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Urban Expansion in Estonia: Monitoring, Analysis, and Modeling

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Press

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LIST OF ORIGINAL PUBLICATIONS

This dissertation is based on the following publications referred to in the text by their respective Roman numerals.

I. **Mozaffaree Pour N**, Oja T (2022) Prediction Power of Logistic Regression (LR) and Multi-Layer Perceptron (MLP) Models in Exploring Driving Forces of Urban Expansion to Be Sustainable in Estonia. *Sustainability*, *14*(1), 160. https://doi.org/10.3390/su14010160

II. **Mozaffaree Pour N**, Oja T (2021) Urban Expansion Simulated by Integrated Cellular Automata and Agent-Based Models; An Example of Tallinn, Estonia. *Urban Science*, *5*(4), 85. https://doi.org/10.3390/urbansci5040085

III. **Mozaffaree Pour N**, Oja T (2020) Simulation of Urban Expansion in Estonia for 2046 Using Cellular Automata Model Based on the CORINE Land Cover Database. Proceedings of the 3rd International Conference on Geo-informatics and Data Analysis: ICGDA 2020, Marseille, France, April 15–17, 2020, pp 14–18. https://doi.org/10.1145/3397056.3397057

IV. **Mozaffaree Pour N**, Karasov O, Burdun I, Oja T (2022) Simulation of Land Use/Land Cover Changes and Urban Expansion in Estonia by a Hybrid ANN–CA–MCA Model and Utilizing Spectral–Textural Indices. Environmental Monitoring and Assessment. 194, 584. https://doi.org/10.1007/s10661-022-10266-7

Author's contribution to the articles: '*' denotes a minor contribution, '**' denotes a moderate contribution, '***' denotes a major contribution.

	Article I	Article II	Article III	Article IV
Original idea	***	***	***	***
Study design	***	***	***	**
Data processing and analysis	***	***	***	***
Interpretation of the results	***	***	***	**
Writing the manuscript	***	***	***	***

LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
ANN–CA– MCA	Hybrid Model consisting of Artificial Neural Networks, Cellular Automata, and Markov Chain Analysis
CA	Cellular Automata
CA–Agent	Integrated Cellular Automata and Agent-Based Models
CORINE	Coordination of Information on the Environment
ETAK	Estonian Topographic Database
LR	Logistic Regression
LULC	Land Use/Land Cover
MCE	Multi–Criteria Evaluation
MCA	Markov Chain Analysis
MLP	Multi–Layer Perceptron

ABSTRACT

Urban expansion is characterized by the low–density, spatially discontinued, and scattered development of urban-related constructions beyond the city boundaries. Since urban expansion changes the agricultural and forest lands, and slight changes in urban areas can affect biodiversity and landscape on a regional scale in the long-term, spatiotemporal monitoring of urban expansion and modeling of the future are essential to provide insights into the long-term trends and consequences.

In Estonia, after the regaining independence in 1991, the Land Reform Act was passed, and the transfer of "land" from the state to private ownership began. Since then, Estonia has experienced the decentralization of residential areas affecting the transformation of agricultural and industrial regions around Tallinn, changes in people's lifestyles, and the settling of wealthy people in single-family houses in the suburbs of Tallinn, Tartu, and Pärnu. During this period, Estonia's population has declined dramatically 15 %.

This doctoral thesis aims to "monitor, analyze and model the urban expansion over the past three decades in Estonia and simulate its future". This is the first comprehensive study about modeling urban expansion and analyzing the factors influencing urban expansion in Estonia. So, this dissertation explores the expansion of urban areas in Estonia utilizing various sets of remotely sensed data, driving forces and predictors, and modeling approaches including logistic regression, cellular automata, agent-based, and artificial neural network models to highlight the importance of these factors in representing the reality and detecting urban expansion footprints through time.

To achieve the main objective of the thesis, three tasks were set:

1. Analyze the physical driving factors and predictors (spectral–textural indices) of urban expansion over the past three decades in Estonia.
2. Evaluate the performance of several modeling approaches for investigating the past trends and simulating the future of urban expansion in Estonia.
3. Test the model performances by applying several datasets with different spatial resolutions.

These tasks are addressed in four original research articles on urban expansion in two Estonian counties (Harju County, containing the nation's capital, Tallinn, and Tartu County, where the country's second major city, Tartu, is located), Tallinn and its 15 km buffer zone, and throughout the country. The research data was drawn from three primary remote sensing sources: (1) the time–series CORINE land cover database with 100 m spatial resolution (level 1 class; artificial surfaces considered urban), (2) Landsat imagery products with a spatial resolution of 30 m for extracting urban expansion and spectral–textural indicators of landscape physiognomy, and (3) a 30 m spatial resolution land cover dataset provided by Parente et al. (2021). Besides, some other spatial data, including the road net-

works (main and local roads, railways) and the states' administrative boundaries, were downloaded from the Estonian Land Board geoportal (ETAK database). Much software, including QGIS 3.10, ArcGIS 10.6, IDRISI, and GEOSOS–FLUS, and platforms consisting of the Repast platform used in the AgentAnalyst extension for ArcMap 10.6 and Google Earth Engine cloud computing platform was employed to process the data, analyze, and simulate urban expansion.

By applying two models of LR and MLP neural networks, the proximity factors were analyzed, and the relationship between the physical driving forces and the urban expansion was evaluated. The results indicated that urban expansion in Harju County and Tartu County was influenced mainly by proximity to main roads, the core of Tallinn and Tartu, and existing residential areas. Then, the most influential drivers and constraints were evaluated with a multi-criteria evaluation (MCE) function and AHP technique to create a suitability map of urban expansion in Harju County. Besides the factors and constraints, behavioral rules and adjacent neighborhoods were applied to investigate urban expansion through dynamic interactions between cellular agents in Tallinn and its 15 km buffer zone and to simulate the future of urban expansion in 2030 by performing integrated CA and agent-based models. The integrated CA–Agent model had a simulation accuracy exceeding 86%; it predicted a continued infilling expansion (12.22 km^2 adding to built-up areas) around Tallinn by 2030.

Through this research, the hybrid models of ANN, CA, and MCA (ANN–CA–MCA) utilized spectral–textural properties of landscapes. Spectral–textural indicators of landscape physiognomy have high potential in detecting the changes in urban expansion and monitoring their footprints. The accuracy of predictions reached up to 90%, confirming the high capabilities of morphologic indices in projecting the past trends of changes in urban expansion and their significant importance in representing reality.

Overall, the scattering patterns of new constructions are expected to continue as the infilling development in the vicinity of main cities and existing residential areas, taking advantage of main roads and fed by the existing infrastructures in the future. Based on this, several courses of action are suggested to reduce the adverse impacts of urban expansion on the environment in long-term spatial planning in Estonia:

- Enhancing public awareness by organizing cultural and nature tourism and motivating people to be involved in the conventional agricultural sector in the way of learning environmental sustainability,
- Maintaining the importance of living and economic environments of the existing settlements to prevent the scattering of new ones,
- Efficient regulations and policies by the local government regarding the conservation of biodiversity and Estonia's natural landscapes and reduction of agricultural and forest lands' conversion to built-up areas,
- Protecting urban green areas surrounding main cities, and
- Restrictions on infrastructure expansion in remote areas.

1. INTRODUCTION

1.1. Background

Land use/land cover (LULC) change encompasses the transformation of terrestrial earth surfaces (Sankarrao et al., 2021) due to human-environment interactions (Abdullah et al., 2019; Li et al., 2017; Verburg, Veldkamp, et al., 2004). LULC changes play essential role in changing the climate (Lin et al., 2007; Mehta et al., 2013; Wu et al., 2013), biodiversity (Huang & Liao, 2019; Lawler et al., 2014; Seto et al., 2012), soil quality (Criado et al., 2020; Zambon et al., 2018), hydrology (Lin et al., 2007; Zeng et al., 2018), landscape (Lee & Chang, 2011; Liu et al., 2009; Verburg, Veldkamp, et al., 2004), deforestation (Mansaray et al., 2016; Salghuna et al., 2018), agricultural shifts (Forkuor & Cofie, 2011; Girma et al., 2022), wetlands degradation (Hartig et al., 1997; Ondiek et al., 2020) and urban expansion (Hashem & Balakrishnan, 2015; Roy & Kasemi, 2021).

Urban expansion mainly refers to the low–density, spatially discontinued, and dispersed expansion of urban-related constructions into suburbs and beyond the city boundaries (Ciommi et al., 2018; Egidi et al., 2020; Saganeiti et al., 2021), which transforms the non–urban lands into urban (Zhang et al., 2020). Different factors govern urban expansion. From the macro-level standpoint, urbanization (Xu et al., 2019; Zambon et al., 2019), industrialization (Kandpal & Saizen, 2019; Wu & Zhang, 2012), population changes (Liu et al., 2009; Mansaray et al., 2016; Xu et al., 2019) and economic growth (Abdullah et al., 2019; Gibson et al., 2015) are leading causes of urban expansion. From the micro-level standpoint, physical and environmental factors, including infrastructure developments (Angel et al., 2011; Sankarrao et al., 2021; Wu et al., 2019), elevation (Aburas et al., 2017; Zhao et al., 2017), proximity factors such as distance to roads (Poelmans & Van Rompaey, 2010; Traore & Watanabe, 2017), rivers or water areas (Salem et al., 2019; Sarkar & Chouhan, 2020), existing residential areas (Abbas et al., 2021; Falah et al., 2020) and the central business district (CBD) or city center/core (Grigorescu et al., 2021; Simwanda & Murayama, 2018) are significant causatives.

Since urban expansion is the source of remarkable variations in the LULC (Al–Hameedi et al., 2021), quantitative spatiotemporal analysis and modeling, identifying the local causative factors and exploring the indicators of its changes lead to better insight into its long-term processes and consequences, which are critical for making effective decisions and policies (Li et al., 2018). Besides, the dataset's availability and consistency should be considered related to the study area. Long-term records of remote sensing datasets are critical for monitoring, analyzing, and modeling urban expansion. Accessible regional and continental datasets provide a good platform for spatial and territorial analysis on different territorial levels, while high-resolution remotely-sensed data (more detail and a smaller grid cell size) is more suitable for small-scale and local monitoring.

There has been an increasing interest in urban expansion modeling in recent years. Modeling urban expansion helps realize urban evolution mechanisms and yields more profound insight into the future for developing a spatial planning framework. Questions have been raised about the dynamic, descriptive, and analytical aspects of urban expansion modeling. Different models have been utilized to address the complexity of urban expansion over time, understand its mechanism and driving factors, and predict future spatial patterns. The configuration of a single or hybrid/integrated urban expansion model depends on the research application and aims of the analysis; it can reflect on the non–linearity, complexity, scale dependency, and realities of urban expansion. Hence, many studies have applied synthesized models to determine the evolving dynamics of urban expansion, investigate the predictions of changes, visualize the spatio-temporal patterns of the past and simulate the future spatial footprints of urban expansion to benefit urban planners and policymakers' decisions.

1.2. Urban Expansion Models

Since urban expansion is a dynamic and complex process, many spatial models have been constructed to investigate, predict, and simulate it. Simulation models can develop scenarios for future-oriented decision–making (Harb et al., 2020). It can be done by preparing a projection of LULC changes, expecting the future urban land demands, and spatial distribution of these demands (Mustafa et al., 2017). Scholars have long debated the evolution and importance of urban expansion modeling using various approaches, including logistic regression, cellular automata, agent-based, and artificial neural network models. Here, some modeling approaches are described to provide a deeper insight into the urban expansion models applied in this thesis:

1.2.1. Logistic Regression Model

A considerable amount of literature has been published to explore the capabilities of logistic regression (LR) in determining the causative factors of urban expansion and predicting the potential future expansion (Azhdari et al., 2018; Bonilla–Bedoya et al., 2020; Sarkar & Chouhan, 2020; Wu et al., 2019; Xiong & Tan, 2018; Zhao et al., 2017). The parametric LR model provides a valuable understanding of drivers and their weights in the urban expansion (Traore & Watanabe, 2017). While it is a predictive model (Eyoh et al., 2012), LR mainly describes the relationships between the binary dependent variable and different independent variables and their intensity (Luo et al., 2019). So, it estimates the influences of contributing factors. Grigorescu et al. (2021) explored the potential of a binary LR in modeling the future of urban expansion in Romania and determined the coefficients of the influential factors over time. Salem et al. (2021) analyzed various driving factors of urban expansion in Delhi and simulated the most probable locations and future urban expansion patterns. To highlight the scale dependency of causative factors of expansion, Shu et al. (2014) applied LR, and explored spatiotemporal differences in small towns' scale, and suggested different policies and planning guidelines.

Proximity analysis is the most applied method in urban expansion modeling using the LR model. It evaluates the distances' influence on new expansions (Grigorescu et al., 2021). Traore & Watanabe (2017) used two categories of drivers, including five socioeconomic proximity variables and two landscape topography variables, and found a high probability of urban expansion in high–elevation areas and near main roads. Mustafa et al. (2018) explored twelve topographic, socioeconomic, and proximity factors as causative factors of urban expansion in Belgium. Their findings showed that the LULC policy, slope, and distance to roads are the most significant factors of urban expansion in their study area. Incorporating proximity factors in urban expansion modeling provides valuable insight into protection and development in spatial planning for local governments as policymakers. Here, the methodological analysis of LR and quantifying the relationship between urban expansion and physical driving forces in two Estonian counties are described in section 2.3 and more thoroughly in **Article I.**

1.2.2. Cellular Automata Model

Cellular automata (CA) has been the most popular model employed by researchers since its conceptualization by Ulam and Von Neumann in the 1940s (Langton, 1984). CA model is a rule-based and dynamic model capable of simulating the complex urban expansion process with simple rules (Harb et al., 2020; Li et al., 2017, 2018; Li & Gong, 2016; Liang et al., 2020; Tan et al., 2015; Vaz et al., 2012; Xu et al., 2019). It is a bottom-up approach implemented in a lattice or irregular surface. The evolution of urban expansion over time is based on two other essential functions, the rules of transition, which mines the state of a cell over time (Xu et al., 2021), and neighborhood effects (Cao et al., 2015; Pan et al., 2021; Santé et al., 2010). The CA model assumption is generally based on the effects of past changes on future transitions (Santé et al., 2010), but the specific transition rules vary regarding geographical regions and neighborhood interactions. So, accompanying different models reinforce the CA model's capabilities and can increase the simulation's popularity, efficiency, and accuracy (Li & Gong, 2016) as follows:

- MCA provides information about the transformation and the conditional probability of cells beneficial in determining the trends of urban expansion changes over time. Integrated CA with Markovian chain analysis (MCA) has been implemented in much research (Deep & Saklani, 2014; Faqe et al., 2016; Liping et al., 2018; Ramachandra et al., 2013; Rimal et al., 2018; Saloni Jain et al., 2016).
- Several studies enhanced the CA model with agent-based models to explore the drivers of urban expansion, boost the behavioral rules by defining the dynamic agents, and determine more realistic neighborhood effects to simulate urban expansion (Liu et al., 2020; Liu et al., 2013; Mustafa et al., 2017; Tan et al., 2015; Xu, 2019).

- The application of the analytic hierarchy process (AHP) in a CA–MCA model is beneficial in computing the weights of driving forces (Tajbakhsh et al., 2016) in a multi-criteria evaluation (MCE) function. MCE is a process in which multiple layers are aggregated to yield a single output map of suitability.
- Integration of CA with ANN is efficient for data–mining and enhancing the transition rules of the CA models (Abbas et al., 2021; Xu et al., 2021). Besides, the improvements of CA model elements, such as the cells' structure, neighborhood characteristics, and transition rules, have been widely reported by researchers in the last decades for the simulation of more realistic urban expansion (Aslan & Koc–San, 2020; Falah et al., 2020; He et al., 2018; Li et al., 2018; Li et al., 2017; Purevtseren et al., 2020; Tajbakhsh et al., 2016; Xu et al., 2019).

The comprehensive frameworks of the CA model integrated with MCA–agent-based models, MCA–AHP, and MCA–ANN models are more thoroughly described in sections 2.4 and **Articles II, III,** and **IV**.

1.2.3. Agent-Based Model

The agent-based model has been widely applied to model urban expansion since the 2000s (Xu, 2019). It reveals the dynamic interaction between agents and the environment to decide on a response to these interactions (Tan et al., 2015). Agents can be structured based on their attributes, behaviors, and goals (Li & Gong, 2016). In general, agents characterize the human, land parcels, or any discrete entity (attributes) making decisions and behaving (behaviors) in a way that impacts urban expansion processes (goals). Processing and exchanging the information with the other agents, which are autonomous and dynamic with different attributes and actions, are based on behavior rules. So, the agents' decisions and behaviors can change based on this information and the environment. The model's outcome emerges from agents' interactions over time (Groff et al., 2019) and the probability of changes in the agent's behavior (Mustafa et al., 2017).

Several attempts have been made to investigate the behaviors of human agents on urban expansion and its spatial changes to simulate future expansion (Jokar Arsanjani et al., 2013; Liu et al., 2020; Liu et al., 2013; Tian et al., 2011; Tian & Qiao, 2014; Zeng et al., 2018). Some authors have reported parcel agents' behaviors in urban expansion changes (Kuru & Yüzer, 2021; Long et al., 2014). It demonstrated the adjustable characteristics of this model applicable to discrete geographical entities. So far, the spatial and temporal reflection of dynamic interactions between cellular agents were described comprehensively in section 2.4.1 and **Article II**.

1.2.4. Artificial Neural Network Model

Recently, researchers have shown an increased interest in applying artificial neural networks (ANN) in modeling urban expansion (Abbas et al., 2021; Losiri et al., 2016; Sankarrao et al., 2021; Wang et al., 2020; Yatoo et al., 2020). ANN is inspired by the human brain acting similarly by transferring the information from neurons signal to one another. It is a machine learning algorithm (Wang, 1994) and can be trained to estimate the probability of occurrence from non–linear functions dependent on many input layers (Liu et al., 2017). In general, the ANN is comprised of an input layer, one or more hidden layers, and an output layer with different numbers of nodes/neurons in each layer (Wang et al., 2020). The ANN models can learn how neurons' weights change and calibrate to achieve the desired output (Gharaibeh et al., 2020; Saha et al., 2021). The most prominent type of ANN for urban expansion modeling is a multi–layer perceptron (MLP) algorithm suitable for investigating the drivers of changes (Chettry & Surawar, 2021; Kafy et al., 2020; Leta et al., 2021; Losiri et al., 2016; Mondal et al., 2020; Sankarrao et al., 2021) through a backward stepwise constant forcing equation. The methodological analysis of MLP exploring the relationship between urban expansion and physical driving forces in two Estonian counties is described in section 2.3 and more thoroughly in **Article I**.

When it comes to urban expansion simulation, it is essential to consider the complexity of defining the transition rules and spatial dependency of variables. So far, ANN is a practical data–mining algorithm for enhancing the transition rules in a CA model; among the various combinations, ANN–CA has been the most frequently used. Zhang et al. (2020) applied integrated MLP and CA–MCA models to assess the urban expansion in China, utilizing eleven environmental and socio-economic factors to investigate expansion patterns and simulate the future. Xu et al. (2019) applied the same algorithms to produce the urban suitability map and simulate the urban expansion in South Auckland using nine environmental and proximity drivers. Additionally, they used two other tools, AHP and LR, to compare the model outputs and prove the ANN performance. Likewise, in this study, a self–adaptive ANN algorithm combined with a CA–MCA model for simulating urban expansion in Estonia was applied, illustrated in section 2.4.3 and more thoroughly described in **Article IV**.

1.3. Research Objectives

"Land" was a state property during the Soviet-era occupation of Estonia. After the collapse of the Soviet Union and the regaining independence in 1991, the land reform act was passed, and transferring the land from state to private ownership started. Since then, Estonia has experienced a scattering of residential areas by transforming agricultural–industrial suburbs (Kährik et al., 2012), mainly around Tallinn. These socioeconomic and political shifts led to the expansion of recreational areas and coastal settlements near Tallinn (Ratas et al., 2014), changed the people's lifestyle (Oja, 2020), changed the farmlands (Reimets et al., 2015), and moved wealthy people to settle in detached houses in the suburbs (Jauhiainen, 2006; Tammaru et al., 2009). While footprints of urban expansion in a scattering form raised gradually in the last three decades, the population in Estonia decreased dramatically by 15.31 % (Statistical database, 2022), and the internal migration from elsewhere in Estonia moved people mainly to the fringe of major cities of Tallinn, Tartu, and Pärnu (Jauhiainen, 2006).

