention and well-considered approach in the spatial planning process.

The analysis of the distribution map of transformation uncertainty shows how difficult it is to indicate the directions of changes occurring in space; at the same time, however, it is possible to identify areas of high spatial uncertainty, i.e., zones where numerous changes occur, yet their specific trajectories are difficult to predict. Based on these findings, it can be concluded that for the analyzed area, a significant part of the municipality is characterized by a stable land use pattern, while areas with high uncertainty partially overlap with areas at risk, which indicates not only a probable rapid change in the land use, but also high uncertainty regarding the direction of these changes.

The research carried out in the Sokółka municipality successfully achieved its main objective, which was to identify spatially unstable areas prone to land use and land cover (LC) transformations. The utilization of BDOT10k data and the Digital Terrain Model (DTM), integrated within the GIS environment and modeled using ANN and CA algorithms in the MOLUSCE module, enabled the precise identification of areas where the direction of land use change exhibits recurrent instability. Thus, the obtained results confirm the thesis that the analysis of land cover dynamics constitutes an effective tool for diagnosing locations particularly susceptible to functional conflicts and spatial destabilization.

The recurrent localization of unstable areas across three consecutive time periods indicates the persistence of spatial pressures and the continued existence of local transformation hotspots. The identified zones confirm trends observed in the literature, according to which the highest transformation dynamics occur at the interface of competing land use types. This particularly applies to areas adjacent to excavation sites, industrial grounds, transport infrastructure, and ecologically valuable areas (Basheer et al., 2022; Beshir et al., 2023).

The results obtained for Sokółka align with observations from other studies, in which LC modeling reveals the greatest instability in areas characterized by a complex landscape structure and high exposure to anthropogenic factors. Analyses based on CA-Markov, ANN, or PLUS models have previously pointed to similar clusters of instability. These studies were conducted, for example, in the suburban zones of dynamic cities (Hussain et al., 2025), in areas of resource exploitation and agricultural transformation (N'Danikou et al., 2025), or in regions of high ecological value susceptible to investment pressure (Blissag et al., 2024).

The problem of spatial instability is also associated with limitations characteristic of predictive models. The study of Sokółka confirmed several difficulties previously indicated in the literature. These may concern input data quality, which is particularly typical for historical data (Da Silva & Skinner, 2014). They may also be related to the interpretation of diverse land cover classes (Taher et al., 2025). Other issues include model sensitivity to the temporal variability of remote sensing data, also noted in studies tracking urban and agricultural transformations (Ait El Haj et al., 2023) or the difficulty in capturing non-linear change processes, reported especially in analyses involving areas of rapid urbanization or strong environmental pressures (Wentz et al., 2006).

Despite these limitations, the high value of the Kappa coefficient and the low validation error confirm that the applied model is adequate for the local scale and demonstrates high effectiveness in identifying spatial instabilities. Consequently, the study results constitute valuable support for spatial policy-enabling early detection of sensitive areas, minimization of spatial conflict risks, and the protection of areas with high environmental and cultural values.

The conducted research confirms that the analysis of spatiotemporal land cover dynamics, supported by machine learning tools and simulation models, constitutes a key instrument for identifying problem areas. These methods, as evidenced by other studies, significantly support the spatial planning process and the assessment of landscape risks (Ouma & Tateishi, 2008). Future analyses, enriched with additional socio-economic and environmental data, may further increase the precision and stable interpretability of spatial instability patterns.

Conclusions

The conducted research successfully achieved its main objective, which was to identify spatially unstable areas exposed to the risk of land cover (LC) transformations in the Sokółka municipality. By integrating multi-temporal BDOT10k data with Digital Terrain Model information and applying advanced modeling techniques implemented in the MOLUSCE module – combining Artificial Neural Networks (ANN) with Cellular Automata (CA) – it was possible to delineate zones characterized by persistent transformation uncertainty. These zones represent areas where future development directions are highly unpredictable and may therefore become hotspots of spatial conflicts.

