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Hichem OMRANI, Omar CHARIF, Philippe GERBER, and Reine Maria BASSE[1]
Katalin Bódis[2]

CEPS/INSTEAD[1]
EC JRC, IET, REU, ISPRA (VA), Italy[2]

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Simulation of land use changes using cellular automata and artificial neural network*

Hichem Omrani [a,*], **Omar Charif** [a], **Philippe Gerber** [a], **Katalin Bódis** [b] **and Reine Maria Basse** [a]

[a] GEODE, CEPS/INSTEAD, Luxembourg

[b] EC JRC, IET, REU, ISPRA(VA), Italy

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Abstract

This paper presents a method integrating artificial neural network (ANN) in cellular automata (CA) to simulate land use changes in Luxembourg and the areas adjacent to its borders. The ANN is used as a base of CA model transition rule. The proposed method shows promising results for prediction of land use over time. The ANN is validated using cross-validation technique and Receiver Operating Characteristic (ROC) curve analysis, and compared with logit model and a support vector machine approach. The application described in this paper highlights the interest of integrating ANNs in CA based model for land use dynamic simulation.

Keywords: Artificial neural network; Cellular automata ; Modelling; Land use changes; Spatial planning and dynamics.

This paper is a collaborative effort (e-mail of corresponding authors: hichem.omrani@ceps.lu, reine-maria.basse@ceps.lu).

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1 Introduction

In the last decades, land demands in Europe specifically in an attractive region like Luxembourg became an important issue for stakeholders. The population of Luxembourg keeps growing and the impact of this growth is visible especially when analyzing the land use changes over time. The importance of land use change in the scientific literature shows how much it is challenging for researchers from computer science, and geography or geo-spatial science to propose to the decision makers a suitable future land use [20].

Land use refers to different spatial interactions which make their features difficult to analyse. The spatial interactions induce neighbourhood effects and so introduce the emergence of new patterns that need to be simulated in order to understand the hidden process of the land properties. Thus, the main question is how to simulate land process and consequently how to simulate the land use patterns? Which spatial and explicit tool in computer science and geography has to be applied to answer those problems?

The land use patterns of Luxembourg and areas adjacent to its borders can be simulated based on CA concept using several variables (e.g., slope, amount of built-up area surrounding a given cell, etc.). These variables will be described in the section 3 which explains the land use changes. This simulation allows us to understand the spatial interaction as well as the land use patterns that emerged from the neighbourhood effects of each cell and its assigned land use function.

This paper is organized in five sections. The next section gives a short overview of the CA model, its main components and its relevance to land use changes analysis. Section 2 presents the methodological aspects using ANN for predicting land use changes. Section 3 presents the application, its results and a comparison with various models. Section 4 draws conclusions and discussion.

2 Related work

The concept of CA was introduced in the 1940's when Von Neumann and Ulman [8, 32, 36, 37] were investigating "complexity field" in order to analyse the behaviours of complex systems [38]. Stephen Wolfram was following the same concept and has introduced CA as a model of complexity [42, 43]. But, twenty years before Wolfram, in the 1960's, John Conway presented his game of life characterized by the following simple rule: alive cell stays alive if 2 or 3 of its neighbours are alive, otherwise it dies. A dead cell will come to life if at least three of its neighbours are alive [12]. This "game" became the most famous basic rule in CA concept and greatly contributed to the popularity of CA. Later in the last century, CA has been applied in different fields like physics, mathematics, computer science, biology, philosophy and geography. From the end of 70s to the end of 90s, CA was presented as one of the most relevant tools for understanding complex systems [9, 34, 43] particularly land use patterns [4, 35, 40]. Therefore, sensitivity of CA to the spatial configuration (e.g., land use features, transport networks, physical constraints) and neighbourhood relationship [26] has been extensively investigated by researchers in order to simulate urban growth and future land use requirements [2, 4, 35, 41]. A simple CA has five fundamental properties: (1) a regular discrete lattice of cells; (2) the evolution of each cell takes place in discrete time points; (3) each cell is in one of a finite set of states that are exhaustive (no other states are possible) and exclusive (a cell cannot be in more than one state at any one time); (4) the future state of the cells is determined by the current states of the cell itself and the cells in the neighbourhood following transition rules (these rules are identical for all cells in the lattice); (5) the neighbourhood relation influences the studied cell. These properties allow CA to simulate complex systems [9, 41, 42]. Indeed, land use is among the most complex system that needs to be understood for better land planning [20]. Because of the dependance of cell transition at time (t+1) on the situation of the cell and its neighbourhood at time (t), the transition rule is one of the most components of the simulation that needs to be well determined for guaranted good simulation in the context of CA based land use model [9]. A variety of methods is used in the literature, as transition rules in CA for predicting land use, among them: (logit) [1, 18, 19, 27, 28, 46], a combination of linear and geometric formulations [14, 23] and rule-based model [5]. Recently, new artificial intelligence methods have been applied to simulate land use changes [31, 45]. They have been proposed as alternatives for land use modelling.

