MODELLING THE SPATIAL PATTERNS OF SUBURBANISATION IN THE POST-SOCIALIST STATES: A ROMANIAN CASE STUDY

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ABSTRACT

The uncontrolled urban sprawl in the post-communist European states represents a phenomenon that caught the interest of Urban Geography researchers as well as architects and sociologists. The transition to the capitalist economy in Central and Eastern Europe determined a chaotic spatial distribution of new residential, industrial and commercial developments in the suburbs, which recorded an unprecedented accelerated pace, due to the continously increasing demand. The built-up areas of the post-socialist cities are currently extending over their administrative limits, forming heterogeneous territories which in most cases connect the urban core with the surrounding villages.
In order to elaborate adequate policies that should provide solutions to the issues caused by the unsustainable suburbanisation, it is imperative to monitor the spatial patterns of this process. Using land cover data from 1990 and 2006, as well as the digital elevation model and the road network, the Machine Learning techniques computed the transition potentials of each land use class to convert into built-up area. After validation, the prediction tools provided by Geographic Information System software revealed an overview of the suburbanisation patterns of the following years, based on the current evolution. The study highlights the areas that should receive a more dedicated focus from the authorities, in order to prevent a disorganized evolution of the city and also to provide a sustainable development of the suburbs. This way, more informed decisions could be made by the stakeholders, who will be aware of the suburbanisation dimensions and also collaborative solutions could be set up.

Keywords: urban sprawl, suburbs, CA-Markov, Machine Learning, spatial patterns

INTRODUCTION

Since the communist regimes collapsed at the beginning of the last decade of the 20th Century, the states that formed the Eastern Block have faced numerous challenges in their transition to a market economy. One of the most notable changes has been recorded in what concerns land use management. The harsh socialist planning regulations were abolished and the state-owned lands were restored to the initial private owners [1], [2]. As a consequence of the liberalisation, private interests outpaced the public ones [3], leading to the so-called process of “urban sprawl”. The precise and compact land use patterns were rapidly turned into a mosaicked pattern as a result of the fragmentation of the arable land in the proximity of the cities, which became the arena of an unprecedented

transformation into built-up land in order to fulfil “the demand for housing that had accumulated during the socialist years” [4].
As second-tier cities exert a considerable influence on the region, they attract numerous people, implicitly increasing the demand for housing. As a result, the new individual and collective suburban residential developments, alongside with industrial and commercial buildings have emerged along the main roads, creating heterogeneous areas connected to the urban core [4] which in most cases link cities and villages, inheriting features of both settlement types. Initially perceived as territories of open green areas, offering opportunities of relaxation and leisure [5], the suburbs fail in most cases to provide basic urban facilities (health, education, transport, infrastructure etc.) and impact the environment [6]. While the urban growth rate records high levels, leading to a densification of residential space, this paper aims to predict the patterns of suburbanisation for the year 2030 in the city of Iași by monitoring the post-socialist trends of built-up area expansion, using Machine Learning algorithms. This way, it will be possible to forecast the future situation if no action is taken in order to improve the spatial planning documents and management, while the legislative void is being maintained. Therefore, planners and public authorities would get an insight of the areas that are at the risk of suburbanisation and will be able to act consciously in order to impose restrictions and plan future investments in various facilities [6], while creating or modifying policies and processes that will diminish the negative effects of unsustainable urban growth [4].

THEORY

The predictions of the urban growth patterns are performed using various techniques of forecasting land use changes. As the suburbanization represents a complex process, triggered by a series of politic, economic, social, cultural and spatial drivers that shaped the landscape in an unprecedented manner, the models that have been used by scholars take into consideration spatial data as land use raster maps on one side and explanatory factors that determined the past and current built-up space patterns on the other side [6]. Therefore, the model is trained by learning the input and the output data, in order to provide the desired results in accordance with “all possible inputs” [7]. The most common models used in forecasting land use changes are represented by statistical models, neural networks and cellular models [8] [9].
Artificial neural networks, designed after the neurons’ interconnecting system and the brain’s capacity to “observe relationships in data” [10]. Pijanowski et. al. [10] performed this type of model in Michigan’s Grand Traverse Bay Watershed, placing it in the category of regression-type models. Using 10 predictor variables, the model had a 46% predictive ability, while the preliminary tests revealed that the high quality views represented the most decisive factor of the urbanisation in the given study area [10].
Cellular Automata models are focused, as the name suggests, on the interaction between cells that incorporate temporal and spatial information, making it a reliable option for “dynamic simulation” [11]. Moreover, these cells also take into account the values recorded in the neighbourhood [11] being one of the most used urban growth models [9]. The results of the CA model implemented by Iacob et. al. [12] on two Romanian second-tier cities (Cluj-Napoca and Iași) reveal the perpetuation of the chaotic urban sprawl patterns, leading to the incorporation of some municipalities into the surface of Iași city [12].
Markov analysis is able to perform predictions of the future state of the land by taking into consideration “the states”, as well as “the rates of conversion between land-use types”