The results clearly confirm the thesis that analyzing LC dynamics is an effective method for diagnosing spatial instability. The repeated appearance of low-certainty zones across three temporal intervals (2014-2017, 2017-2020, 2020-2023), together with statistically significant correlations between certainty maps, demonstrates the durability and consistency of these patterns. The total area of unstable zones (223.42 ha) is primarily located at the boundaries between contrasting land uses, such as industrial areas, open-pit mineral extraction sites, transport infrastructure, and water reservoirs. The location of these zones reflects underlying functional tensions and confirms that interfaces between different land use forms are particularly susceptible to instability and conflict potential.

The spatial pattern of instability is not random. Areas such as the industrial zone of Sokółka, extraction sites near Lipowa Góra, or the western part of the municipality adjacent to the Jesionowe Góry reserve show clear signs of increasing anthropogenic pressure. These areas also demonstrate a higher likelihood of landscape fragmentation and loss of natural value if transformative processes continue unchecked. While the majority of the municipality remains characterized by stable land use forms, the overlap between high-uncertainty zones and areas at risk of transformation highlights the need for continuous monitoring and active management of these spaces.

Although the modeling approach proved highly effective (as evidenced by a Kappa coefficient of 0.97 and low validation error), several challenges typical of LC studies were identified. These include sensitivity to the quality and consistency of multi-temporal spatial data, limitations in capturing abrupt or non-linear transformations, and the general difficulty of predicting changes driven by socio-economic dynamics that are not directly represented in geospatial data. Nevertheless, the modeling framework applied in this study is well-suited for detecting unstable areas at the local scale and provides reliable insights for spatial management.

The findings have important implications for spatial planning in the Sokółka municipality. Early identification of unstable zones enables preventive actions aimed at reducing environmental pressure, protecting ecologically valuable areas, and minimizing the likelihood of spatial conflicts. The results can support the development of planning documents, zoning decisions, and environmental protection strategies, particularly in areas where different land use interests intersect.

Future research should consider expanding the model to include socio-economic and environmental variables, as well as higher-resolution or more frequently updated datasets. Such improvements may enhance the precision of instability detection and allow for deeper understanding of the drivers behind spatial transformations. The methodological

approach presented here can also be applied in other municipalities, offering a robust framework for assessing spatial conflict potential.

Overall, the study demonstrates that integrated analysis of LC dynamics and predictive modeling provides a valuable basis for diagnosing spatial instability and supporting sustainable land management at the local level.

Unless otherwise stated, the sources of tables and figures are the authors', on the basis of their own research.

The first author was supported by the National Science Centre, Poland (grant no. 2024/53/N/HS4/01115).

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Appendix 1

Table 1. Summary of data used in the analysis

Name	Definition	Source	Native date (years)	Native resolution	Preprocessing	Final resolution
<i>PTWP</i>	Inland waters	GUGiK BDOT10k	2014, 2017, 2020, 2023	The geometry of BDOT10k objects is acquired with an accuracy of no less than 1.5 m. For objects that are difficult to unambiguously identify in the field (e.g., those poorly visible on an orthophotomap), an accuracy of no less than 5 m is permissible (Journal of Laws 2010, No. 76, item 489).	<ul style="list-style-type: none"> • Coordinate reference system set to EPSG:2180; • Layers merged to form a single land cover layer; • Land cover codes reclassified to numerical values for MOLUSCE compatibility; • Data clipped to the study area boundaries; • Conversion to raster format; • Pixel size resampled to 24.98 m² (4.998 m × 4.998 m) due to resolution rounding errors 	5,488x 5,299
<i>PTZB</i>	Urban development					
<i>PTLZ</i>	Forests					
<i>PTRK</i>	Shrubs					
<i>PTUT</i>	Permanent cultivation					
<i>PTTR</i>	Arable land					
<i>PTKM</i>	Roads					
<i>PTGN</i>	Wasteland					
<i>PTPL</i>	Square					
<i>PTSO</i>	Landfill					
<i>PTWZ</i>	Excavation area					
<i>PTNZ</i>	Remaining un-developed land					
<i>DTM</i>	Digital Terrain Model	GUGiK	2022-2024	1 m	<ul style="list-style-type: none"> • Coordinate reference system set to EPSG:2180; • 96 raster tiles merged into a single mosaic; • Clipped to the study area boundaries and resampled to a pixel size of 24.98 m² (4.998 m × 4.998 m) due to rounding errors during resolution adjustment. 	