The two methods recently applied are artificial neural network (ANN) [21] and support vector machine (SVM) [15, 16, 33, 47]. They both showed competitive performance [16, 31]. The mentioned advanced techniques are involved in the study described in this paper and their results are compared to logit model. A classification of applied transition rules in CA modelling is given in Table 1. This section presents the methodological aspects in detail. The

Table 1: Methods of CA transition rules to predict land use dynamics in recent urban model applications

Modelling method	Transition rule	References
Mathematic /	Logit	[46]
Econometric	MNL	[27]
− − −	LGF	[23]
Conditional /	Basic	[44]
If-then	Fuzzy	[5]
Mathematic /	ANN	[21, 22]
AI	SVM	[16, 45, 47]

Notes: Logit: logistic regression, MNL: multinomial logit, LGF: linear and geometric formulations, ANN: artificial neural network, SVM: support vector machine and AI: artificial intelligence.

land use modelling is a nonlinear regression problem which can be tackled using ANN. Here the ANN is used to define the transition rule of the CA model for predicting land use changes. The most widely used ANN is multilayer perceptron network (denoted by MLP) [6]. MLP has been applied in the framework of predicting land use change [21, 22]. We used a conventional MLP with one hidden layer trained using back propagation method by minimizing the mean squared error (MSE) function. This approach is known to provide good estimates of the output given the observed values of input variables. Let $y = (y_1, y_2)$ be the output (e.g. built-up and not built-up land) which is expressed as a function of the input $x = (x_1, x_2, \ldots, x_q)$ (see Fig. 1) as follows (1):

$$y_k = \Psi\left(\sum_{j=1}^{p} v_{jk}\Phi\left(\sum_{i=1}^{q}\omega_{ij}x_i + \omega_{0j}\right) + v_{0k}\right) \tag{1}$$

where the ω_{ij} and v_{jk} are weights assigned to the connections between the input layer and the hidden layer, and between the hidden layer and the output layer, respectively, ω_{0j} and v_{0k} are biases (or threshold values in the activation of a unit). Φ is an activation function, applied to the weighted sum of the output of the preceding layer (in this case, the input layer). Ψ is also an activation function applied, by each output unit, to the weighted sum of the activations of the hidden layer. This expression can be generalized to networks with several hidden layers. The output of the ANN will not be exactly equal to 0 or 1. When Ψ is softmax function, the output will be the probabilities of belonging to a class. These values are in the range (0,1). The input x will be assigned to the class of the highest posterior probability. Figure 1 shows the ANN architecture with an input layer, one hidden layer with h units and one output layer.