[8], [11]. As being a statistical tool [9], with a quantitative focus in prediction by analysing trends, but lacking spatial capabilities [8], [9], [11]. Markov analysis is combined with Cellular Automata, developing the CA-Markov which is widely used in urban growth studies. Being a hybrid method, it inherits the capabilities of monitoring the temporal dynamic and probabilities of the land use change from the Markov model, while the Cellular Automata offers a spatial context, all in a GIS environment, which indicates the initial states, "parameterize M-CA model, to calculate transition probabilities and determine the neighbourhood rules" [9] Using land use maps from satellite images of 1989 and 2011, Nouri et. al. [9] use the CA-Markov model in order to predict the land use patterns for 2021, which reveal the necessity of implementing policies for environmental protection.

DATA & METHODS

The city of Iași and its metropolitan area houses around 500 thousands people, being one of Romania's second-tier cities. The capitalist economic development completely reshaped the strict urban borders, creating a scattered pattern of the built-up area in most of its peripheral zones, mostly former agricultural lots (cereals, orchards, vineyards etc.) being converted into built-up areas. Being the second most populous city at the end of the communist era, Iasi has maintained its rank by continuously attracting people from the North East Region due to the social, economic and educational facilities [13]. Awarded as the "Emerging City of the Year" in 2018, it has experienced numerous investments in industrial, residential and commercial sites, mostly located outside the administrative limits and along the main roads and extending further from these main transport routes.

As the chaotic development is the result of the lack of local spatial planning documents and the lack of respecting the national laws, developers being driven by the profit opportunities, the new created areas are far from being sustainable. The inexistence of basic urban facilities increases the dependency to the urban core, generating daily traffic flows from the suburbs to the city, which leads to a monocentric system rather than to a polycentric one [14].

Considering all of the above, this study analyses the suburbanization trends of Iasi city in order to predict the future patterns of this phenomena. We will then be able to detect the next real estate "booms" and authorities will be able to prevent the risks of conflicts similar to the ones that nowadays govern this area.

In order to reach the goal of the study, two types of data were needed to perform the CA-Markov Model, which will set the probability of a pixel belonging to a specific land use type to change its category [8].

First of all, two past land use raster data were required as a base for implementing the model. We have selected the Corine Land Cover data from Copernicus for the years 1990 and 2006. Then, the same type of data was acquired for the year 2012 in order to validate the prediction results. Using ArcGIS Pro software, the land use subclasses were merged and reclassified in order to obtain 5 main land use classes as follows: built-up areas, arable land, forests, wetlands and water bodies. Then, the vector data was converted into raster data, which is mandatory in performing the CA-Markov model as data at pixel level needs to be provided.

Secondly, as urban sprawl patterns are driven by several factors, some of them were included in our simulations as explanatory variables in order to improve the accuracy [15]. It is important to mention that only spatial drivers were taken into account as they could be represented at pixel level:

- Proximity to roads: each pixel were given a specific value as urban sprawl probability decreasing within the distance from the transport routes. Euclidean Distance tool was used in ArcGIS Pro;
- Proximity to built-up area: the same geoprocessing as for the proximity to roads;
- Digital Elevation Model: ASTER Global DEM was obtained from NASA's Earth Data which is used to explain the probability of built-up development depending on the terrain's features;
- Transition potential of selected land use classes to convert into built-up area, assessed by the Multi-Layer Perceptron (MLP) neural network in TerrSet.

All the rasters obtained were further processed using ERDAS Image in order to prepare the data to be included in the Land Change Modeller tool provided by TerrSet. The last mentioned software represents the GIS environment that uses the CA-Markov model in order to predict the spatial land use patterns for 2012. Using the above-mentioned data as input, relationships between layers were assessed and established using Multi-Layer Perceptron (MLP) neural network [16], generating trends that aided in achieving the goal of the study. These trends depend on the identified rates of transition potential which were calculated from the observed patterns of conversion of the selected land use classes into built-up land. Once the predicted land use is obtained, the software compares it with the actual land use data from 2012 to validate it, while images for the year 2030 are further being generated following the same trend.