It is also worth pointing out that suburbanization in eastern European countries after the collapse of the Soviet Union mainly decentralized people and urban functions from the center to the suburbs (Grigorescu et al., 2021). Therefore, urban expansion in Estonia and some neighboring countries is quite different from most cities worldwide due to its geopolitical context (Hamilton et al., 2005). As urban expansion changes the agricultural and forest lands and small percentages of changes in urban areas can affect long–term biodiversity and landscape on a local scale (Li et al., 2017), the spatiotemporal monitoring and modeling of the future of urban expansion in Estonia is essential.

Therefore, **the primary aim of this study is to monitor, analyze and model urban expansion over the past three decades in Estonia, and to simulate the future**. This is the first comprehensive study about modeling urban expansion and analyzing the factors influencing urban expansion in Estonia over the past decades. This dissertation explores the expansion of urban areas in Estonia utilizing several modeling approaches, different sets of data, and many driving forces and predictors. We assumed that: (i) Spectral–textural properties of landscape provide a sufficient proxy in the detection of urban expansion footprints and transitions over time, (ii) Implementation of integrated/hybrid models improves the model accuracy in representing urban expansion, and (iii) The dataset's spatial resolution impacts the model performance.

Therefore, to achieve the main objective, the following tasks were set out:

a) Analyze the physical driving factors (**Article I–III**) and predictors (spectral–textural indices) (**Article IV**) of urban expansion over the past three decades in Estonia.

b) Evaluate the performance of several modeling approaches for investigating the past trends and simulating the future of urban expansion in Estonia by implementing two single model approaches of LR and MLP models (**Article I**) and three integrated/hybrid models, including the CA–Agent model (**Article II**), CA–MCA–AHP model (**Article III**), and ANN–CA–MCA model (**Article IV**).

c) Test the model representations by applying datasets with different spatial resolutions (**Article I–IV**).

2. MATERIALS AND METHODS

2.1. Study Area

This thesis comprises four original research articles that studied urban expansion in Estonia. Figure 1 shows the study areas addressed in **Articles I–III**; **Article IV** addressed the whole of Estonia. Area 1 represents two Estonian counties, including Harju County, containing the nation's capital, Tallinn, and Tartu County, where the country's second major city, Tartu, is located. Their total area covers approximately 767,544.04 ha. In **Article I,** we analyzed the driving forces of urban expansion by applying two models of LR and MLP to investigate the weights of influence for twelve selected driving factors in those counties. The analysis period was between 1990 to 2018, when the significant sociopolitical changes in Estonia happened.

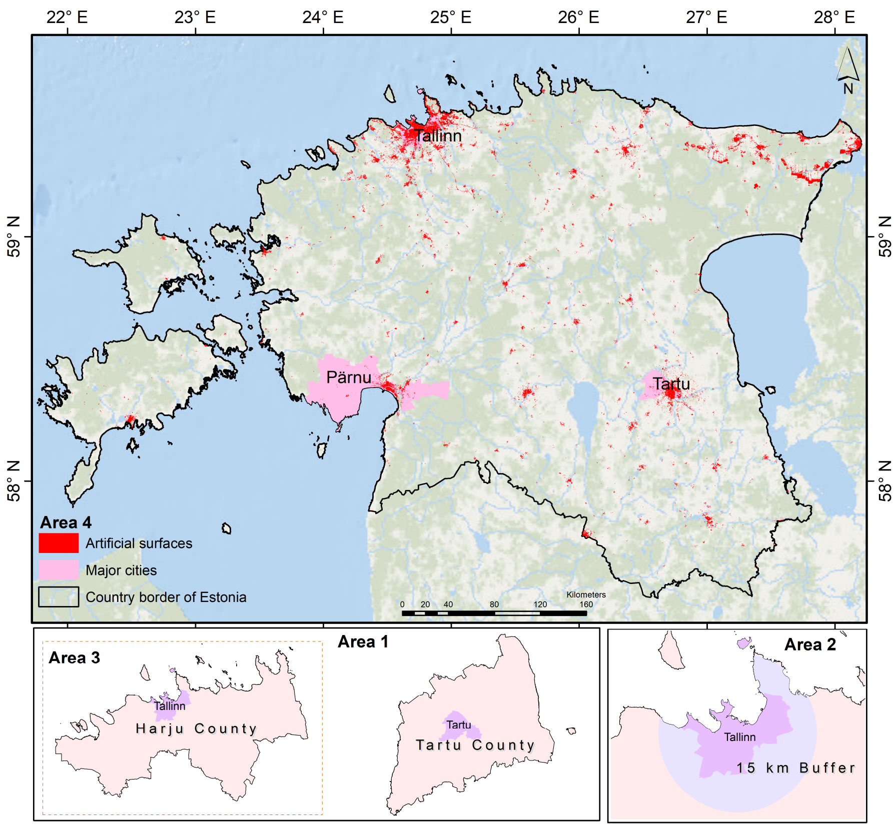

Figure 1. The area of study for urban expansion modeling. Area 1 indicates the **Article I** task, Area 2 shows the task was done in **Article II**, Area 3 illustrates the task in **Article III**, and Area 4 refers to the **Article IV** task.

Our focus in **Article II** was on built-up areas in Tallinn, and its 15 km buffer zone (Figure 1, Area 2) to monitor the process of urban expansion between 1990 and 2018 and simulate its future trend in 2030. While Tallinn covers a 159.37 sq. km area, considering the 15 km buffer zone, the study area is about 506 sq. km. Essentially, the sea area in the buffer has been excluded. Statistics (Statistical database, 2022) indicate that the population of Tallinn in 1990 was 479,666, experiencing a decrease of 10.19%, reaching 430,805 in 2018.

In **Article III,** "urban expansion" in Harju County, which includes the country's capital, was evaluated (Figure 1, Area 3) to monitor the changes from 1990 to 2018 and simulate its future in 2046. We employed the CORINE land cover dataset; the level 1 category was used to emphasize the urbanization process, including artificial surfaces, agriculture, forest, water, and wetlands.

We extended the study area to countrywide Estonia in **Article IV** (Figure 1, Area 4) to analyze the footprints of urban expansion between 2000 and 2019 and simulate the artificial surfaces for 2030. We mainly focused on the three major cities of Tallinn, Tartu, and Pärnu, explaining the urban expansion. It is essential to point out that based on statistics of Estonia (Statistical database, 2022), the country's population has decreased by 11% from 2000 to 2019, while the internal migration mainly led the population to the surroundings of Tallinn, Tartu, and Pärnu, the rest of the regions (majority of the territory) have decreased population (Oja, 2020).

2.2. Research Data and Image Processing

To assess and analyze urban expansion, timely and accurate data is essential. Over the past decades, there has been a dramatic increase in the application of remote sensing data to detect and analyze urban expansion, and many researchers have reported the utilization of satellite data in this field (Deribew, 2020; Niang et al., 2020; Kushwaha et al., 2021; Mahmoud et al., 2019). Here, to evaluate the third assumption concerning the dataset's resolution used for modeling, the research data was drawn from three primary remote sensing sources: the CORINE land cover database (**Article I** and **Article III**), Landsat imagery products (**Article II** and **Article IV**), and a land cover dataset provided by Parente et al. (2021) (**Article IV**).

While the basic coordinate system of the research articles was set to the primary Estonian projection system of Lambert Conformal Conic (Estonia_1997_Estonia_ National_Grid, EPSG 3301), the resolution of data was different depending on the database. **Articles I** and **III** used the time–series CORINE land cover dataset (level 1 classes; artificial surfaces considered urban). Some other spatial data were downloaded from the Estonian land board geoportal (ETAK database) and were rasterized to 100m resolution.

In **Article II,** we monitored the footprints of urban expansion with the remotely sensed data of higher spatial resolution (30 m). We used the SCP plugin (Semi-automatic Classification Plugin) in the open-source software QGIS 3.10 to extract the Landsat images of the United States Geological Survey (USGS) with radiometric and geometric corrections. Then, we processed the data, classified it with a maximum likelihood (ML) classifier, and validated the images to check the accuracy of the classified maps of LULC (Table 1). For further analysis, the built-up areas of 1990, 2006, and 2018 were extracted from LULC maps.

Table 1. Landsat products. Source: **Article II**, Table 1 and 2.

Product Description	**Date of Acquisition**	**Ground Resolution**	**Overall accuracy (%)**	**Kappa**
TM_Landsat5	1990/05/13	30 m	98.20	0.96
TM_ Landsat5	2006/06/10	30 m	97.80	0.96
OLI/TIRS_Landsat8	2018/05/26	30 m	97.00	0.95

The other spatial layers were extracted from the ETAK database and include road networks (main and local roads, railways), waterbodies (watercourses and lakes), and the administrative boundary of Tallinn. Polygon data of airport and wetlands was extracted from the CORINE Landcover database. The reference year of these data was 2018 and was resampled to 30 m resolution to be consistent with the classified maps and applicable for modeling purposes.

In **Article IV**, we used two data types to perform the hybrid ANN–CA–MCA simulation model. First, we used the level 1 class of data provided by Parente et al. (2021) for 2000, 2011, and 2019 to analyze LULC and urban expansion. Second, we used the cloud computing platform of Google Earth Engine to process the optical remotely sensed data, and we extracted 147 spectral–textural indicators of landscape physiognomy for those anchor years. Since textural indices are mathematically designed to indicate opposite landscape attributes (e.g., diversity-heterogeneity), they are highly multicollinear. So, we conducted the multicollinearity analysis, and the final selection of non–collinear predictors were 19 spectral–textural indices presented in Table 2.

This thesis used several platforms and software to process the data, analysis, and simulation. Employed software includes QGIS 3.10, ArcGIS 10.6, IDRISI, and GEOSOS–FLUS and used platforms consisted of Repast platform used in the AgentAnalyst extension for ArcMap 10.6 and Google Earth Engine cloud computing platform.

Table 2. Selected predictors of LULC transformation and urban expansion; NDBI stands for Normalized Difference Built-up Index, NDVI – Normalized Difference Vegetation Index, NDWI – Normalized Difference Water Index. Source: **Article IV**, Table 2.

Variables (Aliases)	Description	Landscape interpretation	Formula reference
blue_entropy_21	Blue band Shannon's entropy	Diversity of landscape composition regarding water elements, cultural features, and soil/vegetation edges	(Shannon, 1948)
green_gearys_21	Green band Geary's C	Spatial clusters of cultural features and vegetation	(Anselin, 2010)
hue_dvar_21	Hue band GLCM Difference variance	Cultural features, highly urbanized areas	(Haralick et al., 1973)
ndbi_corr_21	NDBI GLCM Correlation	Urban/non–urban gradients	(Haralick et al., 1973)
ndbi_gearys_21	NDBI Geary's C	Clusters of built-up areas	(Anselin, 2010)
ndbi_idm_21	NDBI GLCM Inverse Difference Moment	Water bodies, wetlands, vegetation clusters	(Haralick et al., 1973)
ndbi_shade_21	NDBI GLCM Shade	Landscape edges and coastal areas	(Conners et al., 1984)
ndvi_prom_21	NDVI GLCM Prominence	Coastal areas	(Conners et al., 1984)
ndwi	NDWI	Sea and inland water bodies	(McFEETERS, 1996)
nir_gearys_21	NIR band Geary's C	Vegetation clusters	(Anselin, 2010)
nir_mean_21	NIR band Mean	Inner parts of vegetation patches	
nir_sd_21	NIR band Standard Deviation	Edges of vegetation patches, landscape gradients, coastal areas	
sat_asm_21	Saturation band GLCM Angular Second Moment	Water bodies and wetlands	(Haralick et al., 1973)
sat_dent_21	Saturation band GLCM Difference Entropy	Urbanized areas, roads, cultural features	(Haralick et al., 1973)
sat_savg_21	Saturation GLCM Sum of Average	Water bodies, (semi)natural vegetation clusters	(Haralick et al., 1973)
swir1_gearys_21	SWIR1 band Geary's C	Bare soil, coastal areas	(Anselin, 2010)
swir1_sd_21	SWIR1 band Standard Deviation	Bare soil, coastal areas, land cover edges	
val_dent_21	Value band GLCM Difference Entropy	Urbanized areas, roads, cultural features, bare soil	(Haralick et al., 1973)
wetness	Tasseled Cap Wetness band	Canopy moisture content	(Kauth & Thomas, 1976)

2.3. Analysis of LR and MLP Models (Article I)

In **Article I**, to distinguish the relationship between the independent categorical variables and the urban expansion as the binary dependent variable, we employed the LR and MLP models. To obtain the regression coefficients in the LR model, a binary (0 and 1) dependent variable and 12 independent variables were defined as the model inputs, with a 10% sampling rate based on stratified random sampling. The following formula estimates the probability of the LR model:

$$P(y = 1|X) = \frac{\exp(\sum BX)}{1 + \exp(\sum BX)} \tag{1}$$

where *P* represents the probability of the dependent variable being 1; *X* is the independent variable ($X = (x_0, x_1, x_2, \ldots, x_k)$, $x_0 = 1$); and *B* is the estimated parameter, $B = (b_0, b_1, b_2, \ldots, b_k)$.

The MLP function has two crucial forward, and backward propagation steps to complete the adjustments in neuron connection weights (Eastman, 2012). In the process of feedforward learning, neuron weights are associated based on a threshold, and reaching this threshold; the neuron is activated and able to send the data to the next layer. The input of a single node is weighted according to equation (2):

$$net_j = \sum_{i=1}^{m} W_{ij}\, O_i \tag{2}$$

where W_{ij} represents the weights between nodes *i* and *j*, and O_i is the output from node *i*. In our research, a sigmoidal function *f* is the activation function, and the weights will be applied before the signal reaches the subsequent layer. The output from node j is calculated by equation (3):

$$O_j = f(net_j) \tag{3}$$

When the forward pass is finished, the comparison will be made between the output nodes and the expected activities. Then the backpropagation process started adjusting the weights to learn the process thoroughly. To process the MLP model, we applied 50% of samples for training the algorithm and 50% for validation using 10,000 iterations.

Here, we defined Y = 1; when land is converted from non–urban into urban between 1990 and 2018; otherwise, Y = 0; non–urban/no changes (Figure 2), and 12 independent variables (Table3). Besides, to reduce multicollinearity, we performed a Pearson correlation analysis.

Table 3. Independent variables, explanation, and description (The table information is extracted from **Article I**).

Independent variables	Explanation	Description
X1	Distance from near cities	The likelihood of urban expansion concerning proximity to near cities associated with accessibility and commercial uses
X2	Distance from the core of cities: Tallinn and Tartu	The likelihood of urban expansion concerning proximity to the core of Tallinn and Tartu is associated with accessibility and commercial uses
X3	Distance from green urban areas	Urban expansion likelihood proximate to green urban areas and the importance of conservation of urban green spaces
X4	Distance from industrial or commercial units	Accessibility to the industrial or commercial units for job seekers in industry and the likelihood of urban expansion near these places
X5	Distance from airport	Importance of urban expansion concerning the distance from airport due to the negative impacts of its noise and emissions
X6	Distance from sport and leisure facilities	The likelihood of urban expansion concerning proximity to sports and leisure facilities as a residential preference for settlement selection
X7	Distance from main roads	Role of roads as accessibility factors that connect urban centers to periphery areas and affect the scattering of new construction around cities and urban expansion
X8	Distance from agricultural lands	Likelihood of urban expansion on agricultural lands due to the ease of encroachment for construction purposes
X9	Distance from forest lands	Importance of forest lands in trade-offs of urban expansion
X10	Distance from existing residential areas	The likelihood of urban expansion near existing residential areas while taking advantage of environmental attractions in the suburbs
X11	Distance from water areas	Visual qualities of water areas and their location attractiveness for housing development
X12	Distance from wetlands	Importance of wetlands in trade-offs of urban expansion

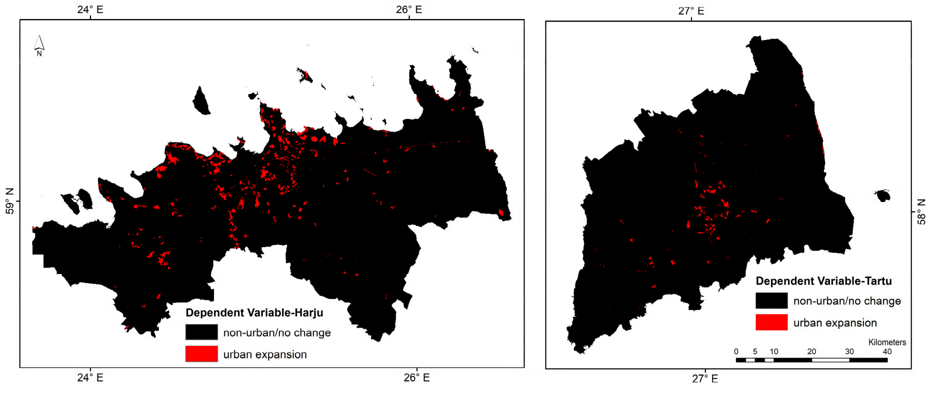

Figure 2. Dependent variable (Y): urban expansion in Harju County and Tartu County between 1990–2018. Source: **Article I**, Figure 2.

2.4. CA Model Implementation (Articles II–III–IV)

A CA model consists of cell space, state, neighborhood, and transition rules. Improvements of the CA model elements such as the cells' structure, neighborhood characteristics, and transition rules help better and more realistic simulation and representation of future urban expansion. Here, the model elements applied in **Articles II**, **III,** and **IV** are described from a deeper perspective.

Numerous studies have attempted to investigate the application of lattice/regular grid cells in the CA model (Al–sharif & Pradhan, 2015; Falah et al., 2020; Jafari et al., 2016; Wu et al., 2010). Some studies suggest that irregular CA in the form of patch-based (Alaei Moghadam et al., 2018; Chen et al., 2019; Yang et al., 2020) or vector-based (Long & Wu, 2017; Lu et al., 2020; Taillandier et al., 2017) can produce a more realistic spatial representation of geographical entities at fine scales (Chen et al., 2017; Otgonbayar et al., 2018). This study investigated an integrated regular environment with irregular cells (**Article II**) and regular grid cells' CA (**Articles III and IV**).

Extensive efforts have been devoted to the configuration of neighborhood effects, an essential subset of a CA model (Chen et al., 2017b; He et al., 2018; Khalilnia et al., 2013; Liao et al., 2014, 2016; Pan et al., 2021). Defining the neighborhood size and weights is a critical step in reducing the over–and under–estimation of these effects (Verburg, et al., 2004). Different neighborhood implementations were analyzed to capture the influence of neighboring cells and their interactions in the CA model. Among others, in a regular CA, the Moore neighborhood, which is based on a kernel cell, and its neighbors (3 × 3, 5 × 5, 7 × 7, or larger odd neighbor cells), is the most applied neighborhood function (Falah et al., 2020; Liao et al., 2016; Liu et al., 2013; Omrani et al., 2017). In an irregular CA, different shapes (Pan et al., 2021; Pan et al., 2010) or influential regions neighborhoods (Otgonbayar et al., 2018) are considered to be the most applied neighborhood functions. Here, we used several neighborhood functions.

In **Article II,** an adjacent neighborhood function was implemented. The Moore neighborhood function was applied with 5 × 5 cells (**Article III**) and 7 × 7 cells (**Article IV**).

Transition rules have been identified as major contributing factors to a CA model. Defining the driving factors of urban expansion in a historical approach by revisiting the past conversions (Jafari et al., 2016; Khalilnia et al., 2013; Liao et al., 2016; Wang et al., 2020), suitability analysis (Fu et al., 2018; Karimi Firozjaei et al., 2019; Saxena & Jat, 2020; Tajbakhsh et al., 2016) and spatial demand allocations for the future specifications of urban expansion (Dang & Kawasaki, 2017; Liang et al., 2018; Lv et al., 2021) are the most widely used techniques for determining the transition rules. Enhancing the transition rules will result in the model's performance. So, different models and tools were applied to boost the transition rules in a CA model. Among others, LR (Liao et al., 2016; Liu et al., 2015; Shafizadeh–Moghadam et al., 2017), MCA (Gharaibeh et al., 2020; Rimal et al., 2018; Xu et al., 2019), ANN (Girma et al., 2022; He et al., 2018; Losiri et al., 2016), AHP (Aburas et al., 2017; Tajbakhsh et al., 2016; Yang et al., 2011), agent-based (Dahal & Chow, 2014; Liu et al., 2020; Xu, 2019) and random forest (Liang et al., 2021; Lv et al., 2021; Qian et al., 2020) are the most applied methods. In this study, MCA and agent-based model combinations were applied in **Article II**, MCA and AHP integration was employed in **Article III,** and MCA and ANN models were implemented in **Article IV** and described in the following sections (2.4.1, 2.4.2, and 2.4.3).