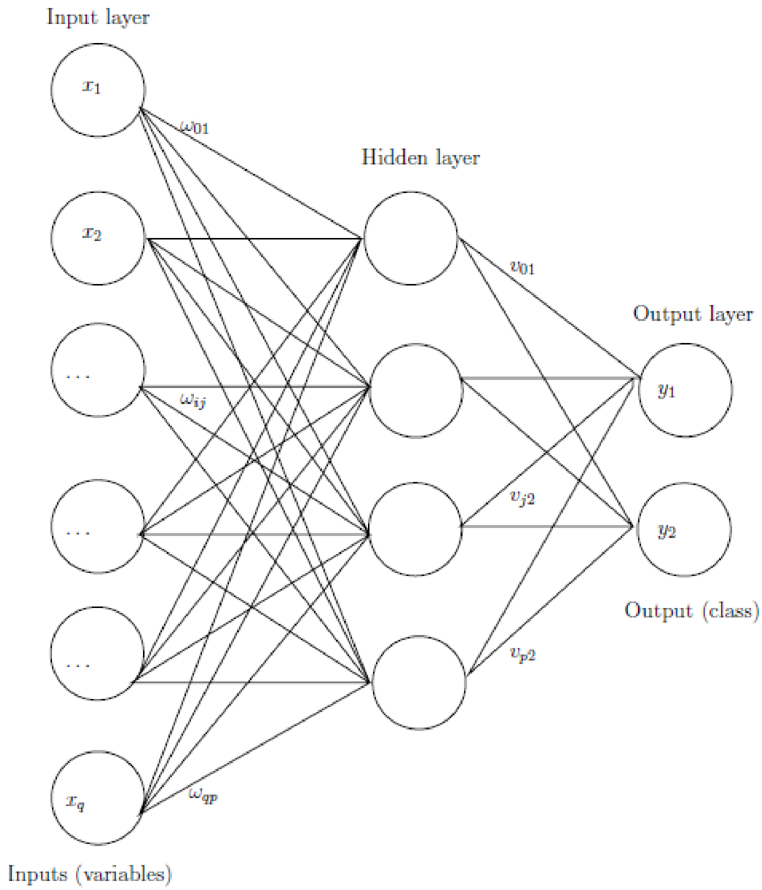

Figure 1: Architcture of ANN topology.

2.1 Methods assessment and comparison

We assess and compare methods by their (prediction) success rates. The success rate is defined as the percentage of correct predictions made by the model when compared with the actual classifications in the test dataset. A summary of the predictions is obtained by the confusion matrix (classification table). The element in cell $(k; h)$, is the number of observations for which observed and predicted classes are respectively k and h. Overfitting is a well studied problem in neural networks and other complex methods [24]. A model with a very good fit for a learning sample may yield a poor prediction on a test sample. The problem of overfitting is addressed by fitting the model on a learning sample and evaluating the success rates on the complementary test sample. The model was validated by cross-validation technique (N replications) and Receiver Operating Characteristic (ROC) curve analysis.

2.1.1 Cross-validation

We want to avoid the vagaries of choosing a particular partitioning (sub-samples), and therefore we evaluate the success rates on a large number of partitions by cross-validation. We split the dataset (sample) S into training (learning) sub-sample L (60%) and testing sub-sample T (40%) by a random process. We fit the model to L and evaluate the success rate on T. We replicate this process of partitioning, fitting the model and evaluating the success rate N times, obtaining N sets of the success rates. Their average is the overall success rate. We use this method throughout.

2.1.2 ROC curve analysis

The confusion matrix forms the basis for many common metrics. The numbers along the major diagonal represent the correct decisions made, and the numbers off this diagonal represent the errors between the classes. The true positive rate (denoted by `tp rate`, also called hit rate and recall) and the false positive rate (noted by `fp rate`, also called false alarm rate) are estimated as:

$$\texttt{tp rate} = \frac{\text{Positive correctly classified}}{\text{Total positives}} \tag{2}$$

$$\texttt{fp rate} = \frac{\text{Positive incorrectly classified}}{\text{Total negatives}} \tag{3}$$

where total positives and total negatives are the numbers of observations observed respectively as positive and negative.

Additional metrics are:

$$\texttt{sensitivity} = \texttt{tp rate} \tag{4}$$

$$\texttt{specificity} = \frac{\text{Negative correctly classified}}{\text{Total negatives}} = 1 - \texttt{fp rate} \tag{5}$$

ROC graphs are two-dimensional graphs in which (`sensitivity`) is plotted on the Y axis and (`1-specificity`) is plotted on the X axis. A ROC graph depicts relative trade-offs between (`sensitivity`) and (`1-specificity`). Several points in ROC space are important to note. The lower left point (0;0) represents the strategy of never issuing a positive classification; such a classifier commits no false positive errors but also gains no true positives. The opposite strategy, of unconditionally issuing positive classifications, is represented by the upper right point (1;1). The point (0;1) represents perfect classification. We will show here after the performance from ANN model using ROC analysis.

3 Application

3.1 Study area

Despite its small area ($2,586\ km^2$) and population (around $500,000$ habitants), Luxembourg benefits from the strategic geographic location and appears as an important contributor in decision making in the European Union (Fig. 2). Indeed, Luxembourg is one of the most attractive metropolitan areas in Europe [30]. Its attraction is due to the socioeconomic development of the society and specifically to the strong economic sectors (financial and industrial) that have been developed since the end of 1970's.