RESULTS & DISCUSSION

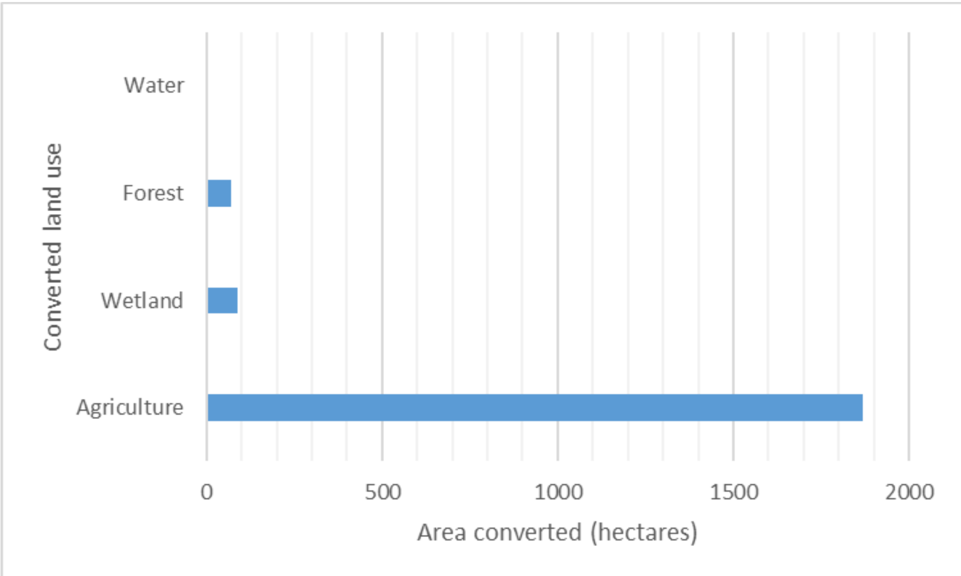

Figure 1. Land use conversion into built-up area in Iași city.

Analysing the land use classes that have contributed more to the conversion into built-up land, former agricultural areas have represented the arena of land trading since the last decade of the previous century, with 1790 hectares out of almost 1950 that were transformed into artificial surface. This represents the result of the land restitution to private owners, who chose to sell their lots rather than investing into agriculture. It could be easily observed that the most traded areas are located in the southwestern as well as in the western parts of the city. Most of these converted lots tend to form clusters in the vicinity of main roads and extend along them, linking the urban core with adjacent rural municipalities, which recorded spectacular increases in terms of population. The high availability of this type of land and the ease of conversion compared with the wetlands (less than 90 hectares converted into urban land), forests (70 hectares that were adjacent to the border of the built-up area in 1990) or water, which is impossible or requires major investments for conversion into built-up land. It is a high probability that the above mentioned surface areas may differ as a result of different pixel classification as well as the technology of surface generalisation of Corine Land Cover data.