2.4.1. Integrated CA–Agent Model Framework (Article II)

After evaluating the driving forces of urban expansion in two Estonian counties to find the most influential drivers (**Article I)**, through **Article II,** we applied the most influential drivers alongside many other factors to investigate urban expansion in Tallinn and its 15 km buffer zone. We selected influential factors, including distance to main roads, Tallinn, and built-up areas. We defined some constraints such as buffer of main lakes, watercourses, airport, and wetlands to analyze the suitability of urban expansion. Besides, we established some behavioral rules and neighborhood status for cellular agents to act in the CA–Agent model and make decisions for development over time. We also used the same study period in **Article I** for analysis (1990–2018). We then simulated the study area's future (the year 2030).

In **Article II,** we explained the capabilities of an integrated CA–Agent model as the second thesis assumption. While the framework's base model was a parcel–agent-based urban growth model developed by Li (2013), we improved the application of the base model's parameters, input data, procedures, and behavioral rules for our analysis. The built-up areas were dispersed in irregular polygons; however, the undeveloped cells were resized to the square polygon grids ranging from 127 to 8100 m^2. We defined the adjacent neighbors and used the ArcGIS polygon neighbor tool to delineate the heterogeneity of neighborhood effects.

Markovian transition probability (MCA) in the CA–Agent model was performed to add complexity to the agent's behavior and calculate the built-up transition probability for two periods from 1990 to 2006 and 2006 to 2018. The Euclidean distance tool was used for suitability analysis, and the constraints were analyzed using the buffer tool and fuzzy overlay analysis in the GIS environment (Figure 3). The CA–Agent model constraints were permanent during the run process and precalculated to extract the number of unbuildable cells. The ranges of suitability factors were between 0 and 100. During the model run, cellular agents normalized suitability rates to reach the actual value for each factor. The constraints and factors were converted to raster (all the operations of cells run in the raster environment).

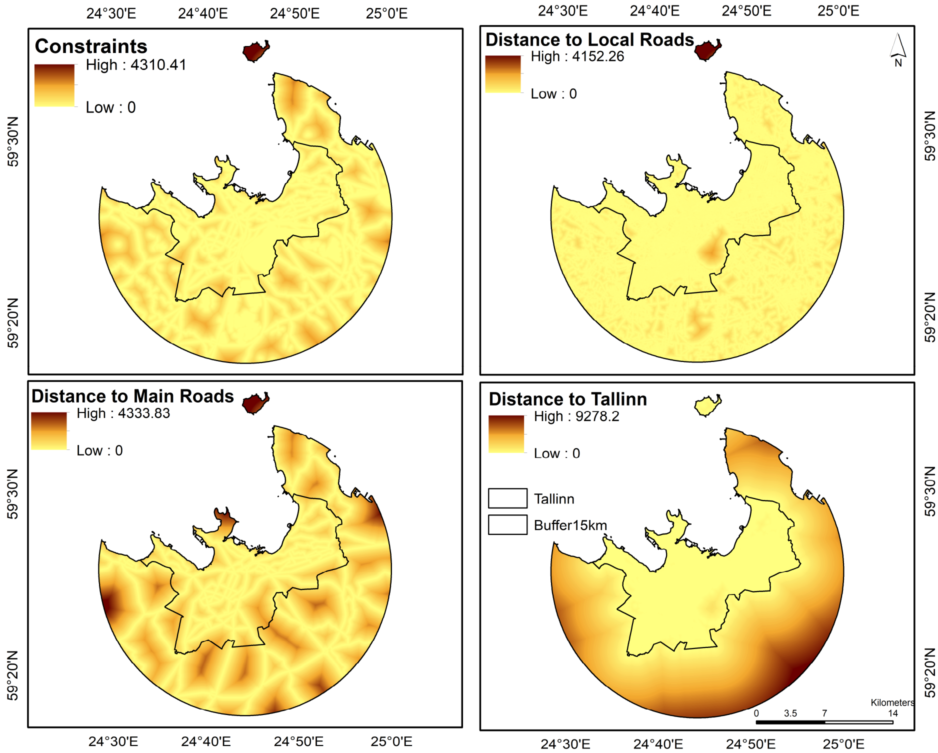

Figure 3. Suitability analysis: suitability factors consist of "distance to Tallinn", "distance to main roads", and "distance to local roads". ("neighborhood status" as a suitability factor was implemented into the model by its table records). Six constraints were defined to limit the buildable lands, which was a fuzzy overlay combination of "50m buffer of main lakes", "30m buffer of railways", "25m buffer zone of watercourses", "50m buffer of main roads", "50m buffer of the airport", and "50m buffer of wetlands". Source: **Article II**, Figure 5.

Behavioral rules were one of the most critical parts of the CA–Agent model and formed the development status of agents. These rules depended on different factors: the status of a cell, its neighbors, suitability criteria, constraints, and accessibility factors. Some of the behavioral rules defined for the model include: "**if** the cellular agent's ratio of unbuildable area to total area exceeds the threshold, **then** the agent will not be developed"; "**if** it falls in a constraint area, **then** it exhibited change"; and "**if** more neighbors are built up, **then** it is likely to develop." Consequently, the CA–Agent model can consider many rules that reflect the actual urban expansion process over time and space. Therefore, the number of cells changing their states was entirely defined by behavioral rules.

The CA–Agent model was run for two timesteps of 12 years to simulate urban expansion in 2018 (simulation validation) and 2030. The basic workflow of data preparation, spatial data analysis, and the CA–Agent model implementation is performed in Figure 4.

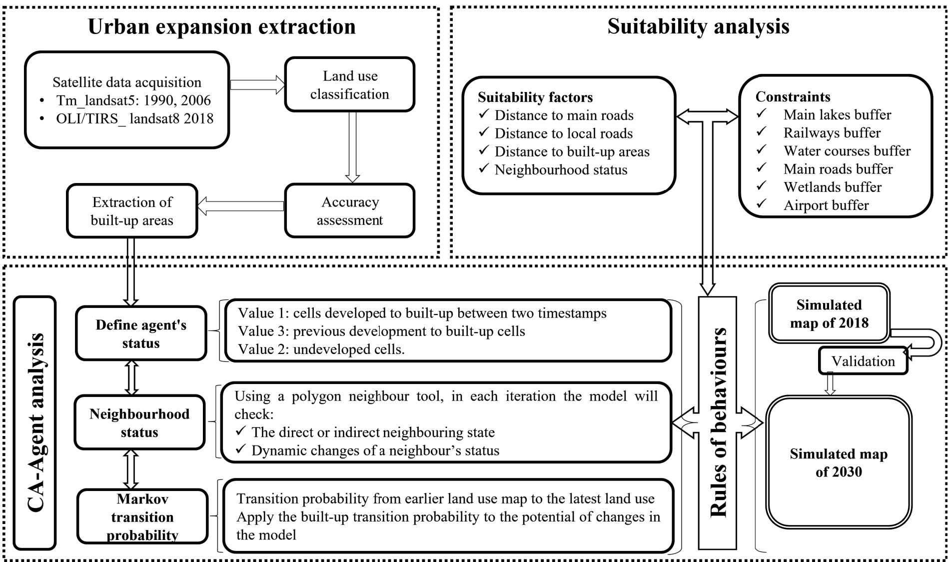

Figure 4. The basic workflow of data preparation, spatial data analysis, and the CA–Agent model implementation. Source: **Article II**, Figure 2.

2.4.2. CA–MCA–AHP Model Framework (Article III)

In **Article III,** we used slope, distance to built-up, distance to water bodies, and distance to roads as the main driving forces of urban expansion in Harju County and defined buffer of water areas as constraints performed in an MCE function to investigate urban expansion. Then we analyzed the suitability of urban expansion in Harju County (from 1990 to 2018) and simulated the future (2046).

In **Article III,** we explained the capabilities of an integrated CA–MCA–AHP model as the second thesis assumption. We improved the application of the CA model by performing an MCE function using the AHP technique to create a suitability map in the GIS environment (Figure 5). Markovian transition probability (MCA) was performed to produce the following outputs; a transition probability matrix, a transition areas matrix, and a set of conditional probability images applicable in the CA model. It should be noted that these weights were held constant throughout the simulation.

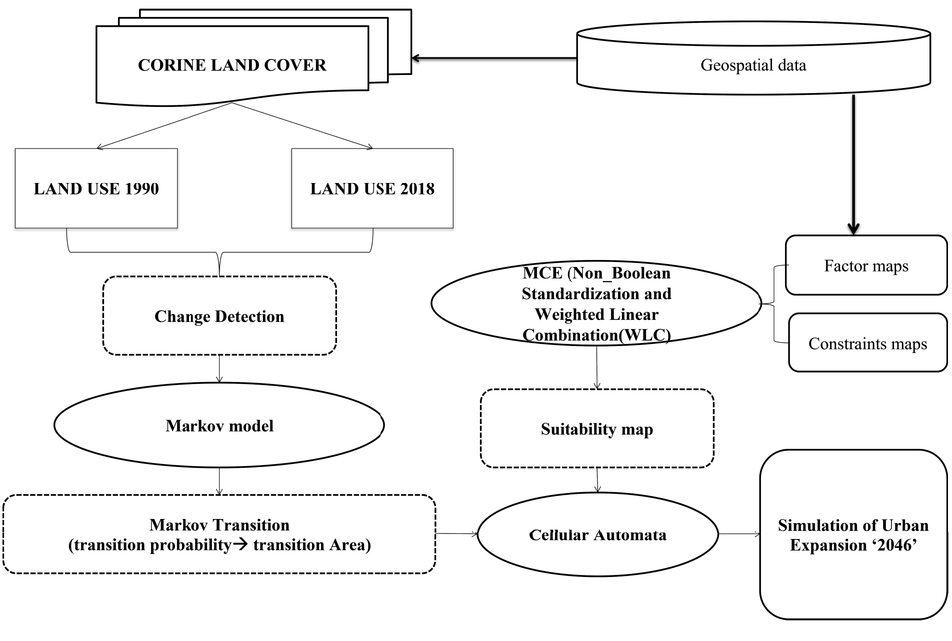

Figure 5. The basic methodology adopted in **Article III.** Source: **Article III**, Figure 1.

Using MCE is an effective way to weigh the different factors and constraints of an actual situation in a case study and make a transition suitability map as an input to the model. In **Article III**, we used a cell size of 100 m with a reference unit of 1 meter as cell spaces. We performed the transition rules from non-urban to urban with a Moore neighborhood function of 5 × 5 cells.

2.4.3. Hybrid ANN–CA–MCA Model Framework (Article IV)

Article IV assumed that landscapes' spectral and textural properties adequately proxy LULC transitions and urban expansion. So, the hybrid ANN–CA–MCA model was performed for multiple LULC classes, including artificial surfaces, agriculture, forest, wetlands, and water. Here, the data concerning changes in the class of artificial surfaces is presented to maintain the focus. It is essential to point out that in **Article IV,** areas of urban fabric, industrial, and mineral extraction sites were classified as a single main class of artificial surfaces on a countrywide scale. While the class of "artificial surfaces" covers the term "urban" in most locations in Estonia, it is meaningless for the vast mining and industrial sites in the northeast of Estonia. So, further analysis is based on the changes in the class of artificial surfaces and, consequently, the artificial surface in the three major cities of Tallinn, Tartu, and Pärnu visualized as urban expansion. Overall, Figure 6 shows the schematic framework of the implemented model.

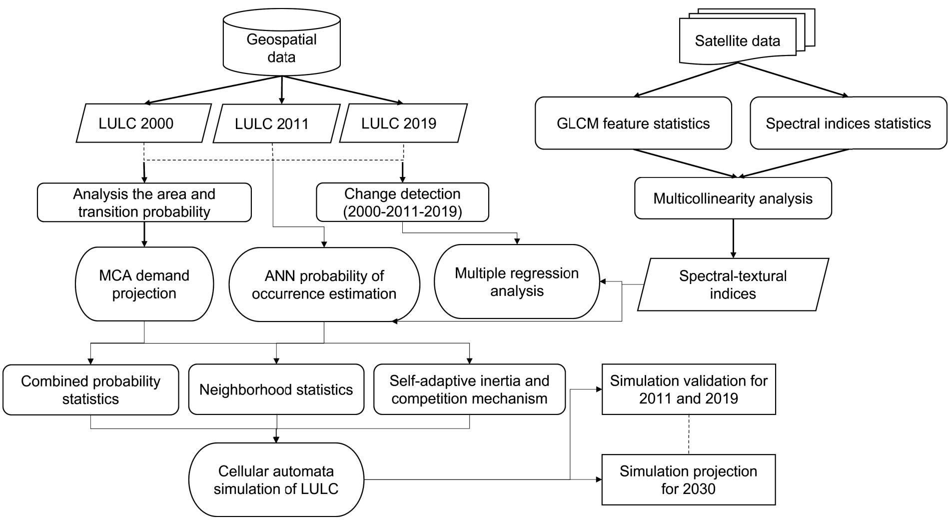

Figure 6. A schematic framework of the hybrid ANN–CA–MCA model. Source: **Article IV**, Figure 2.

To estimate the spatial probability of occurrence and define the transition rules, we used ANN by self–learning/adaptive inertia algorithm suitable for the CA model simulation. Also, we performed multiple regression analysis to analyze the relationships between artificial surfaces' probability of occurrence (dependent variable) and 19 spectral–textural indices (independent variables). The regression analysis was used to estimate the importance of spectral–textural indices on artificial surfaces' probability of occurrence in 2011, 2019, and 2030. Then to project the future land demand, we used MCA.

The initial configuration of the hybrid ANN–CA–MCA model was set as follows; a discrete square grid cell with a spatial resolution of 50×50 m described the quantity and degree of development. The neighborhood's weights that are variant through time were calculated based on the evolution ratio of each LULC type, and its size was set to 7×7 grid units of the Moore neighborhood.

2.5. Accuracy Assessment Methods

To identify the model accuracy and performance, validation of the model output against the actual reference map is essential. So, in this thesis, we tested and validated the prediction results using different validation tests, including Relative Operating Characteristic Curve (ROC), kappa coefficient, overall accuracy, $K_{location}$, $Q_{disagreement}$, MediumGrid (m), $A_{disagreement}$, and user/producer's accuracy. Table 4 represents the description and references of the methods applied.

Table 4. An overview of the accuracy assessment methods used in the thesis.

Accuracy assessment method	Description	References
Relative Operating Characteristic Curve (ROC)	Probability of true-positive opposed to false-positive identified urban expansion	**Articles I**
Kappa coefficient	The agreement between observed and expected correct in the classified/simulated map and ground truth map; represents the agreements and the pattern's consistency	**Articles II, IV**
Overall accuracy	The overall proportion/percentages of correctly classified/ simulated areas by reference pixel samples	**Articles II, IV**
$K_{location}$	The kappa for the grid-cell level location to monitor how well the grid cells are located on the landscape	**Articles II**
$Q_{disagreement}$	The amount of disagreement regarding the fails in specifying the correct quantity of each category in comparison map with the reference map	**Articles II**
MediumGrid (m)	The agreement between the reference map and the simulation map in terms of proportion correct	**Articles II**
$A_{disagreement}$	Error in matching the spatial allocations due to differences in the location of comparison and the reference map categories	**Articles II**
User's accuracy	The statistics of the quality of the simulated map represent the proportion of a pixel mapped into a given class that actually represents that class on the actual map	**Articles IV**
Producer's accuracy	The statistics of the quality of the simulated map represent how well classes of the actual map's pixel are simulated	**Articles IV**

3. RESULTS

3.1. Urban Expansion in Estonia from 2000 to 2019

This section refers to **Article IV** and analyzes the changes in artificial surfaces in Estonia between 2000 and 2019 (Table 5 and Figure 7). About 24.16 sq. km was added to the artificial surfaces during this period, and most new dwelling areas replaced previous agricultural lands. During the later years, the addition of newly built areas has slowed down, so that from 2000 to 2011, the rate of increase in artificial surfaces was 1.64%, reaching 765.00 sq. km, and from 2011 to 2019, the areas of artificial surfaces increased by 1.49% (776.59 km^2).

Table 5. Dynamics of changes in artificial surfaces in Estonia from 2000 to 2019. Source: **Article IV**, Table 3.

Artificial surfaces	Area (Sq.km)			Change (Percentage)		
	2000	**2011**	**2019**	**2000–2011**	**2011–2019**	**2000–2019**
	752.42	765.00	776.59	1.64%	1.49%	3.11%

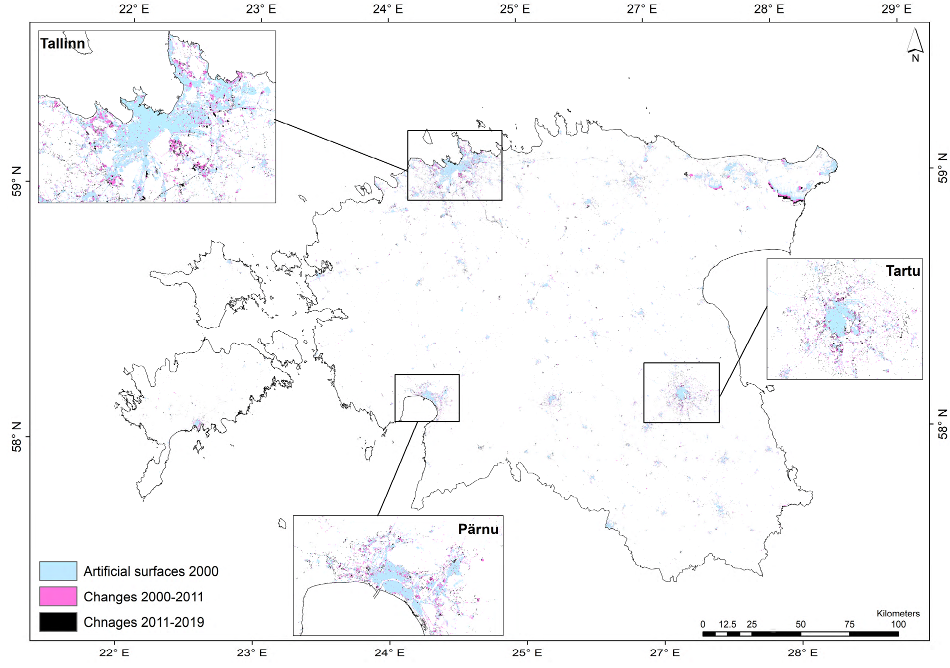

Figure 7. Changes in artificial surfaces in Estonia from 2000 to 2019. Source: **Article IV**, reproduced from Figure 3.

3.2. Driving Forces of Urban Expansion in Two Estonian Counties (Article I)

Based on the results of the LR model presented in Table 6, it can be explained that the distance factors from near cities (X1), the core of main cities of Tallinn and Tartu (X2), sport and leisure facilities (X6), main roads (X7), forest lands (X9), and water areas (X11) in both counties had a negative correlation with urban expansion. This means that where the distance from these variables increases, the tendency for urban expansion decreases (**Article I**).

Table 6. LR Statistical results for Harju County and Tartu County. Source: **Article I**, Table 4. The coefficient values define the importance and the degree of relationship between dependent and independent variables as drivers of urban expansion. The sign of the coefficient (±) shows a positive or negative correlation to the response of the dependent variable. Positive coefficients indicate positive impacts, while negative values determine negative impacts (Eastman, 2012; Siddiqui et al., 2018).

Independent variables	Coefficients	
	Harju County	**Tartu County**
Intercept	**1.51**	**1.18**
X1	–0.09	–0.97
X2	–1.27	–3.48
X3	0.23	–0.54
X4	–0.92	1.26
X5	–1.58	3.53
X6	–0.59	–0.21
X7	–2.19	–0.4
X8	0.81	–2.74
X9	–1.46	–0.57
X10	1.17	–1.85
X11	–1.82	–1.01
X12	0.89	–0.34
Pseudo R^2	0.36	0.43
ROC	0.95	0.97

We applied ROC to validate the LR model results. As seen in Table 6, the ROC values for Harju County and Tartu County were 0.95 and 0.97, respectively, showing that the LR model was a good fit. Besides, the Pseudo R^2 parameter was checked to analyze the model prediction fitness. The results showed that using these variables provides prediction values of 37% in Harju County and 45% in Tartu County. The output of the LR model was a prediction map (Figure 8) verifying where urban expansion occurred in 2018 when the coefficients of proximity factors were employed in the study areas.