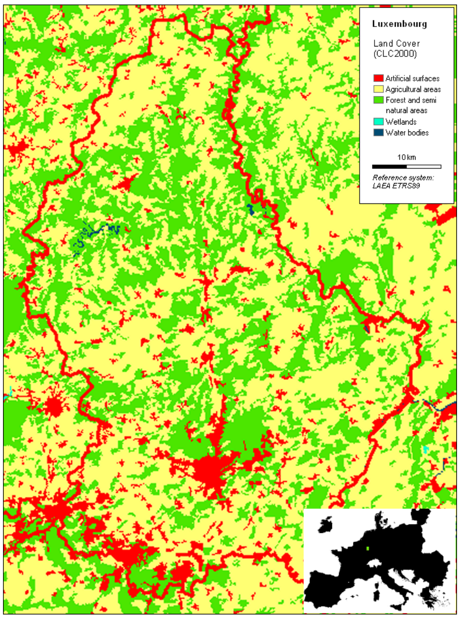

Figure 2: Land use/land cover map of study area (source: [3]).

Surrounded by three main countries (France, Germany and Belgium), Luxembourg attractes all kinds of labour force in order to maintain its economic dynamism that explain the importance of residential and daily mobility in Luxembourg and its bordering land (study area) [13, 29]. This paper assumes the hypothesis that the current situation of Luxembourg reflects a dynamic territory which will impact the land demands and consequently the land use changes in the near future. Thus, the objective of this paper is to investigate the way of possible land use changes of the study area between 2010 and 2050.

3.2 Main inputs

Our simulation of urban changes uses multiple data sources: Corine Land Cover in two periods: 1990 and 2000 [10], Digital Elevation Model (DEM) to show the physical constraint of the study area (Fig. 2). The source of the processed elevation data is the global SRTM dataset (Shuttle Radar Topography Mission) [7, 11]. The elevation model is used to calculate the slope presented in Fig. 3 (in the right). The mentioned data sources were used to construct a dataset with unique patterns. This dataset was split randomly into training (60%) and testing datasets (40%), to be used in the ANN model, as described in Table 2.

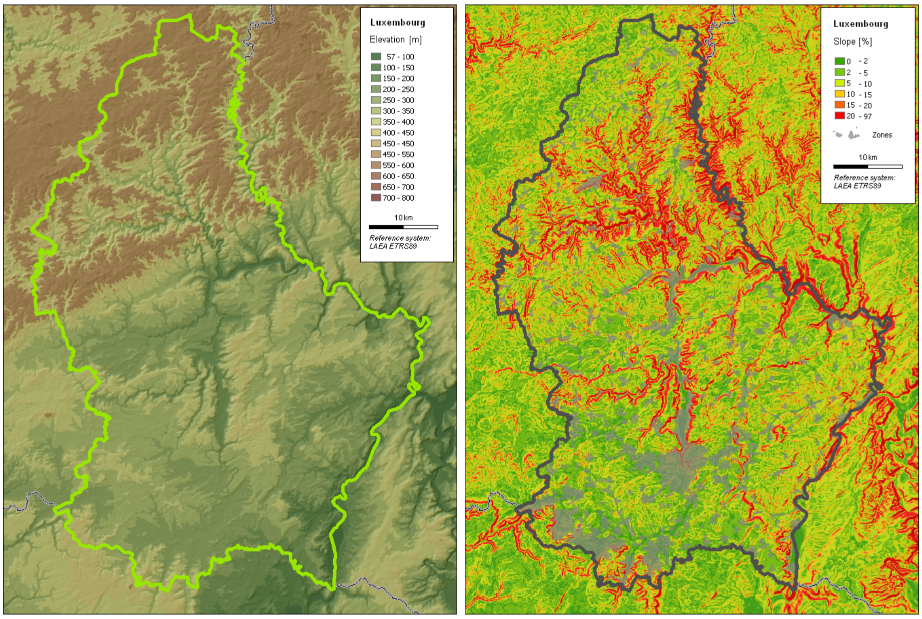

Figure 3: Physical aspects of study area: SRTM-based DEM, slope with highlighted urban zone (source: [3]).