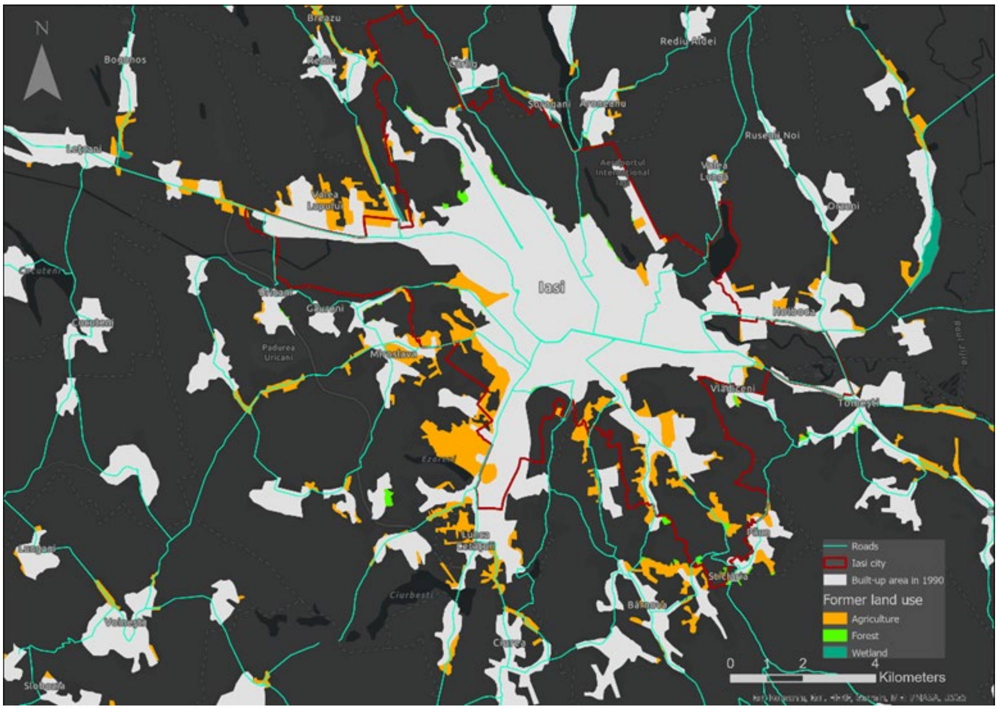

Figure 2. Former land use in 1990 which transformed into built-up land in 2006.

Table 1. Variables used in the Multi-Layer Perceptron (MLP) neural network.

Model	Accuracy (%)	Skill measure	Influence order
With all variables	60.84	0.4778	N/A
Proximity to roads	60.61	0.4748	6 (least influential)
Agriculture land transition potential	55.23	0.4031	4
Overall transition potential	35.09	0.1346	1 (most influential)
Proximity to built-up area	60.45	0.4727	5
Forest transition potential	53.79	0.3838	3
Digital Elevation Model	51.96	0.3594	2

The above table accounts for the variables included in the Multi-Layer Perceptron (MLP) neural network, which is used in the training of the model in order to prepare it for the possible outputs in terms of prediction. Based on the changes recorded by land use classes (which are the dependent variables) between 1990 and 2006, the neural network is able to make connections by assessing the transition potential for each raster cell. Therefore, each explanatory variable is evaluated and gets assigned a rank, depending on its role and importance in determining a land use change into urban. Several models (over 15) were

run by including and excluding variables in order to obtain the best accuracy (60.84% in this case).
As expected, the transition potentials computed by the MLP based on the land use data from 1990 and 2006 represent the base of the model training, ranking 1, 3 and 4 within the explanatory variables. The absence of only one of these 3 variables could reduce the overall accuracy of the model with 5 to 25 percent. The transition potentials were calculated by analysing the trends of change recorded by land use cells that experienced conversion into built-up land, considering the values of the neighbourhood as well in order to gain spatial coherence for the possible outputs that will be generated. Trends of potential transition were generated for the other variables, the most notable influence being exerted by the Digital Elevation Model, which is relevant in explaining the patterns of urban sprawl depending on the particularities of the terrain. Even if the roads have guided the directions of urban growth, their proximity have the lowest influence in this process because of the lower availability of land bordering them, spatial patterns of built-up area tending to scatter chaotically further from roads, in undeveloped and inaccessible sites, which lack basic infrastructure in terms of transport and utilities due to the inexistent spatial management. The lack of spatial coherence is also proven by the low influence of the proximity to the built-up area.

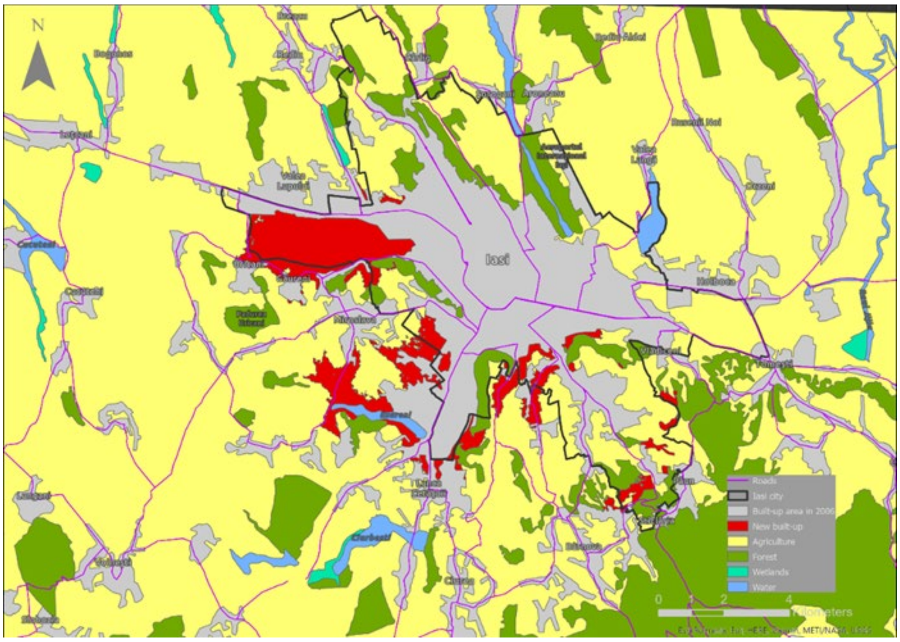

Figure 3. Predicted urban sprawl for 2030.