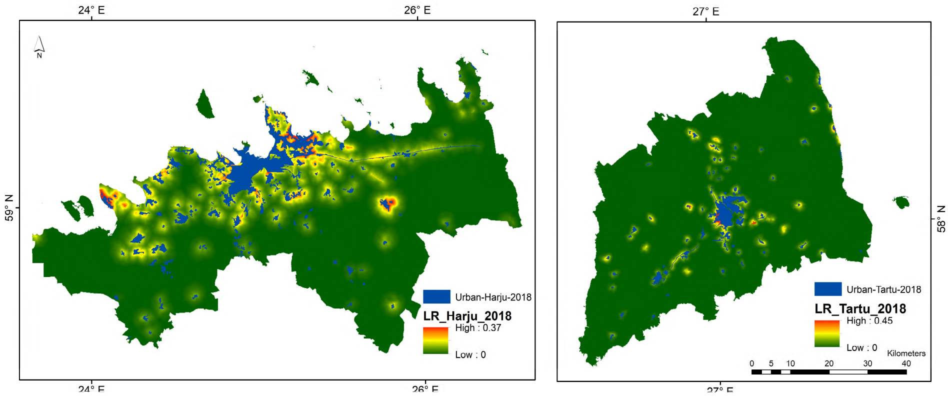

Figure 8. Predicted map of urban expansion using LR model for 2018 and overlay with the actual urban expansion maps (CORINE land cover dataset) in 2018. Source: **Article I**, Figure 10.

The output of the MLP model provided a detailed statistical analysis and a predicted map based on the strength of the independent variables. The statistical analysis includes three main categories of information: (1) Model sensitivity when a single variable is constant. After training the whole variables to check the strength of independent variables, it holds the input values of a selected variable constant to remove its variability. (2) Except one variable, all variables are held constant. It shows complementary information about the existence of intercorrelation between independent variables. The results will prepare the most and least influential driving forces (Table 7). (3) Backward stepwise constant forcing keeps every variable constant, in turn, to distinguish which other variables have a minor effect on the model. This trend will remain constant for every probable pair of variables and check the least effective ones until only one variable is left (Table 8). It is a practical algorithm to remove powerless variables and reduce the likelihood of overfitting (Eastman, 2012).

In the case of Harju County, the most influential independent variable was "distance from existing residential areas (X10)" and the least influential was "distance from sports and leisure facilities (X6)". The variables "distance from the core of Tallinn (X2)", "distance from green urban areas (X3)", and "distance from main roads (X7)" were the most influential among the other variables. The most influential driving force in Tartu County was "distance from the core of Tartu (X2)," and the least influential was "distance from the airport (X5)". The results showed that "distance from existing residential areas (X10)" in Harju County and "distance from the core of Tartu (X2)" in Tartu County had more strength than the other variables

Likewise, the predicted map of the MLP model (Figure 9) verified 79% of the prediction based on the defined variables for Harju County and 49% for Tartu County, where urban expansion happened in 2018.

Table 7. Statistical information of the MLP model's sensitivity (Steps 1 and 2). Source: **Article I**, Table 5.

Independent Variables	**Force Constant a Single Variable**				**Except One, Force Constant All Independent Variables**	
	Harju County		**Tartu County**		**Harju County**	**Tartu County**
	R^2	**Influence Order**	**R^2**	**Influence Order**	**R^2**	
With all variables	0.04	N/A	0.02	N/A	0.0390	0.0217
X1	0.04	9	0.02	8	0.0009	0.0000
X2	0.03	2	0.01	1 (most influential)	0.0031	0.0018
X3	0.03	3	0.01	2	0.0039	0.0012
X4	0.04	8	0.01	5	0.0015	0.0009
X5	0.03	5	0.02	12 (least influential)	0.0025	0.0000
X6	0.05	12 (least influential)	0.01	4	0.0000	0.0011
X7	0.03	4	0.01	3	0.0036	0.0012
X8	0.04	10	0.02	9	0.0021	0.0000
X9	0.03	6	0.02	11	0.0022	0.0000
X10	0.02	1 (most influential)	0.02	6	0.0067	0.0004
X11	0.04	11	0.02	7	0.0000	0.0002
X12	0.04	7	0.02	10	0.0000	0.0000

Table 8. Statistical results of backward stepwise constant forcing (step 3). Source: **Article I**, Table 6.

Harju County			Tartu County		
Model	**Variables Included**	**R^2**	**Model**	**Variables Included**	**R^2**
With constant variables	All variables	0.0390	With constant variables	All variables	0.0217
Step1: X (6)	(1,2,3,4,5,7,8,9,10,11,12)	0.0442	Step1: X (5)	(1,2,3,4,7,6,8,9,10,11,12)	0.0217
Step2: X (6,11)	(1,2,3,4,5,7,8,9,10,12)	0.0467	Step2: X (5,9)	(1,2,3,4,7,6,8,10,11,12)	0.0217
Step3: X (6,11,8)	(1,2,3,4,5,7,9,10,12)	0.0497	Step3: X (5,9,12)	(1,2,3,4,7,6,8,10,11)	0.0215
Step4: X (6,11,8,1)	(2,3,4,5,7,9,10,12)	0.0477	Step4: X (5,9,12,8)	(1,2,3,4,7,6,10,11)	0.0211
Step5: X (6,11,8,1,12)	(2,3,4,5,7,9,10)	0.0468	Step5: X (5,9,12,8,1)	(2,3,4,7,6,10,11)	0.0206
Step6: X (6,11,8,1,12,4)	(2,3,5,7,9,10)	0.0466	Step6: X (5,9,12,8,1,11)	(2,3,4,7,6,10)	0.0186
Step7: X (6,11,8,1,12,4,9)	(2,3,5,7,10)	0.0405	Step7: X (5,9, 12,8,1,11,10)	(2,3,4,7,6)	0.0159
Step8: X (6,11,8, 1,12,4,9,5)	(2,3,7,10)	0.0307	Step8: X (5,9, 12,8,1,11,10,4)	(2,3,7,6)	0.0107
Step9: X (6,11,8,1,12,4,9,5,2)	(3,7,10)	0.0205	Step9:X (5,9,12,8,1,11,10,4,6)	(2,3,7)	0.0067
Step10: X (6,11,8,1,12,4,9,5,2,7)	(3,10)	0.0129	Step10:X (5,9,12,8,1,11,10,4,6,7)	(2,3)	0.0038
Step11:X (6,11,8,1,12,4,9,5,2,7,3)	(10)	0.0067	Step11:X (5,9,12,8,1,11,10,4,6,7,3)	(2)	0.0018

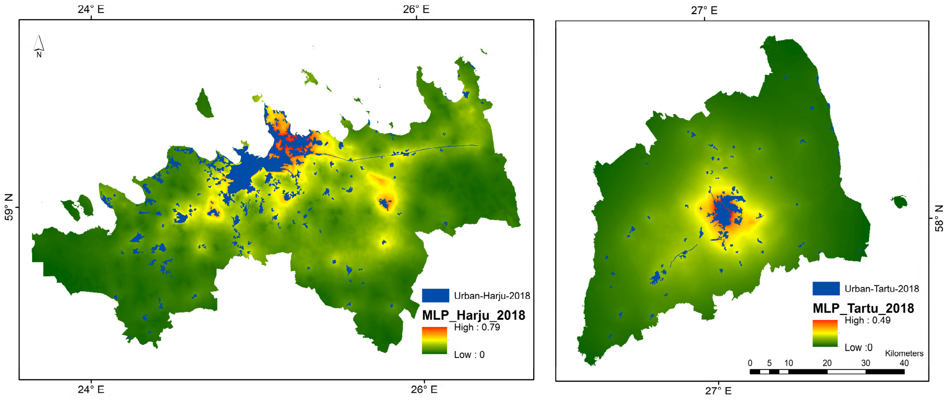

Figure 9. Predicted urban expansion in relation to 12 independent variables using MLP for Harju County and Tartu County. The overlay of urban areas in 2018 was conducted to visualize the predicted urban expansion with the actual maps (CORINE land cover dataset) in both counties. Source: **Article I**, Figure 11.

3.3. Integrated CA–Agent Model Simulation Results (Article II)

The integrated CA–Agent model was implemented in **Article II**. As Figure 10 represents, cellular agents have three different values; Value 1 is allocated to the cells developed to be built up between two timestamps (1990–2006 and 2006–2018), Value 3 is the previous development to be built up (the initial development of Tallinn and surroundings), and Value 2 shows the undeveloped cells. During the model run, Value 2 agents, which range from 127 to 8100 sq. m area, have less likelihood of being developed in the neighboring areas unless they have a high probability of being located in Tallinn or a large cell. We took advantage of Markovian transition probability results set to 0.84 to allocate the CA–Agent model probabilities and perform suitability analysis by applying different constraints based on the guidelines of Estonian legislation on new constructions named "Riigi Teataja".

To evaluate the model parameters and their application in the study area, we performed the model once for simulating urban expansion in 2018 and then validated it against the actual map in 2018. Table 9 illustrates the high accuracy of the simulated map after applying the accuracy assessment. $K_{standard}$ (0.86), $K_{location}$ (0.89), and MediumGrid (m) (0.91) demonstrated high model performance, and the $Q_{disagreement}$ (0.02) and $A_{disagreement}$ (0.07) declared minor cell error match in the simulation result. Therefore, the CA–Agent model runs reached an acceptable prediction, so we performed the second run of 12-time steps for simulating the urban expansion by 2030 (Figure 11).

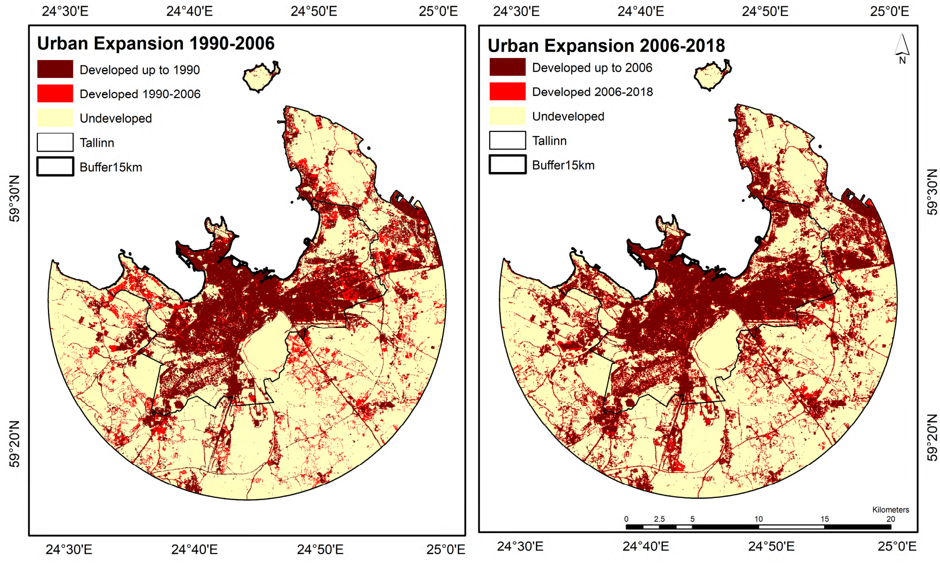

Figure 10. The urban expansion between 1990–2006 and 2006–2018 represents the state of the agents. Source: **Article II**, Figure 4.

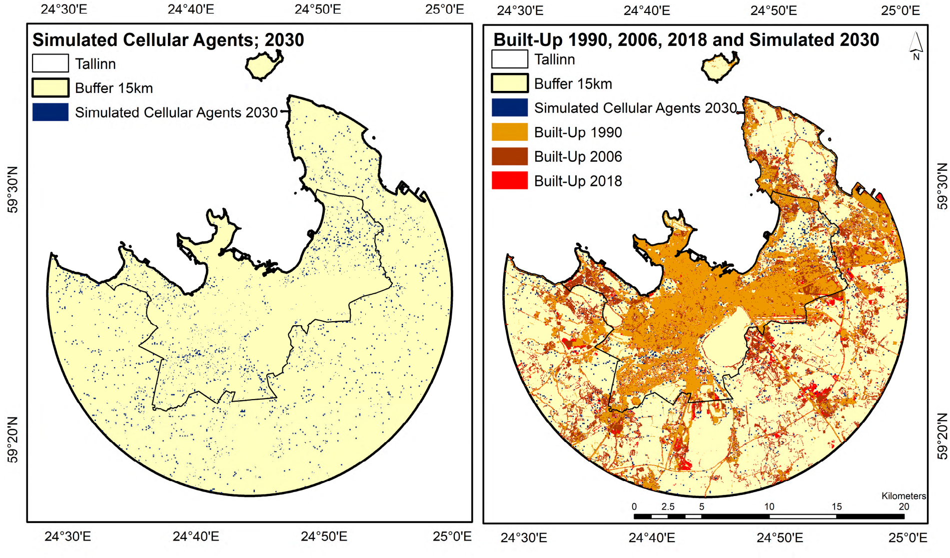

Figure 11. Simulated map of urban expansion applying the CA–Agent model for 2030. Source: **Article II**, Figure 7.

Table 9. Validation results of the simulated map and actual map in 2018. Source: **Article II**, Table 7.

Image Comparison results (Degree from 0–1)	
$K_{standard}$	0.86
$K_{location}$	0.89
MediumGrid (m)	0.91
$Q_{disagreement}$	0.02
$A_{disagreement}$	0.07

According to Table 10, built-up areas consisting of residential, industrial, and other impervious surfaces increased by 40.80 sq. km (+25.03% change) in Tallinn and its 15 km buffer zone between 1990 and 2018. Besides, urban expansion from 1990 to 2006 had risen by 18.15%, which was faster than the expansion between 2006 and 2018 with an 8.40% increase. The CA–Agent model results also predicted the continued increase reaching 175.24 km^2 in 2030, which means a 30.25% increase from 1990 to 2030 due to the development of 2881 cells. The expansion rate was slower (6.97%) from 2018 to 2030.

Table 10. Urban expansion in Tallinn and its buffer zone from 1990 to 2030. Source: **Article II**, Tables 4 and 8.

Built-Up Areas				**Increased Area by sq. km**			**Percentage of Change**		
1990	**2006**	**2018**	**2030**	**1990–2006**	**2006–2018**	**2018–2030**	**1990–2006**	**2006–2018**	**1990–2030**
122.22	149.32	163.02	175.24	27.10	13.70	12.22	18.15	8.40	30.25

3.4. CA–MCA–AHP Model Simulation Results (Article III)

In **Article III**, we applied an MCE function to evaluate the performance of the CA–MCA–AHP model. Combined constraint maps of water buffer zones with factors including slope, distance to built-up, distance to water bodies, and distance to roads were analyzed and weighted with an AHP technique to determine their influence on urban expansion and produce a suitability map in the Harju County (Figure 12). Zero values can limit the suitable areas for urban expansion. The most suitable areas are shown in red, mostly near existing built-up areas, low suitable areas in green to yellow, and unsuitable areas in black to dark blue colors.

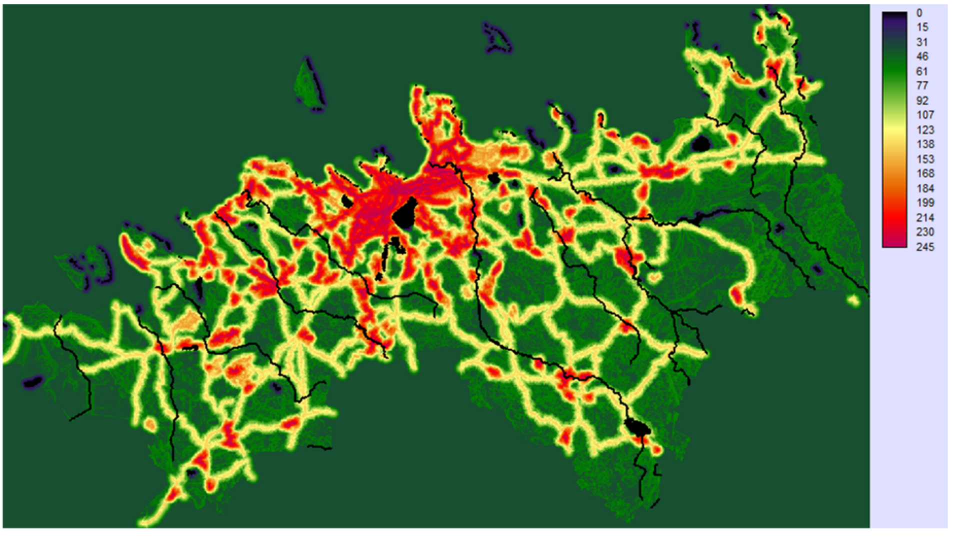

Figure 12. MCE function output as suitability map for urban expansion in Harju County. Source: **Article III**, Figure 14.

Based on the transition rules extracted from MCA and the suitability map utilized by the MCE function, urban expansion in Harju County for 2046 was simulated, and the results indicated that the expansion trend is mainly near the existing built-up areas and roads (Figure 13). Meanwhile, the city of Tallinn expanded mainly to the northwest and northeast from 1990 to 2018, and this process continued to 2046.

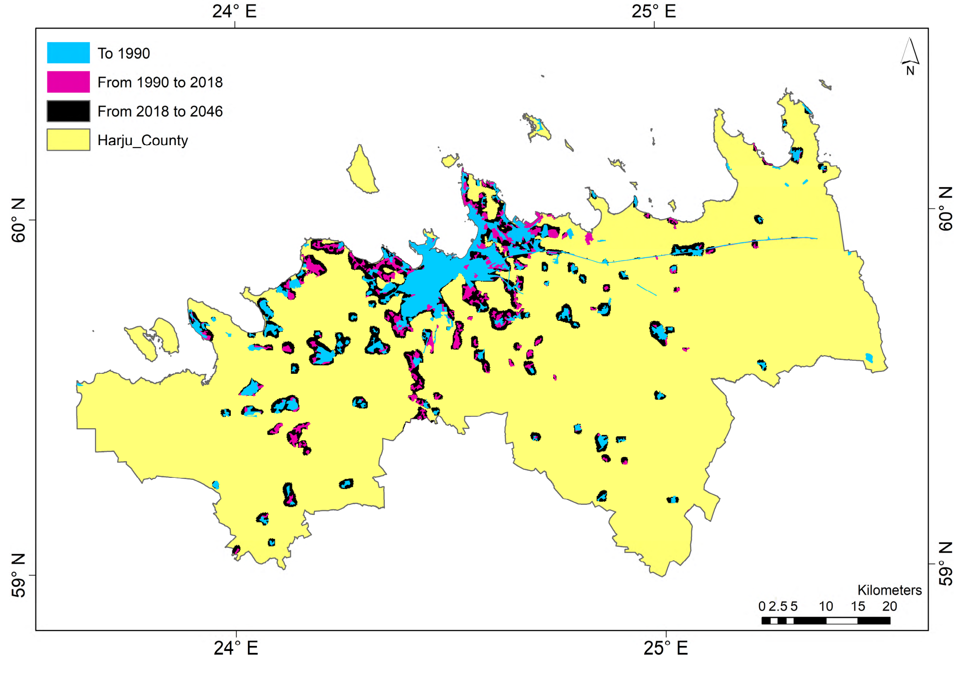

Figure 13. Urban expansion in Harju County during 1990–2018 and simulated 2046. Source: **Article III**, Figure 16.

3.5. Hybrid ANN–CA–MCA Model Simulation Results (Article IV)

This study explored the changes in LULC and artificial surfaces using the hybrid ANN–CA–MCA model in the GIS environment. Several inputs were analyzed and put into the model for future simulation. Besides, the demand quantity was a primary input of the simulation model calculated by MCA. The estimation of demands was based on the transition probability and area of the changes in LULC from 2011 to 2019 (Table 11). The results showed that it is 78.30% probable that artificial surfaces remain the same, and their probability of transitions was mainly affected by agricultural lands by 13.03%.

Table 11. Transition probability and demand prediction for simulation of artificial surfaces in 2030. Source: **Article IV**, Table 5.

	Transition Probability					Demand prediction 2030 (cells)
2011 (row), 2019 (columns)	**Artificial surfaces**	**Agri-culture**	**Forest**	**Wet-lands**	**Water**	
Artificial surfaces	0.7830	0.1303	0.0807	0.0010	0.0050	314814

Using a back propagation-ANN algorithm, the probability of occurrence was estimated to be one primary input in the simulation model. Table 12 illustrates the relationships between artificial surfaces' probability of occurrence (dependent variable) and 19 spectral–textural indices (independent variables). The statistical results of the multiple regression analysis revealed the importance of spectral–textural indices on the expansion of artificial surfaces. The adjusted R^2 value was 0.94 for the probability of occurrence in 2011 and 0.93 in 2019 and 2030, which indicated that artificial surfaces' probability of occurrence is explained extremely high by spectral–textural indices.