The inputs used in this application are: the slope value, the amount of built-up area in the neighbourhood (Moore neighbourhood configuration) and the state of each studied cell (Table 3). Table 4 shows the land use statistics in the observed periods (1990 and 2000). The ArcGIS software and Matlab tool were used respectively for spatial data processing and for simulation.

3.3 Calibration of neural network model

For ANN calibration, the number of units in the hidden layer is found by comparing the rates of correct prediction for several numbers h. These rates are displayed in Fig. 4. Our choice of

Table 2: Summary of distribution of land use classes

	Total dataset		Training dataset		Test dataset	
Land use	Number	Per (%)	Number	Per (%)	Number	Per (%)
Not built-up land	3290	75.84	1956	75.17	1334	76.84
Built-up land	1048	24.16	646	24.83	402	23.16
Sum	4338	100	2602	100	1736	100

Table 3: Explanatory variables and description

Category	Variable	Description	Number of modality
Spatial	Neighbours	Amount of built-up cells in the 3×3 neighbourhood	1
Physical	Slope	Slope value of cell	1
Physical	State	State of cell (0: built-up cell, 1: not built-up cell)	1

Table 4: Land cover statistics in observed periods 1990 and 2000

Year	Built-up land (number of cells)	Not built-up land (number of cells)	Proportion of built-up land (in %)
1990	28.251	492.654	5,42
2000	29.858	491.047	5,73

Note: Configuration of the raster grid: squared grid with a resolution of 100×100 meters (cell size of 1ha) and Moore neighbourhood.

$h^\star = 4$ is based on the highest success rate achieved (success rate=85.54% and time=25sec). An iterative training error (as black line) and test error (as red line) of the network is shown in Fig. 5. The results of prediction with SVM and ANN are listed in Table 5, with a comparison to the standard logit model according to the success rate (number of correctly predicted cells divided by the total number of cells). The parameter estimates of the logistic regression model is given in Table 6.

Based on the results, the ANN-MLP outperformed the Logit and the SVM models in terms of (Table 5). The ANN-MLP improved the overall prediction accuracy (performance) nearly by 0.43% (85.54% vs. 85.11%) over the logistic model. Although the three models are very effective in predicting the not built-up land, with a success rate above 89%, ANN-RBF has a greater capability to predict not built up land and improved the success rate by 2.39% and

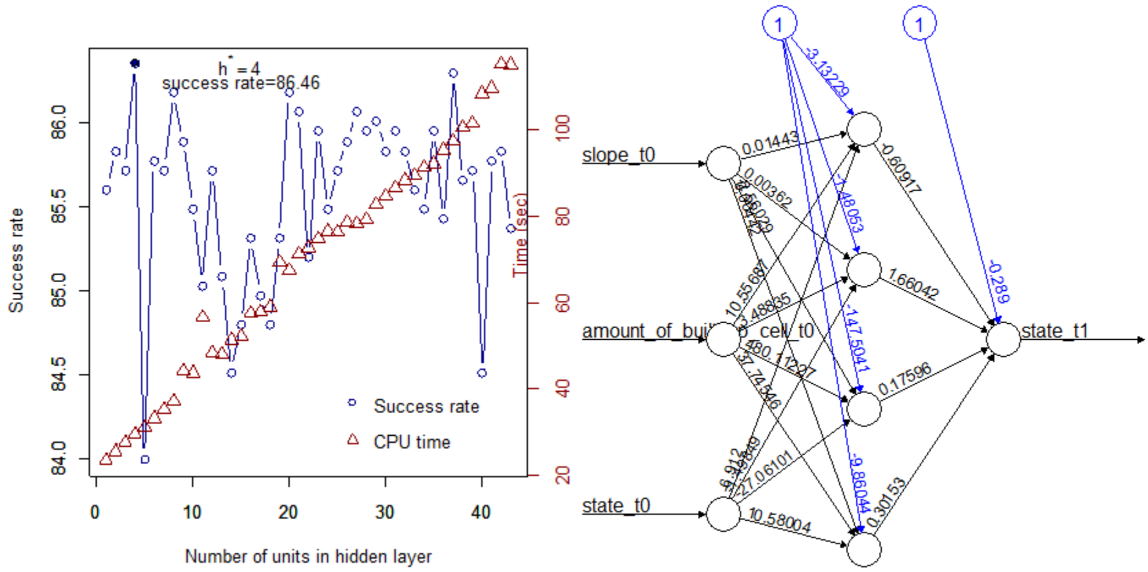

Figure 4: Success rate for number of units in the hidden layer, with optimal number highlighted ($h^{\star} = 4$; success rate=85.54 and computation time = 25sec); Weights of the neural network (inputs: slope of cell(t_0), amount of built-up land in the neighbourhood(t_0) and cell state(t_0); output: cell state(t_1); optimal number of units in the hidden layer: $h^{\star} = 4$.