The land use prediction results for 2012 has revealed quite accurate results of built-up area expansion in the vicinity of the existent urban core in 2006. More precisely, it has performed the best accuracy in predicting expansion into the gaps of the built-up space (either between the urban and rural surface or inside rural areas), which have been reported as filled by the model, overlapping the 2012 land cover data. However, it showed modest results in predicting growth in some areas, focusing its highest potential in the western suburban area, which tended to be overestimated. Overall. The estimated built-up area was 4.5% higher than in reality. Therefore, the prediction for 2030 depicts a considerable growth in this direction, which might be confirmed by the ongoing and future private developments into industrial platforms and also the announced public

investments into a new road that will improve the accessibility. The other categories of land use changes have been considered by the model but haven't recorded considerable amounts of conversion, as confirmed by the land use data (differences between 1-5%).
As it could be seen in the map that was generated for the year 2030, the city will continue to expand in areas that were formerly occupied by land for agriculture. The model predicts that the scattered pattern will perpetuate and the competition for the undeveloped lots of arable land between already built sites will intensify due to the increasing demand for land for buildings. As a result, the suburban land will become a contiguous extended area. Therefore, rural municipalities in the southern, western and southwestern parts will be completely absorbed by the city, even though they present completely different features, landscape and facilities.
The role of the roads in suburbanisation is also confirmed in this case as two stripes of potential development are identified in the southern part of the city, extending over the administrative limit of Iasi municipality by following the transport routes. In the south of Miroslava village, the built-up area is sprawling along the road and scatters on multiple sides, connecting in the end with three other rural settlements. This case is relevant to be mentioned as this type of suburbanisation process is displayed completely outside the urban area, questioning the availability of land lots in the proximity of the urban core in the southern, western and southwestern parts.
One of the limitations of the model is that it may concentrate the highest transition potential on some areas, focusing on the territories with high suitability as in the case of the western part of the city, in the vicinity of Valea Lupului municipality, where a large portion of flat agriculture land was identified. Therefore, other areas (for example, the northwestern part of the city) which recorded a high pace of development between 1990 and 2006 has almost been neglected by the model.

CONCLUSION

Having all of the above considered, the CA-Markov model predicted a considerable amount of changes for the year 2030. Computed by accounting the trends of land use change to built-up area from 1990 to 2006 and then validated using the land use data from 2012, it offers an overview of the consequences implied by the lack of spatial management for suburban areas. Therefore, in order to prevent unsustainable urban development, public policies especially designed for these emerging territories must be enacted.
As the private investments in housing, industrial and commercial sites are continuously being developed due to the high demand, the weight center of population will tend to slide to the southwest, while the weight center of the facilities will stagnate if no action from local authorities is taken in order to anticipate these movements. The people that will inhabit the sites foreseen by the model will need to depend on the city's facilities as health and educational services, leisure activities or even daily needs (groceries or other types of shops). In a society where the tendency to the 15-minute city is becoming more clearly visible, pointing on the necessity of reaching a wide range of facilities within 15-minute walking or cycling from the resident's home, the suburbs are not able to provide these facilities without the intervention the authorities or the collaboration between them and private actors. Moreover, these territories currently lack pedestrian amenities, therefore the use of personal cars is indispensable, leading to an increasing pressure on the road network. The pressure is also exerted on the utilities networks, which are limited and cannot satisfy the increasing demand without prior investments. The actual situation

shows that buildings are built before connection to utilities. If this process continues its unsustainable path, it will likely become impossible for the new areas to benefit from these amenities in the near future.

The expansion of the built-up area in the vicinity of the forests is forecasted by the CA-Markov model for 2030. As the ratio between artificial and natural surfaces is constantly increasing, environmental policies are fundamental to protect the forests and to encourage the implementation of green belts, which will also prevent the urban sprawl as well as the risk of landslides.

As the suburbs are disposed between the city and the surrounding rural municipalities and the model predicts a contiguous rural-urban territory, the collaboration between local authorities should become a priority in order to elaborate mutual policies that will harmonize the development of the territory in order to achieve the sustainability of suburban areas.

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