While the results explored the uniformity of distribution of color saturation, entropy on the pixel difference of color value, saturation value, and average on the sum of color saturation pixel pairs (sat_asm_21, val_dent_21, sat_dent_21, and sat_savg_21, respectively), were the best positive indicators of the probability of occurrence in 2011 and 2019. Also, correlation among normalized difference built-up index pixel pairs and NIR band mean (ndbi_corr_21 and nir_mean_21) most influenced the artificial surfaces' probability of occurrence in 2030. In contrast, the homogeneity of normalized difference built-up index pixel pairs (ndbi_idm_21) was the most negative influential factor over these periods.

Table 12. Association between spectral–textural indices and artificial surfaces' probability of occurrence in 2011, 2019, and 2030. Source: **Article IV**, Table 6.

Spectral–textural indices	**Probability of occurrence coefficients 2011**	**2019**	**2030**	**Spectral–textural indices**	**Probability of occurrence coefficients 2011**	**2019**	**2030**
intercept	–1.00	–1.27	–1.35	**nir_gearys_21**	1.00	0.99	0.99
blue_entropy_21	7.28	–6.61	0.40	**nir_mean_21**	6.97	1.95	2.71
green_gearys_21	2.75	0.08	1.21	**nir_sd_21**	–3.31	1.89	–1.11
hue_dvar_21	–4.79	–4.47	–1.92	**sat_asm_21**	13.26	10.85	–4.80
ndbi_corr_21	–7.98	–10.30	5.50	**sat_dent_21**	8.78	4.50	–1.81
ndbi_gearys_21	–8.03	9.44	–2.65	**sat_savg_21**	2.97	2.41	1.85
ndbi_idm_21	–12.69	–11.94	–6.74	**swir1_gearys_21**	0.96	1.02	0.97
ndbi_shade_21	1.02	0.97	1.03	**swir1_sd_21**	–4.45	–4.18	–1.19
ndvi_prom_21	1.20	1.16	1.04	**val_dent_21**	10.54	5.19	–1.86
ndwi	–6.89	8.73	–3.83	**wetness**	–3.96	–1.84	1.74
				Adjusted R^2	0.94	0.93	0.93

After performing the CA model to simulate the projection in 2011 and 2019, we validated the results against the actual maps of those years to explore the accuracy of the predicted indices for simulation in 2030 (Table 13). The accuracy assessment indicated excellent simulation results and consistency in the simulation of the patterns (in 2011, the kappa coefficient = 0.8715 and overall accuracy = 93.46%, and in 2019, the kappa coefficient = 0.9094, overall accuracy = 95.38%). Producers' and users' accuracy for both simulations were higher than 70% on artificial surfaces.

Table 13. Statistical results of the accuracy assessments for the simulation of LULC in 2011 and 2019. Source: **Article IV**, Table 7.

Accuracy assessment	**2011**	**2019**
Kappa Coefficient	0.8715	0.9094
Overall Accuracy	93.46%	95.38%
Producer's Accuracy	74.87%	77.32%
User's Accuracy	74.77%	77.41%

Based on the overall conditions set for the hybrid ANN–CA–MCA model, we predicted the changes in artificial surfaces in Estonia for 2030 (Table 14). Taking advantage of spectral–textural remote-sensing indices, the prediction of changes in artificial surfaces was estimated to increase at a rate of 1.33% and expected to reach 787.04 sq. km in total with a similar pattern to the previous periods (a total of 34.62 km^2 growth (+4.40%) from 2000 to 2030).

Table 14. Artificial surfaces dynamic changes in Estonia from 2000 to 2030. Source: **Article IV**, Tables 3 and 8.

Artificial surfaces	**Area (Sq.km)**				**Change (Percentage)**			
	2000	**2011**	**2019**	**2030**	**2000–2011**	**2011–2019**	**2019–2030**	**2000–2030**
	752.42	765.00	776.59	787.04	1.64%	1.49%	1.33%	4.40%

Closer inspection of urban expansion in three major cities in Estonia, including Tallinn, Tartu, and Pärnu, represented in Figure 14, indicated that the new expansion exceeded the cities' boundaries, primarily distributed around the existing urban areas, indicating a prominence of infilling expansion. In Tallinn, where the water restricted expansion to the north and south, the expansion will be situated in the west and east directions. Expansion of artificial areas in the city of Tartu will be located mainly to the south and south-west. Indeed, scattering patterns of expansion in Pärnu as a summer capital will be placed in the northeast. A visual interpretation of urban expansion in these three cities also revealed that the vast majority of expansion was predicted in Tallinn, the capital city, with more population. As the second major city in Estonia, more expansion was predicted for Tartu compared to Pärnu.

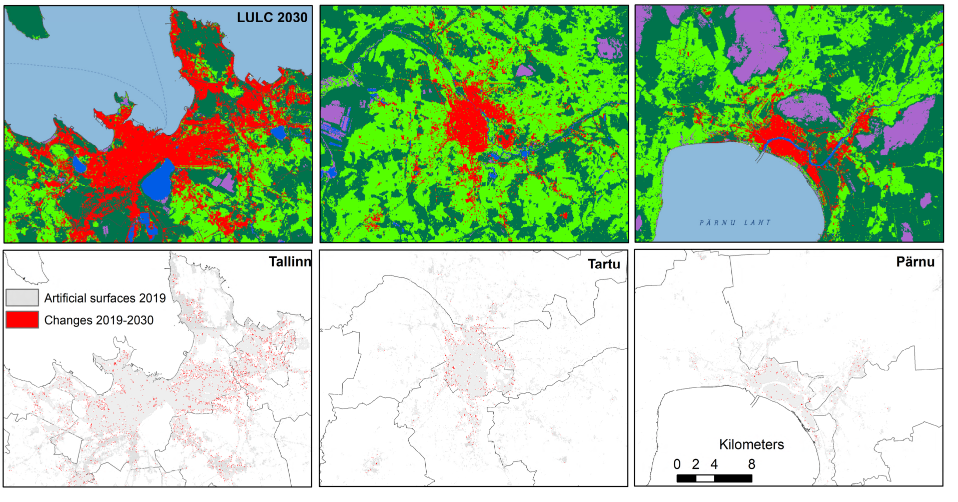

Figure 14. Urban expansion in the main cities of Estonia by 2030. Source: Article **IV**, Figure 7.

4. DISCUSSION

4.1. Driving Forces and Predictors of Urban Expansion in Estonia

For practical purposes, the complexity of urban expansion simulation in cities and suburbs implies a need for distinguishing a reduced set of most influential factors affecting the phenomena. The effects of physical and proximity factors on urban expansion were explored in **Articles I, II, and III,** and extensive research has modeled their influences. For example, Tan et al. (2015) demonstrated that the distance to the city center and major roads negatively influences urban expansion. Similarly, Mustafa et al. (2018) used the factors of distance to roads, towns, and railways, and Liu et al. (2013) applied spatial variables of distance to the town center and roads as the proximity factor affecting urban expansion. Through **Articles I–III**, we employed proximity analysis with different sets of driving factors.

In **Article I**, we applied the proximity analysis, whose importance in modeling urban expansion was noted in prior studies (Abbas et al., 2021; Gharaibeh et al., 2020; Paterson et al., 2015; Patra et al., 2018; Rahnama, 2021; Sohl et al., 2012; Ullah et al., 2019). We used twelve proximity measures for force, including "distance from near cities (X1)", "distance from the core of main cities of Tallinn and Tartu (X2)", "distance from the green urban areas (X3)", "distance from industrial or commercial units (X4)", "distance from airports (X5)", "distance from sport and leisure facilities (X6)", "distance from main roads (X7)", "distance from agriculture land (X8)", "distance from forest land (X9)", "distance from existing residential areas (X10)", "distance from water areas (X11)", and "distance from wetlands (X12)" to investigate their influence on urban expansion in Harju County and Tartu County in Estonia.

One interesting finding was that the footprints of urban expansion mainly were determined proximate to main roads (X7), the core of Tallinn and Tartu (X2), and existing residential areas (X10) in both counties, with different coefficients expressing the dominant role of these factors on urban expansion. In Harju County, based on the LR model, distance from main roads (X7) had the highest strength in urban expansion and then proximity to the core of Tallinn (X2), which this finding was broadly in line with the argument made by Reimets et al. (2015) who mentioned that the distance from the Tallinn was a less important factor than the distance from the main roads. Applying the MLP model also indicated the influence of these factors, while it showed that the most influential independent variable was the distance from existing residential areas (X10). This finding supports the conclusion reached by Samarüütel et al. (2010) that indicated the importance of Tallinn's suburbs transforming into urban and expressed the likelihood of urban expansion and new constructions near the existing areas in the long-term Harju County. In Tartu County importance of proximity to the core of Tartu (X2), existing residential areas (X10), and main roads (X7) indicates the influence of accessibility via main roads to the core of Tartu and existing residential areas. These factors revealed that people tend to settle proximate to existing residential areas or the core of Tartu, taking advantage of roads to commute between work and home while benefiting from environmental attractions in the suburbs.

A closer look into the LR model results showed that in both counties, the distance from water areas (X11) was negatively correlated with urban expansion expressing the attraction of water for housing development (Tammaru et al., 2009) and distance from the forest (X9) also had a negative impact on urban expansion, indicating the importance of forest land in trade-offs of urban expansion. In Tartu County, the distance from agricultural lands (X2) ranked amongst the most influential factors of urban expansion, highlighting the importance of these lands in people's lives and the tendency for conversion to urban expansion.

The MLP model revealed that footprints of urban expansion are also apparent in proximity to the airport (X5) in Tallinn, while this factor is the least influential in Tartu County. The reason for this could be the spatial location of Tallinn international airport (Lennart Meri), which is inside the city's boundary, with many residential settlements shaped in the periphery of the airport area during the last decades, while in Tartu County, the airport location (Ülenurme) is situated outside city's boundary and less expansion was observed there. Besides, distance from green urban areas (X3) ranked amongst the influential factors of urban expansion, indicating the importance of urban greenery despite its reduction under the expansion of urban areas (Muhamad Nor et al., 2021).

Further work in **Articles II** and **III** was done based on applying physical driving forces for modeling purposes in Harju County. In **Article II,** we applied the most influential drivers consisting of "distance to Tallinn", "distance to main roads", and "neighborhood status; representing the status of a cellular agent concerning its neighboring residential area" alongside many other constraints and behavioral rules to investigate urban expansion in Tallinn and its 15 km buffer zone and then simulate the future of urban expansion in 2030. Applying these factors to the integrated CA–Agent model determined that the simulation's accuracy reached 86%, indicating the high importance of defined driving factors and integrated model implementation in projecting the accurate urban expansion. Also, in **Article III,** combined constraint maps of water buffer zones with factors including slope, distance to built-up, distance to water bodies, and distance to roads were analyzed and weighted with an AHP technique in order to determine their influence on urban expansion and produce suitability map in Harju county.

It was assumed that the landscape's spectral–textural properties provide an adequate proxy in detecting urban expansion footprints and transitions over time. This assumption was addressed in **Article IV**, where we revisited utilizing spectral–textural information of landscape physiognomy as predictors of change. We modeled urban expansion with a hybrid ANN–CA–MCA model to investigate the impacts of the proposed indicators on modeling. The results indicated that applying the spectral–textural indices by the hybrid ANN–CA–MCA model upgraded the accuracy of predictions reaching up to 90%, indicating the morphologic indices' high capabilities in projecting accurate urban expansion and their significant importance in representing reality. In terms of artificial surfaces transitions over time, multiple regression analysis showed the dominant role of textural indices in representing diversity-related indices (e.g., difference entropy). While covering all aspects and predictors of the urban expansion transitions requires sufficient knowledge about the study area and trends of changes, adopting spectral–textural indices helps overcome the selection limitations and reliability in simulation results. Therefore, the assumption that landscapes' spectral–textural properties provide a sufficient proxy for urban expansion transitions was proved, and it is suggested to use spectral–textural indices for modeling the future of urban expansion.

4.2. Models' Performance in Predicting Urban Expansion in Estonia

In this thesis, different models have been utilized to address the complexity of urban expansion for analyzing past patterns and predicting future spatial patterns. The configuration of a single or hybrid/integrated urban expansion model should answer the evolving dynamics of urban expansion and the future spatial footprints of urban expansion to benefit urban planners' and policymakers' decisions. So, **Article I** set out to investigate the prediction power of two single models of LR and MLP. It showed a lower degree of prediction power for single models of LR (37% for Harju County, 45% for Tartu County) and MLP (79% for Harju County and 49% for Tartu County). While the dataset's spatial resolution and selected driving factors are important input factors in the models, the implementation of these two single models proved the importance of hybrid models in representing the reality and detection of urban expansion footprints. Therefore, concerning the main objective of the thesis and to assess the second assumption, further works in **Articles II, III,** and **IV** were done with integrated/hybrid models.

In **Article II,** We integrated the CA with MCA and agent-based models (CA–Agent model) to simulate urban expansion in Tallinn and its 15 km buffer zone. The integrated CA–Agent model results determined the simulation accuracy reached up to 86%, indicating the importance of integrated model implementation in projecting the accurate urban expansion. In **Article III,** we applied the CA model with MCA and MCE models (CA–MCA–AHP) to simulate urban expansion in Harju County. The results indicated the high value of several models' configurations in projecting the future of urban expansion. **Article IV** synthesized the CA model with MCA and ANN models (ANN–CA–MCA) in the GIS environment to simulate urban expansion in country-wide Estonia. The results proved that applying the hybrid ANN–CA–MCA model also improved predictions' accuracy, reaching up to 90%. Therefore, the results assert that combined models are beneficial to assure that simulation accuracy in representing the future is more realistic. It is worth discussing the essential findings of the implemented CA model's components applied in this thesis:

(i) Cell space and state: Numerous research has attempted to investigate the application of lattice/regular grid cells in the CA model (Al–sharif & Pradhan, 2015; Falah et al., 2020; Jafari et al., 2016; Wu et al., 2010). Implementing different cell spaces is a way to address the heterogeneity in space. Previous studies developed some approaches to answering the heterogeneity in the CA model cell space, including the patch-based approach of landscape metrics (Fenta et al., 2017; Lin et al., 2020; Liu et al., 2020; Yang et al., 2016), applying different cell sizes (**Article II**), partitioned grid cells (Lu et al., 2019; Xu et al., 2018; Xu et al., 2021), and specifying different neighborhood characteristics (Tong & Feng, 2019). Whereas in **Article II,** we applied different cell sizes approach to address the heterogeneity. The defined space for undeveloped cellular agents in the CA–Agent model was square cells ranging from 127 to 8100 m with three different states. A cellular agent's final state changed to built-up when a cell passed the complete assessment tests. Therefore, applying an irregular structure of cells with different sizes can better represent the reality of the non-uniform space of urban expansion. The spatial resolutions of cells in **Article III** were regular square grid cells of 100 × 100 m and in **Article IV** were regular square grid cells of 50 × 50 m, which multiple LULCs defined the transitions from non-urban to urban. One important finding was that pixel-level and non-uniform spatial information derived from spectral–textural indices provided higher accuracy for the hybrid cell-based model while addressing the heterogeneity in space.

(ii) Transition rules: Transition rules are major contributing factors in a CA model. We defined the driving factors of urban expansion with suitability analysis approaches (**Articles II and III**) and spatial demand allocation (**Article IV**) for the future specifications of urban expansion to determine the transition rules. Besides, this study confirms that MCA (**Articles II, III, and IV**) estimated the transition probability and potential future changes. Previous studies developed MCA transition probability to answer the changes in cell state. Berberoğlu et al. (2016) have shown that conditional probabilities of the Markov model are reliable for allocating the to-be-changed state of cells. A similar application of the MCA model was obtained by Aburas et al. (2017) in predicting the quantity of urban and non-urban areas. However, consistent with the literature, to overcome the limitations of the MCA model, we applied three other mining models to boost the transition rules: the agent-based model (**Article II**), AHP (**Article III**), and ANN (**Article IV**).

Article II synthesized the probabilities, transition rules, and interaction with other cellular agents and environments into one model. These capabilities allowed the cellular agents to decide to develop or not. Instead of randomly assigning the probability values, MCA extracted the spatial conversion during the time to interact with cellular agents and mine the transition rules. Transition rules were defined in several steps; consisting of searching the lands, collecting information (cell's size, the least area needed for building a dwelling, the location, and adjacent neighboring cells) for the probable development status, assessing the situation (based on the behavioral rules, suitability, and probability of developing a cell), investigating the thresholds and reaching the development decision. **Article III** utilized the AHP technique to explore the suitability of urban expansion in Harju County based on several factors and constraints. **Article IV** employed the ANN algorithm to discover the spatial probability of occurrence in non-linear systems like urban systems and mine the transition rules based on a competition mechanism using the spectral–textural predictors. The high value of adjusted R-square also detected this algorithm's effectiveness for estimating the probability of occurrence; indeed, it reflected the diversity and complexity of transitions over time.

(iii) Neighborhood: Defining the neighborhood size, shape, and weights is critical in reducing the over–and under–estimation of the models' outcome. In **Article II,** we did not replicate the previous research applying Moore neighborhood (Falah et al., 2020; Liao et al., 2016; Liu et al., 2013; Omrani et al., 2017), different shapes (Pan et al., 2021; Pan et al., 2010) or influential regions (Otgonbayar et al., 2018); instead, we applied the adjacent cell's neighborhood considering the polygon neighbor list, which could cover all the possibilities of the accessibility by neighbors. The adjacent neighborhood was based on the spatial and quantity influence of neighbors. Through the adjacent polygon neighbor list, the cellular agent assessed the number and proportion of neighbors that have developed at each time step and made its development decision. If no immediate neighbor or neighbor's neighbor has been developed, developing the probability value of cellular agents was small. However, in **Article III,** a Moore neighborhood function with 5 × 5 cells and in **Article IV,** 7 × 7 cells with different weights were applied. Here, it is nice to point out that the most interesting finding of implementing different neighborhood functions is to properly mine the transition rules and answer the reality of model representation and prediction. So, applying the proposed neighborhood functions accompanying different factors and tools, roughly impacts the models' accuracy.

4.3. Dataset Spatial Resolution for Modeling Urban Expansion in Estonia

In this research, we used three primary remote sensing sources: (1) the time–series CORINE land cover database with 100m spatial resolution (level 1 class; artificial surfaces considered urban), (**Article I** and **Article III**), (2) Landsat imagery products with a spatial resolution of 30m for extracting urban expansion and spectral–textural indicators of landscape physiognomy (**Article II** and **Article IV**), and (3) a 30m–spatial resolution land cover dataset provided by Parente et al. (2021) (**Article IV**).

The most prominent finding to emerge from the analysis is that using the time–series CORINE land cover database with 100m spatial resolution in **Article I** impacts the low prediction power of two single models of LR and MLP. The prediction power of LR was determined to be less than the MLP model (LR = 37% for Harju County, 45% for Tartu County, and MLP = 79% for Harju County and 49% for Tartu County). In **Article II,** applying a new classified map with a spatial resolution of 30 m for a smaller area (Tallinn and its 15 km buffer zone) in an integrated CA–Agent model determined that the accuracy of the simulation reached up to 86%. Through **Article IV**, we used a dataset with a spatial resolution of 30 m, and we reclassified the data to 50 m resolution for LULC monitoring purposes and computationally convenience. Also, the results of the hybrid ANN–CA–MCA model revealed the accuracy of predictions upgraded and reached up to 90%.

It was assumed that the dataset's spatial resolution impacts the model performance, and the model implementation results indicated the importance of the dataset's spatial resolution. Besides, other factors such as selected driving factors, predictors, and models impact the models' output in representing the reality and detection of urban expansion footprints.

(i) Urban expansion in Estonia

Suburbanization in eastern European countries after the collapse of the Soviet Union mainly decentralized people and urban functions from the center to the suburbs (Grigorescu et al., 2021). The construction of new settlements in scattering form has been a characteristic attribute of urban expansion in the main cities of Estonia over the past three decades. It reveals the reality of people's decisions and actions over time on land, while the population experienced a dramatic decrease. Hence, the results of model implementation in this research confirmed that the scattering patterns of new constructions are expected to continue as the infilling development form, proximate to main cities and existing residential areas, taking advantage of main roads (**Article I)** and fed by the existing infrastructures in future. **Article II** showed the continued infilling patterns of new developments in Tallinn and its 15 km buffer zone reaching 175.24 sq. km (12.22 km^2 adding to built-up areas) in 2030. Besides, **Article III** indicated that new constructions would be located near the existing built-up areas in Harju County. **Article IV** predicted the expansions of Tallinn, Tartu, and Pärnu in the vicinity of existing constructions, experiencing a 34.62 km^2 growth of artificial surfaces from 2000 to 2030. Scattering patterns of urban expansion around the main cities of Tallinn, Tartu, and Pärnu are continuing, so it is essential to pay attention to the specifications in the spatial plan of Estonia 2030+ in supporting the living and economic environments of the existing settlement to prevent scattering.

(ii) Suggestions for Future Work

- To develop a complete picture of urban expansion in Estonia and its driving forces, socio-economic and governmental policies that influence urban expansion at the macro level seem interesting to investigate.
- While the footprints of urban expansion monitored by different sets of satellite data revealed the reality of people's decisions and actions over time, future studies on how peoples' preferences and actions form the scattering patterns of urban expansion are recommended. Likewise, it shapes a preference-led model considering the human decisions' dimension instead of suitability and constraints-driven models.
- The CA–Agent (**Article II**) model and ANN–CA–MCA model (**Article IV**) provided high accuracy in simulating the future of urban expansion in Estonia. However, further research might benefit from developing and using time-series spatial data at the cadastral level to generate simulations closer to reality and answer the complexity of urban systems.

5. CONCLUSIONS

This thesis set out to monitor, analyze, and model the past, present, and future of urban expansion in Estonia. We used different sets of remotely sensed data, including CORINE land cover datasets and different sets of data derived from Landsat satellite images. We explored many driving forces and spectral–textural properties of landscape as predictors of urban expansion changes. We conducted several modeling approaches consisting of LR, MLP, CA–Agent, MCE, and ANN–CA–MCA to understand the best modeling approaches for representing the reality of urban expansion in Estonia.

Urban expansion in Estonia and some neighboring countries due to its geopolitical context, mainy after the collapse of the Soviet Union is quite different from most cities worldwide. While the population decreased over the past three decades in Estonia, people's interventions on the environment raised gradually, such that utilizing satellite imagery determined the footprints of people's actions over time. Therefore, Monitoring urban expansion in Estonia indicated continued expansion of urban-related constructions in a scattering form.

The diversity in the models and methods, indicators, datasets, extrapolation of past trends, and inherited human-environment interactions has complicated urban expansion modeling. This thesis confirmed that synthesized CA-based models had great potential in simulating urban expansion by applying several driving factors and predictors and utilizing different datasets. Besides, the utilization of spectral–textural properties of landscape physiognomy as continuous indices fundamentally raised the model accuracy. An essential aspect of spectral–textural indices is their pixel-based capabilities and potential to detect the discrete cells of multiple LULC transitions over time. Thus, our research was among the first attempts to evaluate the importance of these factors in representing the reality and detection of urban expansion footprints at the landscape scale over time.

More specifically, this thesis is the first comprehensive modeling study about urban expansion in Estonia and its factors over the past decades. The main conclusions emerging from the results were as follows:

- The scattering patterns of urban expansion are a characteristic of urban expansion in the main cities of Estonia from 1990 to 2019, while the population in Estonia decreased dramatically within this period by 15.31%.
- By applying two models of LR and MLP and proximity analysis, the footprints of urban expansion in Harju County and Tartu County mainly were determined proximate to main roads (X7), the core of Tallinn and Tartu (X2), and existing residential areas (X10) in both counties with different weights of influence and coefficients expressing the dominant role of these factors on the urban expansion (**Article I**).
- In Harju County, based on the LR model, distance from main roads (X7) had the highest strength in urban expansion and then proximity to the core of Tallinn (X2). Applying the MLP model also indicated the influence of these

factors, while it showed that the most influential independent variable was the distance from existing residential areas (X10) (**Article I**).

- In Tartu County importance of proximity to the core of Tartu (X2), existing residential areas (X10), and main roads (X7) indicates the influence of accessibility via main roads to the core of Tartu and existing residential areas (**Article I**).
- The prediction power of LR was an estimated expansion of 37% for Harju County and 45% for Tartu County, and MLP showed 80% of predictions by the selected variables in Harju County and 50% for Tartu County from 1990 to 2018 (**Article I**).
- Applying different factors, constraints, behavioral rules, and adjacent neighborhoods by the integrated CA–Agent model determined the simulation accuracy reached up to 86% in Tallinn and its 15 km buffer zone (**Article II**).
- There is a high potential for spectral–textural properties of landscapes for monitoring LULC transitions and modeling the future of urban expansion in Estonia. The results indicated that applying the spectral–textural indices by the hybrid ANN–CA–MCA model upgraded the accuracy of predictions reaching up to 90%, indicating the morphologic indices' high capabilities in projecting accurate urban expansion and their significant importance in representing reality (**Article IV**).
- The scattering patterns of new constructions are expected to continue as the infilling development form, proximate to main cities and existing residential areas, taking advantage of main roads and fed by the existing infrastructures in the future (**Article II, Article III, and Article IV**).
- The continued infilling expansion in Tallinn and its 15 km buffer zone will reach175.24 sq. km (12.22 km^2 adding to built-up areas) in 2030 (**Article II**).
- Implementation of the hybrid ANN–CA–MCA model indicated that artificial surfaces would experience a 34.62 km^2 growth from 2000 to 2030 (**Article IV**).

While scattering patterns of urban expansion around the main cities of Tallinn, Tartu, and Pärnu is continuing, several courses of action are suggested to reduce the adverse effects of urban expansion on the environment in long-term spatial planning in Estonia.

- Enhancing public awareness by organizing cultural and nature tourism and motivating people to be involved in the conventional agricultural sector in the way of learning environmental sustainability,
- Maintaining the importance of living and economic environments of the existing settlements to prevent the scattering of new ones

- Efficient regulations and policies by the local government regarding the conservation of biodiversity and Estonia's natural landscapes and reduction of agricultural and forest lands' conversion to built-up areas,
- Protecting urban green areas surrounding main cities, and
- Regulating restrictions on infrastructure expansion in remote areas.

SUMMARY IN ESTONIAN

Lühikokkuvõte. Linnade laienemine Eestis: seire, analüüs ja modelleerimine

Linnade laienemist iseloomustab vähese tihedusega, ruumiliselt ebaühtlane ja hajutatud areng linna piiridest välja. Kuna linnade laienemine muudab põllumajandus- ja metsamaid ning väikesed muutused linnapiirkondades võivad mõjutada elurikkust ja maastikku pikaajaliselt, on hädavajalik seirata linnade ruumilist laienemist ning modelleerida tulevikutrende, saamaks ülevaadet suundumustest ja tagajärgedest pikemas perspektiivis.

Eestis võeti pärast taasiseseisvumist 1991. aastal vastu maareformi seadus ning algas "maa" üleandmine riigilt eraomandisse. Sellest ajast peale on Eestis toimunud elamupiirkondade detsentraliseerimine, mis on mõjutanud Tallinna ümbruse põllumajandus- ja tööstuspiirkondade muutumist, inimeste elustiili muutusi ning jõukate inimeste elama asumist ühepereelamutesse Tallinna, Tartu ja Pärnu lähiümbrusse. Selle aja jooksul on Eesti rahvaarv vähenenud 15,31%.

Käesoleva doktoritöö eesmärk on analüüsida ja modelleerida linnade laienemist viimase kolme aastakümne jooksul Eestis ning prognoosida selle protsessi tulevikku. Tegemist on esimese põhjaliku linnade laienemise modelleerimisega ja linnade laienemist mõjutavate tegurite analüüsiga viimastel aastakümnetel Eestis. Doktoritöö uurib linnapiirkondade laienemist Eestis, kasutades erinevaid kaugseireandmeid, liikumapanevaid jõude ja parameetreid ning modelleerimismeetodeid, sealhulgas logistilist regressiooni, rakkautomaate, agendipõhiseid ja tehisnärvivõrgu mudeleid.

Seetõttu püstitati töö põhieesmärgi saavutamiseks kolm ülesannet:

1) Analüüsida Eesti viimase kolme aastakümne linnade laienemist määravaid füüsilisi tegureid ja prognoosivaid faktoreid (spektraal-tekstuuriindekseid).
2) Hinnata eri modelleerimismeetodite toimivust Eesti linnade laienemise minevikutrendide uurimisel ja tuleviku prognoosimisel.
3) Testida mudeli jõudlust, rakendades mitut erineva ruumilise eraldusvõimega andmekogumit.

Käesolev töö sisaldab nelja originaaluuringut linnade laienemise kohta kahes Eesti maakonnas (Harjumaa, kuhu kuulub ka riigi pealinn Tallinn ja Tartumaa, kus asub riigi suuruselt teine linn Tartu), eraldi Tallinnas ja selle 15 km puhvertsoonis, ning üleriigiliselt Eestis aastatel 1990–2030. Uurimisandmed on võetud kolmest esmasest kaugseireallikast: aegrida CORINE maakatte andmebaasist 100-meetrise ruumilise eraldusvõimega (klass 1; tehispinnad loetakse linnadeks), Landsati satelliitkujutised (30 m lahutusvõimega) linnade laienemise ja maastiku füsiognoomia spektraaltekstuurinäitajate eraldamiseks ning 30 m lahutusvõimega maakatteandmestik, mida pakuvad Parente jt. (2021). Peale selle kasutati ruumiandmeid veel Eesti Maa-ameti geoportaalist (ETAK andmebaasist), sh teedevõrk (põhi- ja kohalikud maanteed, raudteed) ning riigi halduspiirid. Andmete töötlemiseks ja analüüsimiseks kasutati muuhulgas QGIS 3.10, ArcGIS 10.6, IDRISI ja GEOSOS-FLUS platvorme, ning tarkvara, mis koosneb ArcMap 10.6 Agent-Analyst laienduses kasutatud platvormist Repast ja Google Earth Engine'i pilvandme töötlusplatvormist ning imitatsioonmodelleerimist.

Logistilist regressiooni ja mitmekihilisi pertseptronnärvivõrke kasutades analüüsiti lähedusfaktoreid ning hinnati seoseid füüsiliste liikumapanevate jõudude ja linna laienemise vahel. Tulemused näitasid, et Harju maakonna ja Tartu maakonna linnade laienemist mõjutasid peamiselt põhimaanteede, Tallinna ja Tartu linnatsentri ning olemasolevate elamupiirkondade lähedus. Seejärel hinnati peamisi tegureid ja piiranguid mitme kriteeriumi hindamise (MCE) funktsiooniga, et koostada Harju maakonna linna laienemise sobivuskaart. Lisaks teguritele ja piirangutele arvestati üleminekureegleid ja naaberpiirkondi, et uurida linnade laienemist dünaamiliste interaktsioonide kaudu Tallinnas ja selle 15 km laiuses puhvertsoonis ning imiteerida linna laienemise tulevikku 2030. aastaks integreeritud mobiilsideautomaatide abil ja agendipõhiseid mudeleid (CA–Agent). Nende tegurite kaudu saadi integreeritud CA-Agent mudel täpsusega üle 86%, mis ennustas Tallinna ümbritseva täisehitatud pinna jätkuvat laienemist (asustusaladele lisandub12,22 km^2) 2030. aastaks.

Hübriidmudelitena kasutati tehisnärvivõrkude, rakkautomaatide ja Markovi ahela ühendamist (ANN-CA-MCA mudel). Ennustuste üle 90% täpsus tõestas morfoloogiliste indeksite head prognoosivõimet linna laienemise kirjeldamiseks ja meetodi tähtsust tegelikkuse kujutamisel.

Kokkuvõttes võib järeldada, et 2030. aasta perspektiivis jätkuvad uusehitiste hajumismustrid peamiste linnade ja olemasolevate elamupiirkondade täitevormina, tuginedes põhimaanteedele ja "toidetuna" olemasolevast taristust. Eesti pikaajalise ruumilise planeerimise jaoks pakutakse välja mitmeid tegevussuundi, et vähendada linnade laienemise kahjulikke mõjusid keskkonnale:

- Üldsuse teadlikkuse tõstmine kultuuri- ja loodusturismi korraldamise kaudu ning inimeste motiveerimine lööma kaasa keskkonnasäästlikkuse õppimisel tavapõllumajanduses,
- Olemasolevate asumite elu- ja majanduskeskkondade olulisuse säilitamine, et vältida uute asulate hajumist,
- Kohaliku omavalitsuse tasandil tõhusad regulatsioonid ja poliitikad elurikkuse ja loodusmaastike säilitamisel ning põllu- ja metsamaade hoonestusalaks muutmise vähendamisel,
- Peamisi linnu ümbritsevate rohealade kaitsmine,
- Taristu laiendamise piirangute reguleerimine linnapiirkondade äärealadel.

REFERENCES

Abbas, Z., Yang, G., Zhong, Y., & Zhao, Y. (2021). Spatiotemporal Change Analysis and Future Scenario of LULC Using the CA-ANN Approach: A Case Study of the Greater Bay Area, China. *Land*, *10*(6), 584. https://doi.org/10.3390/land10060584

Abdullah, A. Y. M., Masrur, A., Adnan, M. S. G., Baky, M. A. Al, Hassan, Q. K., & Dewan, A. (2019). Spatio-temporal Patterns of Land Use/Land Cover Change in the Heterogeneous Coastal Region of Bangladesh between 1990 and 2017. *Remote Sensing*, *11*(7), 790. https://doi.org/10.3390/rs11070790

Aburas, M. M., Ho, Y. M., Ramli, M. F., & Ash'aari, Z. H. (2017). Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an Analytical Hierarchy Process and Frequency Ratio. *International Journal of Applied Earth Observation and Geoinformation*, *59*, 65–78. https://doi.org/10.1016/j.jag.2017.03.006

Al-Hameedi, W. M. M., Chen, J., Faichia, C., Al-Shaibah, B., Nath, B., Kafy, A. Al, Hu, G., & Al-Aizari, A. (2021). Remote sensing-based urban sprawl modeling using multilayer perceptron neural network markov chain in Baghdad, Iraq. *Remote Sensing*, *13*(20), 1–26. https://doi.org/10.3390/rs13204034

Al-sharif, A. A. A., & Pradhan, B. (2015). A novel approach for predicting the spatial patterns of urban expansion by combining the chi-squared automatic integration detection decision tree, Markov chain and cellular automata models in GIS. *Geocarto International*, *30*(8), 858–881. https://doi.org/10.1080/10106049.2014.997308

Alaei Moghadam, S., Karimi, M., & Habibi, K. (2018). Simulating urban growth in a megalopolitan area using a patch-based cellular automata. *Transactions in GIS*, *22*(1), 249–268. https://doi.org/10.1111/tgis.12309

Angel, S., Parent, J., Civco, D. L., Blei, A., & Potere, D. (2011). The dimensions of global urban expansion: Estimates and projections for all countries, 2000–2050. *Progress in Planning*, *75*(2), 53–107. https://doi.org/10.1016/j.progress.2011.04.001

Anselin, L. (2010). Local Indicators of Spatial Association-LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Aslan, N., & Koc-San, D. (2020). Spatiotemporal land use change analysis and future urban growth simulation using remote sensing: A case study of antalya. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences – ISPRS Archives*, *43*(B3), 657–662. https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-657-2020

Azhdari, A., Sasani, M. A., & Soltani, A. (2018). Exploring the relationship between spatial driving forces of urban expansion and socioeconomic segregation: The case of Shiraz. *Habitat International*, *81*(September), 33–44. https://doi.org/10.1016/j.habitatint.2018.09.001

Berberoğlu, S., Akin, A., Clarke, K. C., Berbero, S., Akın, A., & Clarke, K. C. (2016). Cellular automata modeling approaches to forecast urban growth for adana, Turkey: A comparative approach. *Landscape and Urban Planning*, *153*, 11–27. https://doi.org/10.1016/j.landurbplan.2016.04.017

Bonilla-Bedoya, S., Mora, A., Vaca, A., Estrella, A., & Herrera, M. Á. (2020). Modelling the relationship between urban expansion processes and urban forest characteristics: An application to the Metropolitan District of Quito. *Computers, Environment and Urban Systems*, *79*(September 2019), 101420. https://doi.org/10.1016/j.compenvurbsys.2019.101420

Cao, M., Tang, G., Shen, Q., & Wang, Y. (2015). A new discovery of transition rules for cellular automata by using cuckoo search algorithm. *International Journal of Geographical Information Science*, *29*(5), 806–824. https://doi.org/10.1080/13658816.2014.999245

Chen, Y., Li, X., Liu, X., Huang, H., & Ma, S. (2019). Simulating urban growth boundaries using a patch-based cellular automaton with economic and ecological constraints. *International Journal of Geographical Information Science*, *33*(1), 55–80. https://doi.org/10.1080/13658816.2018.1514119

Chen, Y., Liu, X., & Li, X. (2017). Calibrating a Land Parcel Cellular Automaton (LP-CA) for urban growth simulation based on ensemble learning. *International Journal of Geographical Information Science*, *31*(12), 2480–2504. https://doi.org/10.1080/13658816.2017.1367004

Chettry, V., & Surawar, M. (2021). Delineating Urban Growth Boundary Using Remote sensing, ANN-MLP and CA model: A Case Study of Thiruvananthapuram Urban Agglomeration, India. *Journal of the Indian Society of Remote Sensing*, *49*(10), 2437–2450. https://doi.org/10.1007/s12524-021-01401-x

Ciommi, M., Chelli, F., Carlucci, M., & Salvati, L. (2018). Urban Growth and Demographic Dynamics in Southern Europe: Toward a New Statistical Approach to Regional Science. *Sustainability*, *10*(8), 2765. https://doi.org/10.3390/su10082765

Conners, R. W. R. W., Trivedi, M. M. M. M., & Harlow, C. A. C. A. (1984). Segmentation of a high-resolution urban scene using texture operators. *Computer Vision, Graphics, and Image Processing*, *25*(3), 273–310. https://doi.org/10.1016/0734-189X(84)90197-X

Criado, M., Santos-Francés, F., Martínez-Graña, A., Sánchez, Y., & Merchán, L. (2020). Multitemporal Analysis of Soil Sealing and Land Use Changes Linked to Urban Expansion of Salamanca (Spain) Using Landsat Images and Soil Carbon Management as a Mitigating Tool for Climate Change. *Remote Sensing*, *12*(7), 1131. https://doi.org/10.3390/rs12071131

Dahal, K. R., & Chow, T. E. (2014). An agent-integrated irregular automata model of urban land-use dynamics. *International Journal of Geographical Information Science*, *28*(11), 2281–2303. https://doi.org/10.1080/13658816.2014.917646

Dang, A. N., & Kawasaki, A. (2017). Integrating biophysical and socio-economic factors for land-use and land-cover change projection in agricultural economic regions. *Ecological Modelling*, *344*, 29–37. https://doi.org/10.1016/j.ecolmodel.2016.11.004

Deep, S., & Saklani, A. (2014). Urban sprawl modeling using cellular automata. *Egyptian Journal of Remote Sensing and Space Science*, *17*(2), 179–187. https://doi.org/10.1016/j.ejrs.2014.07.001

Deribew, K. T. (2020). Spatiotemporal analysis of urban growth on forest and agricultural land using geospatial techniques and Shannon entropy method in the satellite town of Ethiopia, the western fringe of Addis Ababa city. *Ecological Processes*, *9*(1), 46. https://doi.org/10.1186/s13717-020-00248-3

Eastman, J. R. (2012). IDRISI Selva Manual. *IDRISI Selva Manual*, *January*, 1–324.

Egidi, G., Halbac-Cotoara-Zamfir, R., Cividino, S., Quaranta, G., Salvati, L., & Colantoni, A. (2020). Rural in town: Traditional agriculture, population trends, and long-term urban expansion in metropolitan Rome. *Land*, *9*(2). https://doi.org/10.3390/land9020053

Eyoh, A., Olayinka, D. N., Nwilo, P., Okwuashi, O., Isong, M., & Udoudo, D. (2012). Modelling and Predicting Future Urban Expansion of Lagos, Nigeria from Remote Sensing Data Using Logistic Regression and GIS. *International Journal of Applied Science and Technology*, *2*(5), 116–124.

Falah, N., Karimi, A., & Harandi, A. T. (2020). Urban growth modeling using cellular automata model and AHP (case study: Qazvin city). *Modeling Earth Systems and Environment*, *6*(1), 235–248. https://doi.org/10.1007/s40808-019-00674-z

Faqe, G. R., Hedyat, I., Pakiza, H., Hasan, A. S., Sherwan, M. H., & Qurtas, S. (2016). Urban Growth Prediction Using Cellular Automata Markov: A Case Study Using Sulaimaniya City in the Kurdistan Region of North Iraq. *Research on Humanities and Social Sciences*, *6*(14), 108–118.

Fenta, A. A., Yasuda, H., Haregeweyn, N., Belay, A. S., Hadush, Z., Gebremedhin, M. A., & Mekonnen, G. (2017). The dynamics of urban expansion and land use/land cover changes using remote sensing and spatial metrics: the case of Mekelle City of northern Ethiopia. *International Journal of Remote Sensing*, *38*(14), 4107–4129. https://doi.org/10.1080/01431161.2017.1317936

Forkuor, G., & Cofie, O. (2011). Dynamics of land-use and land-cover change in Freetown, Sierra Leone and its effects on urban and peri-urban agriculture – a remote sensing approach. *International Journal of Remote Sensing*, *32*(4), 1017–1037. https://doi.org/10.1080/01431160903505302

Fu, X., Wang, X., & Yang, Y. J. (2018). Deriving suitability factors for CA-Markov land use simulation model based on local historical data. *Journal of Environmental Management*, *206*, 10–19. https://doi.org/10.1016/j.jenvman.2017.10.012

G. Langton, C. (1984). SELF-REPRODUCTION IN CELLULAR AUTOMATA. *Marine Science Bulletin*, 135–144.

Gharaibeh, A., Shaamala, A., Obeidat, R., & Al-Kofahi, S. (2020). Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. *Heliyon*, *6*(9), e05092. https://doi.org/10.1016/j.heliyon.2020.e05092

Gibson, J., Boe-Gibson, G., & Stichbury, G. (2015). Urban land expansion in India 1992–2012. *Food Policy*, *56*, 100–113. https://doi.org/10.1016/j.foodpol.2015.08.002

Girma, R., Fürst, C., & Moges, A. (2022). Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift. *Environmental Challenges*, *6*(November 2021), 100419. https://doi.org/10.1016/j.envc.2021.100419

Grigorescu, I., Kucsicsa, G., Mitrică, B., Mocanu, I., & Dumitraşcu, M. (2021). Driving factors of urban sprawl in the Romanian plain. Regional and temporal modelling using logistic regression. *Geocarto International*, *0*(0), 1–27. https://doi.org/10.1080/10106049.2021.1967465

Groff, E. R., Johnson, S. D., & Thornton, A. (2019). State of the Art in Agent-Based Modeling of Urban Crime: An Overview. *Journal of Quantitative Criminology*, *35*(1), 155–193. https://doi.org/10.1007/s10940-018-9376-y

Hamilton, F. E. I., Andrews, K. D., & Pichler-Milanovic, N. (2005). *Transformation of cities in central and Eastern Europe: Towards globalization*.

Haralick, R. M., Shanmugam, K., Dinstein, I., & Shanmugam, K. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-3*(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

Harb, M., Garschagen, M., Cotti, D., Krätzschmar, E., Baccouche, H., Ben Khaled, K., Bellert, F., Chebil, B., Ben Fredj, A., Ayed, S., Shekhar, H., & Hagenlocher, M. (2020). Integrating Data-Driven and Participatory Modeling to Simulate Future Urban Growth Scenarios: Findings from Monastir, Tunisia. *Urban Science*, *4*(1), 10. https://doi.org/10.3390/urbansci4010010

Hartig, E. K., Grozev, O., & Rosenzweig, C. (1997). Climate change, agriculture and wetlands in Eastern Europe: Vulnerability, adaptation and policy. *Climatic Change*, *36*(1–2), 107–121. https://doi.org/10.1023/A:1005304816660

Hashem, N., & Balakrishnan, P. (2015). Change analysis of land use/land cover and modelling urban growth in Greater Doha, Qatar. *Annals of GIS*, *21*(3), 233–247. https://doi.org/10.1080/19475683.2014.992369

He, J., Li, X., Yao, Y., Hong, Y., & Jinbao, Z. (2018). Mining transition rules of cellular automata for simulating urban expansion by using the deep learning techniques. *International Journal of Geographical Information Science*, *32*(10), 2076–2097. https://doi.org/10.1080/13658816.2018.1480783

Huang, Y., & Liao, T.-J. (2019). An integrating approach of cellular automata and ecological network to predict the impact of land use change on connectivity. *Ecological Indicators*, *98*(May 2018), 149–157. https://doi.org/10.1016/j.ecolind.2018.10.065

Jafari, M., Majedi, H., Monavari, S., Alesheikh, A., & Kheirkhah Zarkesh, M. (2016). Dynamic Simulation of Urban Expansion Based on Cellular Automata and Logistic Regression Model: Case Study of the Hyrcanian Region of Iran. *Sustainability*, *8*(8), 810. https://doi.org/10.3390/su8080810

Jafari, M., Majedi, H., Monavari, S. M., Alesheikh, A. A., & Zarkesh, M. K. (2016). Dynamic simulation of urban expansion through a CA-markov model case study: Hyrcanian region, Gilan, Iran. *European Journal of Remote Sensing*, *49*, 513–529. https://doi.org/10.5721/EuJRS20164927

Jauhiainen, J. S. (2006). Demographic, employment and administrative challenges for urban policies in Estonia. *European Planning Studies*, *14*(2), 273–283. https://doi.org/10.1080/09654310500418291

Jelil Niang, A., Hermas, E., Alharbi, O., & Al-Shaery, A. (2020). Monitoring landscape changes and spatial urban expansion using multi-source remote sensing imagery in Al-Aziziyah Valley, Makkah, KSA. *The Egyptian Journal of Remote Sensing and Space Science*, *23*(1), 89–96. https://doi.org/10.1016/j.ejrs.2018.06.001

Jokar Arsanjani, J., Helbich, M., & de Noronha Vaz, E. (2013). Spatiotemporal simulation of urban growth patterns using agent-based modeling: The case of Tehran. *Cities*, *32*, 33–42. https://doi.org/10.1016/j.cities.2013.01.005

Kafy, A.-Al, Rahman, M. S., Faisal, A.-A., Hasan, M. M., & Islam, M. (2020). Modelling future land use land cover changes and their impacts on land surface temperatures in Rajshahi, Bangladesh. *Remote Sensing Applications: Society and Environment*, *18*(February), 100314. https://doi.org/10.1016/j.rsase.2020.100314

Kährik, A., Leetmaa, K., & Tammaru, T. (2012). Residential decision-making and satisfaction among new suburbanites in the Tallinn urban region, Estonia. *Cities*, *29*(1), 49–58. https://doi.org/10.1016/j.cities.2011.07.005

Kandpal, R., & Saizen, I. (2019). An evaluation of the relative urbanisation in peri-urban villages affected by industrialisation: the case study of Bhiwandi in the Mumbai Metropolitan Region, India. *Spatial Information Research*, *27*(2), 137–149. https://doi.org/10.1007/s41324-018-0221-z

Karimi Firozjaei, M., Sedighi, A., Argany, M., Jelokhani-Niaraki, M., & Arsanjani, J. J. (2019). A geographical direction-based approach for capturing the local variation of urban expansion in the application of CA-Markov model. *Cities*, *93*(October 2018), 120–135. https://doi.org/10.1016/j.cities.2019.05.001

Kauth, R. J., & Thomas, G. S. (1976). Tasselled Cap – a Graphic Description of the Spectral-Temporal Development of Agricultural Crops As Seen By Landsat. *LARS Symposia, Paper 159*, 41–51. http://docs.lib.purdue.edu/lars_symp/159

Khalilnia, M. H., Ghaemirad, T., & Abbaspour, R. A. (2013). Modeling of urban growth using cellular automata (CA) optimized by Particle Swarm Optimization (PSO). *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XL-1/W3*(April 2015), 231–234. https://doi.org/10.5194/isprsarchives-XL-1-W3-231-2013

Kuru, A., & Yüzer, M. A. (2021). Urban growth prediction with parcel based 3D urban growth model (PURGOM). *MethodsX*, *8*, 101302. https://doi.org/10.1016/j.mex.2021.101302

Kushwaha, K., Singh, M. M., Singh, S. K., & Patel, A. (2021). Urban growth modeling using earth observation datasets, Cellular Automata-Markov Chain model and urban metrics to measure urban footprints. *Remote Sensing Applications: Society and Environment*, *22*(September 2020), 100479. https://doi.org/10.1016/j.rsase.2021.100479

Lawler, J. J., Lewis, D. J., Nelson, E., Plantinga, A. J., Polasky, S., Withey, J. C., Helmers, D. P., Martinuzzi, S., Pennington, D., & Radeloff, V. C. (2014). Projected land-use change impacts on ecosystem services in the United States. *Proceedings of the National Academy of Sciences*, *111*(20), 7492–7497. https://doi.org/10.1073/pnas.1405557111

Lee, Y., & Chang, H. (2011). The simulation of land use change by using CA-Markov model: A case study of Tainan City, Taiwan. *2011 19th International Conference on Geoinformatics*, 1–4. https://doi.org/10.1109/GeoInformatics.2011.5980819

Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability*, *13*(7), 3740. https://doi.org/10.3390/su13073740

Li, C., Zhao, J., Thinh, N., & Xi, Y. (2018). Assessment of the Effects of Urban Expansion on Terrestrial Carbon Storage: A Case Study in Xuzhou City, China. *Sustainability*, *10*(3), 647. https://doi.org/10.3390/su10030647

Li, C., Zhao, J., & Xu, Y. (2017). Examining spatiotemporally varying effects of urban expansion and the underlying driving factors. *Sustainable Cities and Society*, *28*, 307–320. https://doi.org/10.1016/j.scs.2016.10.005

Li, G., Sun, S., & Fang, C. (2018). The varying driving forces of urban expansion in China: Insights from a spatial-temporal analysis. *Landscape and Urban Planning*, *174*(February), 63–77. https://doi.org/10.1016/j.landurbplan.2018.03.004

Li, N. (2013). Adding complexity to polygon agents using an urban. In *Agent analyst; Agent-based Modeling in ArcGIS* (pp. 239–308). Esri Press.

Li, Xia, Chen, G., Liu, X., Liang, X., Wang, S., Chen, Y., Pei, F., & Xu, X. (2017). A New Global Land-Use and Land-Cover Change Product at a 1-km Resolution for 2010 to 2100 Based on Human–Environment Interactions. *Annals of the American Association of Geographers*, *107*(5), 1040–1059. https://doi.org/10.1080/24694452.2017.1303357

Li, Xiuquan, Wang, M., Liu, X., Chen, Z., Wei, X., & Che, W. (2018). MCR-modified CA-Markov model for the simulation of urban expansion. *Sustainability (Switzerland)*, *10*(9), 1–18. https://doi.org/10.3390/su10093116

Li, Xuecao, & Gong, P. (2016). Urban growth models: progress and perspective. *Science Bulletin*, *61*(21), 1637–1650. https://doi.org/10.1007/s11434-016-1111-1

Li, Xuecao, Gong, P., Yu, L., & Hu, T. (2017). A segment derived patch-based logistic cellular automata for urban growth modeling with heuristic rules. *Computers, Environment and Urban Systems*, *65*, 140–149. https://doi.org/10.1016/j.compenvurbsys.2017.06.001

Liang, X., Guan, Q., Clarke, K. C., Liu, S., Wang, B., & Yao, Y. (2021). Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. *Computers, Environment and Urban Systems*, *85*(April 2020), 101569. https://doi.org/10.1016/j.compenvurbsys.2020.101569

Liang, X., Liu, X., Chen, G., Leng, J., Wen, Y., & Chen, G. (2020). Coupling fuzzy clustering and cellular automata based on local maxima of development potential to model urban emergence and expansion in economic development zones. *International Journal of Geographical Information Science*, *34*(10), 1930–1952. https://doi.org/10.1080/13658816.2020.1741591

Liang, X., Liu, X., Li, X., Chen, Y., Tian, H., & Yao, Y. (2018). Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landscape and Urban Planning*, *177*(February), 47–63. https://doi.org/10.1016/j.landurbplan.2018.04.016

Liao, J., Tang, L., Shao, G., Qiu, Q., Wang, C., Zheng, S., & Su, X. (2014). A neighbor decay cellular automata approach for simulating urban expansion based on particle swarm intelligence. *International Journal of Geographical Information Science*, *28*(4), 720–738. https://doi.org/10.1080/13658816.2013.869820

Liao, J., Tang, L., Shao, G., Su, X., Chen, D., & Xu, T. (2016). Incorporation of extended neighborhood mechanisms and its impact on urban land-use cellular automata simulations. *Environmental Modelling & Software*, *75*, 163–175. https://doi.org/10.1016/j.envsoft.2015.10.014

Lin, J., Li, X., Li, S., & Wen, Y. (2020). What is the influence of landscape metric selection on the calibration of land-use/cover simulation models? *Environmental Modelling & Software*, *129*(April), 104719. https://doi.org/10.1016/j.envsoft.2020.104719

Lin, Y.-P., Hong, N.-M., Wu, P.-J., & Lin, C.-J. (2007). Modeling and assessing land-use and hydrological processes to future land-use and climate change scenarios in watershed land-use planning. *Environmental Geology*, *53*(3), 623–634 . https://doi.org/10.1007/s00254-007-0677-y

Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLOS ONE*, *13*(7), e0200493. https://doi.org/10.1371/journal.pone.0200493

Liu, D., Zheng, X., & Wang, H. (2020). Land-use Simulation and Decision-Support system (LandSDS): Seamlessly integrating system dynamics, agent-based model, and cellular automata. *Ecological Modelling*, *417*(January), 108924. https://doi.org/10.1016/j.ecolmodel.2019.108924

Liu, M., Hu, Y., Chang, Y., He, X., & Zhang, W. (2009). Land Use and Land Cover Change Analysis and Prediction in the Upper Reaches of the Minjiang River, China. *Environmental Management*, *43*(5), 899–907. https://doi.org/10.1007/s00267-008-9263-7

Liu, X., Liang, X., Li, X., Xu, X., Ou, J., Chen, Y., Li, S., Wang, S., Pei, F., Liu., Liang, X., Li, X., Xu, X., Ou, J., Chen, Y., Li, S., Wang, S., & Pei, F. (2017). A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning*, *168*(October), 94–116. https://doi.org/10.1016/j.landurbplan.2017.09.019

Liu, Yaobin, Dai, L., & Xiong, H. (2015). Simulation of urban expansion patterns by integrating auto-logistic regression, Markov chain and cellular automata models. *Journal of Environmental Planning and Management*, *58*(6), 1113–1136. https://doi.org/10.1080/09640568.2014.916612

Liu, Yaolin, Kong, X., Liu, Y., & Chen, Y. (2013). Simulating the conversion of rural settlements to town land based on multi-agent systems and cellular automata. *PLoS ONE*, *8*(11), 1–14. https://doi.org/10.1371/journal.pone.0079300

Liu, Yongwei, Cao, X., & Li, T. (2020). Identifying Driving Forces of Built-Up Land Expansion Based on the Geographical Detector: A Case Study of Pearl River Delta Urban Agglomeration. *International Journal of Environmental Research and Public Health*, *17*(5), 1759. https://doi.org/10.3390/ijerph17051759

Long, Y., Wu, K.-L., & Mao, Q. (2014). Simulating parcel-level urban expansion for all Chinese cities. *Environmental Science*, 1–23.

Long, Y., & Wu, K. (2017). Simulating Block-Level Urban Expansion for National Wide Cities. *Sustainability*, *9*(6), 879. https://doi.org/10.3390/su9060879

Losiri, C., Nagai, M., Ninsawat, S., & Shrestha, R. (2016). Modeling Urban Expansion in Bangkok Metropolitan Region Using Demographic–Economic Data through Cellular Automata-Markov Chain and Multi-Layer Perceptron-Markov Chain Models. *Sustainability*, *8*(7), 686. https://doi.org/10.3390/su8070686

Lu, Yi, Laffan, S., Pettit, C., & Cao, M. (2020). Land use change simulation and analysis using a vector cellular automata (CA) model: A case study of Ipswich City, Queensland, Australia. *Environment and Planning B: Urban Analytics and City Science*, *47*(9), 1605–1621. https://doi.org/10.1177/2399808319830971

Lu, Yuting, Wu, P., Ma, X., & Li, X. (2019). Detection and prediction of land use/land cover change using spatiotemporal data fusion and the Cellular Automata–Markov model. *Environmental Monitoring and Assessment*, *191*(2), 68. https://doi.org/10.1007/s10661-019-7200-2

Luo, T., Tan, R., Kong, X., & Zhou, J. (2019). Analysis of the Driving Forces of Urban Expansion Based on a Modified Logistic Regression Model: A Case Study of Wuhan City, Central China. *Sustainability*, *11*(8), 2207. https://doi.org/10.3390/su11082207

Lv, J., Wang, Y., Liang, X., Yao, Y., Ma, T., & Guan, Q. (2021). Simulating urban expansion by incorporating an integrated gravitational field model into a demand-driven random forest-cellular automata model. *Cities*, *109*(November 2019), 103044. https://doi.org/10.1016/j.cities.2020.103044

Mahmoud, H., Alfons, R., & M. Reffat, R. (2019). Analysis of The Driving Forces of Urban Expansion in Luxor City by Remote Sensing Monitoring. *International Journal of Integrated Engineering*, *11*(6), 296–307. https://doi.org/10.30880/ijie.2019.11.06.031

Mansaray, L. R., Huang, J., & Kamara, A. A. (2016). Mapping deforestation and urban expansion in Freetown, Sierra Leone, from pre- to post-war economic recovery. *Environmental Monitoring and Assessment*, *188*(8), 470. https://doi.org/10.1007/s10661-016-5469-y

McFEETERS, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, *17*(7), 1425–1432. https://doi.org/10.1080/01431169608948714

Mehta, V. K., Haden, V. R., Joyce, B. A., Purkey, D. R., & Jackson, L. E. (2013). Irrigation demand and supply, given projections of climate and land-use change, in Yolo County, California. *Agricultural Water Management*, *117*, 70–82. https://doi.org/10.1016/j.agwat.2012.10.021

Mondal, B., Chakraborti, S., Das, D. N., Joshi, P. K., Maity, S., Pramanik, M. K., & Chatterjee, S. (2020). Comparison of spatial modelling approaches to simulate urban growth: a case study on Udaipur city, India. *Geocarto International*, *35*(4), 411–433. https://doi.org/10.1080/10106049.2018.1520922

Muhamad Nor, A. N., Abdul Aziz, H., Nawawi, S. A., Muhammad Jamil, R., Abas, M. A., Hambali, K. A., Yusoff, A. H., Ibrahim, N., Rafaai, N. H., Corstanje, R., Harris, J., Grafius, D., & Perotto-Baldivieso, H. L. (2021). Evolution of Green Space under Rapid Urban Expansion in Southeast Asian Cities. *Sustainability*, *13*(21), 12024. https://doi.org/10.3390/su132112024

Mustafa, A., Cools, M., Saadi, I., & Teller, J. (2017). Coupling agent-based, cellular automata and logistic regression into a hybrid urban expansion model (HUEM). *Land Use Policy*, *69*(October), 529–540. https://doi.org/10.1016/j.landusepol.2017.10.009

Mustafa, A., Heppenstall, A., Omrani, H., Saadi, I., Cools, M., & Teller, J. (2018). Modelling built-up expansion and densification with multinomial logistic regression, cellular automata and genetic algorithm. *Computers, Environment and Urban Systems*, *67*(September 2017), 147–156. https://doi.org/10.1016/j.compenvurbsys.2017.09.009

Oja, T. (2020). Change of land-use: Distortion of the meaning of urban and rural. In Helen Sooväli-Sepping (Ed.), *Estonian Human Development Report 2019/2020, Spatial Choices for an Urbanised Society* (pp. 34–43). Tallinn: SA Eesti Koostöö kogu, Estonia; Available online: https://www.inimareng.ee/en/index.html (accessed on 1 December 2020).

Omrani, H., Tayyebi, A., & Pijanowski, B. (2017). Integrating the multi-label land-use concept and cellular automata with the artificial neural network-based Land Transformation Model: an integrated ML-CA-LTM modeling framework. *GIScience & Remote Sensing*, *54*(3), 283–304. https://doi.org/10.1080/15481603.2016.1265706

Ondiek, R. A., Vuolo, F., Kipkemboi, J., Kitaka, N., Lautsch, E., Hein, T., & Schmid, E. (2020). Socio-Economic Determinants of Land Use/Cover Change in Wetlands in East Africa: A Case Study Analysis of the Anyiko Wetland, Kenya. *Frontiers in Environmental Science*, *7*(January). https://doi.org/10.3389/fenvs.2019.00207

Otgonbayar, M., Badarifu, Ranatunga, T., Onishi, T., & Hiramatsu, K. (2018). Cellular automata modelling approach for urban growth. *Reviews in Agricultural Science*, *6*, 93–104. https://doi.org/10.7831/ras.6.93

Pan, X., Wang, Z., Huang, M., & Liu, Z. (2021). Improving an Urban Cellular Automata Model Based on Auto-Calibrated and Trend-Adjusted Neighborhood. *Land*, *10*(7), 688. https://doi.org/10.3390/land10070688

Pan, Y., Roth, A., Yu, Z., & Doluschitz, R. (2010). The impact of variation in scale on the behavior of a cellular automata used for land use change modeling. *Computers, Environment and Urban Systems*, *34*(5), 400–408. https://doi.org/10.1016/j.compenvurbsys.2010.03.003

Parente, L., Witjes, M., Hengl, T., Landa, M., & Brodsky, L. (2021). *Continental Europe land cover mapping at 30m resolution based CORINE and LUCAS on samples*. Zenodo.Org. https://doi.org/10.5281/zenodo.4725429

Paterson, W., Rushforth, R., Ruddell, B., Konar, M., Ahams, I., Gironás, J., Mijic, A., & Mejia, A. (2015). Water Footprint of Cities: A Review and Suggestions for Future Research. *Sustainability*, *7*(7), 8461–8490. https://doi.org/10.3390/su7078461

Patra, S., Sahoo, S., Mishra, P., & Mahapatra, S. C. (2018). Impacts of urbanization on land use /cover changes and its probable implications on local climate and groundwater level. *Journal of Urban Management*, *7*(2), 70–84. https://doi.org/10.1016/j.jum.2018.04.006

Poelmans, L., & Van Rompaey, A. (2010). Complexity and performance of urban expansion models. *Computers, Environment and Urban Systems*, *34*(1), 17–27. https://doi.org/10.1016/j.compenvurbsys.2009.06.001

Purevtseren, M., Choimaa, L., Dashlegtseg, G., Indra, M., & Tsegmid, B. (2020). Urban expansion scenarios based on artificial neural network (case of Erdenet city, Mongolia). *40th Asian Conference on Remote Sensing, ACRS 2019: Progress of Remote Sensing Technology for Smart Future*, *November*.

Qian, Y., Xing, W., Guan, X., Yang, T., & Wu, H. (2020). Coupling cellular automata with area partitioning and spatiotemporal convolution for dynamic land use change simulation. *Science of The Total Environment*, *722*, 137738. https://doi.org/10.1016/j.scitotenv.2020.137738

Rahnama, M. R. (2021). Simulation of land use land cover change in Melbourne metropolitan area from 2014 to 2030: using multilayer perceptron neural networks and Markov chain model. *Australian Planner*, *57*(1), 36–49. https://doi.org/10.1080/07293682.2021.1920994

Ramachandra, T. V, Bharath Aithal, H., Vinay, S., Joshi, N. V, Kumar, U., Rao, K. V., Bharath, H. A., Vinay, S., Joshi, N. V, Kumar, U., & Rao, K. V. (2013). Modelling urban revolution in greater bangalore, India. *30th Annual In-House Symposium on Space Science and Technology, ISRO-IISc Space Technology Cell, Indian Institute of Science, Bangalore*, *November*, 7–8. http://ces.iisc.ernet.in/energy

Ratas, U., Rivis, R., Kont, A., Tõnisson, H., Vilumaa, K., Anderson, A., & Szava-Kovats, R. (2014). Regional variation in the dynamics of Estonia's coastal landscapes. *Journal of Coastal Research*, *70*, 139–144. https://doi.org/10.2112/SI70-024.1

Reimets, R., Uuemaa, E., Oja, T., Sisas, E., & Mander, Ü. (2015). Urbanisation-related Landscape Change in Space and Time along Spatial Gradients near Roads: A Case Study from Estonia. *Landscape Research*, *40*(2), 192–207. https://doi.org/10.1080/01426397.2013.773300

Rimal, B., Zhang, L., Keshtkar, H., Haack, B., Rijal, S., & Zhang, P. (2018). Land Use/ Land Cover Dynamics and Modeling of Urban Land Expansion by the Integration of Cellular Automata and Markov Chain. *ISPRS International Journal of Geo-Information*, *7*(4), 154. https://doi.org/10.3390/ijgi7040154

Roy, B., & Kasemi, N. (2021). Monitoring urban growth dynamics using remote sensing and GIS techniques of Raiganj Urban Agglomeration, India. *The Egyptian Journal of Remote Sensing and Space Science*, *24*(2), 221–230. https://doi.org/10.1016/j.ejrs.2021.02.001

Saganeiti, L., Mustafa, A., Teller, J., & Murgante, B. (2021). Modeling urban sprinkling with cellular automata. *Sustainable Cities and Society*, *65*(June 2020), 102586. https://doi.org/10.1016/j.scs.2020.102586

Saha, T. K., Pal, S., & Sarkar, R. (2021). Prediction of wetland area and depth using linear regression model and artificial neural network based cellular automata. *Ecological Informatics*, *62*(March), 101272. https://doi.org/10.1016/j.ecoinf.2021.101272

Salem, M., Bose, A., Bashir, B., Basak, D., Roy, S., Chowdhury, I. R., Alsalman, A., & Tsurusaki, N. (2021). Urban expansion simulation based on various driving factors using a logistic regression model: Delhi as a case study. *Sustainability (Switzerland)*, *13*(19), 1–17. https://doi.org/10.3390/su131910805

Salem, M., Tsurusaki, N., & Divigalpitiya, P. (2019). Analyzing the Driving Factors Causing Urban Expansion in the Peri-Urban Areas Using Logistic Regression: A Case Study of the Greater Cairo Region. *Infrastructures*, *4*(1), 4. https://doi.org/10.3390/infrastructures4010004

Salghuna, N. N., Rama Chandra Prasad, P., & Asha Kumari, J. (2018). Assessing the impact of land use and land cover changes on the remnant patches of Kondapalli reserve forest of the Eastern Ghats, Andhra Pradesh, India. *The Egyptian Journal of Remote Sensing and Space Science*, *21*(3), 419–429. https://doi.org/10.1016/j.ejrs.2018.01.005

Saloni jain, asfa Siddiqui, Pooman Tiwari, M. S. (2016). Urban Growth Assessment using CA Markov Model: A case study of Dehradun City. *9th International Geographic Union*, *May*, 9.

Samarüütel, A., Steen Selvig, S., & Holt-Jensen, A. (2010). Urban sprawl and suburban development around Pärnu and Tallinn, Estonia. *Norsk Geografisk Tidsskrift – Norwegian Journal of Geography*, *64*(3), 152–161. https://doi.org/10.1080/00291951.2010.502653

Sankarrao, L., Ghose, D. K., & Rathinsamy, M. (2021). Predicting land-use change: Inter-comparison of different hybrid machine learning models. *Environmental Modelling & Software*, *145*(September), 105207. https://doi.org/10.1016/j.envsoft.2021.105207

Santé, I., García, A. M., Miranda, D., & Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning*, *96*(2), 108–122. https://doi.org/10.1016/j.landurbplan.2010.03.001

Sarkar, A., & Chouhan, P. (2020). Modeling spatial determinants of urban expansion of Siliguri a metropolitan city of India using logistic regression. *Modeling Earth Systems and Environment*, *6*(4), 2317–2331. https://doi.org/10.1007/s40808-020-00815-9

Saxena, A., & Jat, M. K. (2020). Land suitability and urban growth modeling: Development of SLEUTH-Suitability. *Computers, Environment and Urban Systems*, *81*(February), 101475. https://doi.org/10.1016/j.compenvurbsys.2020.101475

Seto, K. C., Guneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, *109*(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

Shafizadeh-Moghadam, H., Asghari, A., Tayyebi, A., & Taleai, M. (2017). Coupling machine learning, tree-based and statistical models with cellular automata to simulate urban growth. *Computers, Environment and Urban Systems*, *64*, 297–308. https://doi.org/10.1016/j.compenvurbsys.2017.04.002

Shannon, C. E. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Shu, B., Zhang, H., Li, Y., Qu, Y., & Chen, L. (2014). Spatiotemporal variation analysis of driving forces of urban land spatial expansion using logistic regression: A case study of port towns in Taicang City, China. *Habitat International*, *43*, 181–190. https://doi.org/10.1016/j.habitatint.2014.02.004

Siddiqui, A. A., Siddiqui, A. A., Maithani, S., Jha, A. K. K., Kumar, P., & Srivastav, S. K. K. (2018). Urban growth dynamics of an Indian metropolitan using CA Markov and Logistic Regression. *Egyptian Journal of Remote Sensing and Space Science*, *21*(3), 229–236. https://doi.org/10.1016/j.ejrs.2017.11.006

Simwanda, M., & Murayama, Y. (2018). Spatiotemporal patterns of urban land use change in the rapidly growing city of Lusaka, Zambia: Implications for sustainable urban development. *Sustainable Cities and Society*, *39*(July 2017), 262–274. https://doi.org/10.1016/j.scs.2018.01.039

Sohl, T. L., Sleeter, B. M., Sayler, K. L., Bouchard, M. A., Reker, R. R., Bennett, S. L., Sleeter, R. R., Kanengieter, R. L., & Zhu, Z. (2012). Spatially explicit land-use and land-cover scenarios for the Great Plains of the United States. *Agriculture, Ecosystems & Environment*, *153*, 1–15. https://doi.org/10.1016/j.agee.2012.02.019

Statistical database. (2022). *Statistics Estonia*. Https://Andmed.Stat.Ee/En/Stat. https://andmed.stat.ee/en/stat/rahvastik__rahvastikunaitajad-ja-koosseis__demograafilised-pehinaitajad/RV032

Taillandier, P., Banos, A., Drogoul, A., Gaudou, B., Marilleau, N., & Truong, Q. C. (2017). Simulating urban growth with raster and vector models: A case study for the city of Can Tho, Vietnam. *Lecture Notes in Computer Science*, *May*, 21–38. https://doi.org/10.1007/978-3-319-46840-2_10

Tajbakhsh, M., Memarian, H., & Shahrokhi, Y. (2016). Analyzing and modeling urban sprawl and land use changes in a developing city using a CA-Markovian approach. *Global Journal of Environmental Science and Management*, *2*(4), 397–410. https://doi.org/10.22034/gjesm.2016.02.04.009

Tammaru, T., Leetmaa, K., Silm, S., & Ahas, R. (2009). Temporal and spatial dynamics of the new residential areas around Tallinn. *European Planning Studies*, *17*(3), 423–439. https://doi.org/10.1080/09654310802618077

Tan, R., Liu, Y., Zhou, K., Jiao, L., & Tang, W. (2015). A game-theory based agent-cellular model for use in urban growth simulation: A case study of the rapidly urbanizing Wuhan area of central China. *Computers, Environment and Urban Systems*, *49*, 15–29. https://doi.org/10.1016/j.compenvurbsys.2014.09.001

Tian, G., Ouyang, Y., Quan, Q., & Wu, J. (2011). Simulating spatiotemporal dynamics of urbanization with multi-agent systems—A case study of the Phoenix metropolitan region, USA. *Ecological Modelling*, *222*(5), 1129–1138. https://doi.org/10.1016/j.ecolmodel.2010.12.018

Tian, G., & Qiao, Z. (2014). Modeling urban expansion policy scenarios using an agent-based approach for Guangzhou Metropolitan Region of China. *Ecology and Society*, *19*(3). https://doi.org/10.5751/ES-06909-190352

Tong, X., & Feng, Y. (2019). How current and future urban patterns respond to urban planning? An integrated cellular automata modeling approach. *Cities*, *92*(March), 247–260. https://doi.org/10.1016/j.cities.2019.04.004

Traore, A., & Watanabe, T. (2017). Modeling Determinants of Urban Growth in Conakry, Guinea: A Spatial Logistic Approach. *Urban Science*, *1*(2), 12. https://doi.org/10.3390/urbansci1020012

Ullah, S., Ahmad, K., Sajjad, R. U., Abbasi, A. M., Nazeer, A., & Tahir, A. A. (2019). Analysis and simulation of land cover changes and their impacts on land surface temperature in a lower Himalayan region. *Journal of Environmental Management*, *245*(February), 348–357. https://doi.org/10.1016/j.jenvman.2019.05.063

Vaz, E. de N., Nijkamp, P., Painho, M., & Caetano, M. (2012). A multi-scenario forecast of urban change: A study on urban growth in the Algarve. *Landscape and Urban Planning*, *104*(2), 201–211. https://doi.org/10.1016/j.landurbplan.2011.10.007

Verburg, P. H., de Nijs, T. C. M., Ritsema van Eck, J., Visser, H., & de Jong, K. (2004). A method to analyse neighbourhood characteristics of land use patterns. *Computers, Environment and Urban Systems*, *28*(6), 667–690. https://doi.org/10.1016/j.compenvurbsys.2003.07.001

Verburg, P. H., Veldkamp, A., Willemen, L., Overmars, K. P., & Castella, J.-C. (2004). Landscape level analysis of the spatial and temporal complexity of land-use change. In *Geophysical Monograph Series* (Vol. 153, Issue May 2014, pp. 217–230). https://doi.org/10.1029/153GM17

Wang, F. (1994). The Use of Artificial Neural Networks in a Geographical Information System for Agricultural Land-Suitability Assessment. *Environment and Planning A: Economy and Space*, *26*(2), 265–284. https://doi.org/10.1068/a260265

Wang, Y., Sha, Z., Tan, X., Lan, H., Liu, X., & Rao, J. (2020). Modeling urban growth by coupling localized spatio-temporal association analysis and binary logistic regression. *Computers, Environment and Urban Systems*, *81*(June 2019), 101482. https://doi.org/10.1016/j.compenvurbsys.2020.101482

Wu, D., Liu, J., Wang, S., & Wang, R. (2010). Simulating urban expansion by coupling a stochastic cellular automata model and socioeconomic indicators. *Stochastic Environmental Research and Risk Assessment*, *24*(2), 235–245. https://doi.org/10.1007/s00477-009-0313-3

Wu, F., Zhan, J., Xu, Q., Xiong, Y., & Sun, Z. (2013). A Comparison of Two Land Use Simulation Models under the RCP4.5 Scenario in China. *Advances in Meteorology*, *2013*, 1–7. https://doi.org/10.1155/2013/578350

Wu, K., & Zhang, H. (2012). Land use dynamics, built-up land expansion patterns, and driving forces analysis of the fast-growing Hangzhou metropolitan area, eastern China (1978–2008). *Applied Geography*, *34*, 137–145. https://doi.org/10.1016/j.apgeog.2011.11.006

Wu, W., Zhao, S., & Henebry, G. M. (2019). Drivers of urban expansion over the past three decades: a comparative study of Beijing, Tianjin, and Shijiazhuang. *Environmental Monitoring and Assessment*, *191*(1), 34. https://doi.org/10.1007/s10661-018-7151-z

Xiong, C., & Tan, R. (2018). Will the land supply structure affect the urban expansion form? *Habitat International*, *75*(April), 25–37. https://doi.org/10.1016/j.habitatint.2018.04.003

Xu, G., Dong, T., Cobbinah, P. B., Jiao, L., Sumari, N. S., Chai, B., & Liu, Y. (2019). Urban expansion and form changes across African cities with a global outlook: Spatiotemporal analysis of urban land densities. *Journal of Cleaner Production*, *224*, 802–810. https://doi.org/10.1016/j.jclepro.2019.03.276

Xu, Qiurong, Zheng, X., & Zhang, C. (2018). Quantitative Analysis of the Determinants Influencing Urban Expansion: A Case Study in Beijing, China. *Sustainability*, *10*(5), 1630. https://doi.org/10.3390/su10051630

Xu, Quanli, Wang, Q., Liu, J., & Liang, H. (2021). Simulation of Land-Use Changes Using the Partitioned ANN-CA Model and Considering the Influence of Land-Use Change Frequency. *ISPRS International Journal of Geo-Information*, *10*(5), 346. https://doi.org/10.3390/ijgi10050346

Xu, T. (2019). *Integrating Machine Learning with Cellular Automata and Agent-based Model to Simulate Urban Expansion and Evaluate Land Use Policies* (Issue October). University of Auckland.

Xu, T., Gao, J., & Coco, G. (2019). Simulation of urban expansion via integrating artificial neural network with Markov chain – cellular automata. *International Journal of Geographical Information Science*, *33*(10), 1960–1983. https://doi.org/10.1080/13658816.2019.1600701

Yang, J., Gong, J., Tang, W., & Liu, C. (2020). Patch-based cellular automata model of urban growth simulation: Integrating feedback between quantitative composition and spatial configuration. *Computers, Environment and Urban Systems*, *79*(September 2019), 101402. https://doi.org/10.1016/j.compenvurbsys.2019.101402

Yang, W., Li, F., Wang, R., & Hu, D. (2011). Ecological benefits assessment and spatial modeling of urban ecosystem for controlling urban sprawl in Eastern Beijing, China. *Ecological Complexity*, *8*(2), 153–160. https://doi.org/10.1016/j.ecocom.2011.01.004

Yang, X., Chen, R., & Zheng, X. Q. (2016). Simulating land use change by integrating ANN-CA model and landscape pattern indices. *Geomatics, Natural Hazards and Risk*, *7*(3), 918–932. https://doi.org/10.1080/19475705.2014.1001797

Yatoo, S. A., Sahu, P., Kalubarme, M. H., & Kansara, B. B. (2022). Monitoring land use changes and its future prospects using cellular automata simulation and artificial neural network for Ahmedabad city, India. *GeoJournal*, *87*(2), 765–786. https://doi.org/10.1007/s10708-020-10274-5

Zambon, I., Benedetti, A., Ferrara, C., & Salvati, L. (2018). Soil Matters? A Multivariate Analysis of Socioeconomic Constraints to Urban Expansion in Mediterranean Europe. *Ecological Economics*, *146*(October 2017), 173–183. https://doi.org/10.1016/j.ecolecon.2017.10.015

Zambon, I., Serra, P., & Salvati, L. (2019). The (Evolving) urban footprint under sequential building cycles and changing socio-demographic contexts. *Environmental Impact Assessment Review*, *75*(December 2018), 27–36. https://doi.org/10.1016/j.eiar.2018.11.003

Zeng, Y. N., Yu, M. M., & Li, S. N. (2018). Urban expansion modeling approach based on multi-agent system and cellular automata. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII–3*(3), 2219–2223. https://doi.org/10.5194/isprs-archives-XLII-3-2219-2018

Zhang, X., Zhou, J., & Song, W. (2020). Simulating Urban Sprawl in China Based on the Artificial Neural Network-Cellular Automata-Markov Model. *Sustainability*, *12*(11), 4341. https://doi.org/10.3390/su12114341

Zhang, Y., Liu, X., Chen, G., & Hu, G. (2020). Simulation of urban expansion based on cellular automata and maximum entropy model. *Science China Earth Sciences*, *63*(5), 701–712. https://doi.org/10.1007/s11430-019-9530-8

Zhao, C., Jensen, J., & Zhan, B. (2017). A comparison of urban growth and their influencing factors of two border cities: Laredo in the US and Nuevo Laredo in Mexico. *Applied Geography*, *79*, 223–234. https://doi.org/10.1016/j.apgeog.2016.12.017

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2021	Najmeh Mozaffaree Pour Tõnu Oja (2021). Urban Expansion Simulated by Integrated Cellular Automata and Agent-Based Models; An Example of Tallinn, Estonia. Urban Science, 5 (4, 85). https://doi.org/10.3390/urbansci5040085.
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2020	Mozaffaree Pour, Najmeh; Oja, Tõnu (2020). Simulation of Urban Expansion in Estonia for 2046 Using Cellular Automata Model Based on the CORINE Land Cover Database. Proceedings of the 3rd International Conference on Geoinformatics and Data Analysis: ICGDA 2020, Marseille, France, April 15–17, 2020, pp 14–18. https://doi.org/10.1145/3397056.3397057.

Other Scientific Publications

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2022	Mozaffaree Pour, Najmeh Oja, Tõnu (2022). Prediction Power of Logistic Regression (LR) and Multi-Layer Perceptron (MLP) Models in Exploring Driving Forces of Urban Expansion to Be Sustainable in Estonia. Sustainability, 14 (1). https://doi.org/10.3390/su14010160.
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