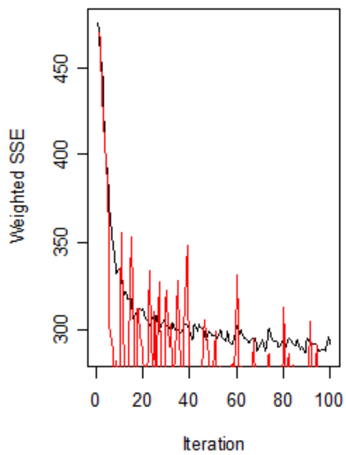

Figure 5: Iterative training error (as black line) and test error (as red line) of the network.

4.1% compared respectively to Logit and ANN-MLP. However ANN-RBF model tends to underestimate built-up lands by misclassifying more built-up cells into not built-up cells. This may be partially due to the fact that the study area is still dominated by not built-up lands (75% of cases, Table 2). However, the ANN-MLP and Logit have demonstrated a greater capability than SVM-RBF to predict built-up land and they improved the prediction accuracy respectively by 25.08% and 17.96%. With the ANN-MLP model, the success rates are 72.68% for built-up land and 89.66% for the not built-up land and its overall prediction accuracy is also high (85.54%). Only ANN-RBF is not satisfactory, the other three methods are about equally good.

Table 5: Success rate of the Logit, ANN and SVM models

	Not built-up (%)	Built-up (%)	Overall (%)	Performance Vs. Logit
Logit	91.37	65.56	85.11	0.00
SVM-RBF ($\gamma^{\star} = 1$)	91.49	64.80	85.03	-0.08
ANN-RBF ($\gamma^{\star} = 1, cost^{\star} = 1$)	93.76	47.60	82.14	-2.97
ANN-MLP ($h^{\star} = 4$)	89.66	72.68	85.54	$+0.43$

Note: An asterisk * is used to highlight the optimal value used in the appropriate model.

Table 6: Parameter estimates of the logistic regression model

Iteration	Constant	Slope	Amount of built-up land	Cell state	Log-lik.	Conv. crit.
0	-1.1440	0	0	0	-1454.8987	0
1	-2.6163	0.0023	6.4098	-0.1738	-1454.8987	-0.5176
2	-3.4877	0.0005	7.8437	-0.1854	-867.2174	-2.7691
3	-3.8763	-0.0010	8.6561	-0.1834	-807.9766	-1.7726
4	-3.9372	0.0013	-8.7899	-0.1829	-802.4295	-0.7441
5	-3.9385	0.0013	-8.7928	-0.1829	-802.3298	1.0010
6	-3.9385	-0.0013	8.7928	-0.1829	-802.3297	4.3690
7	-3.9385	-0.0013	8.7928	-0.1829	-802.3297	11.0869
St.err.	0.1678	0.0084	0.3588	0.1395	NA	NA

Note: Slope, amount of built-up land and cell state are the explanatory variables (continuous and categorical). The computation time needed for running Logit model is equal to 0.09 sec with 7 iterations. Log-lik is the Log-likelihood value, Conv. crit is the convergence criteria and St. Err is the standard error related to each coefficient. Significant negative (respectively positive) value of parameter indicates negative (respectively positive) effect.

3.4 Results: simulation of land use changes

Figure 6 shows the prediction accuracy (success rate) as a function of the cut-off value for classifications. The validation of Logit, ANN-MLP and SVM-RBF using cross-validation is conducted and boxplots of the success rate is shown in Fig. 7. The methods do not differ much in their rates (percentages), but the variation across replicates (that is, uncertainty) is greater for ANN than for the SVM, and is lowest for logit. The areas under the accuracy curves generated by the ANN model is much larger than those generated by the logistic regression model and SVM. A ROC curve of ANN is shown in Fig. 8 where the true positive rate (sensitivity) is plotted in function of the false positive rate (1-specificity) for different cut-off values.

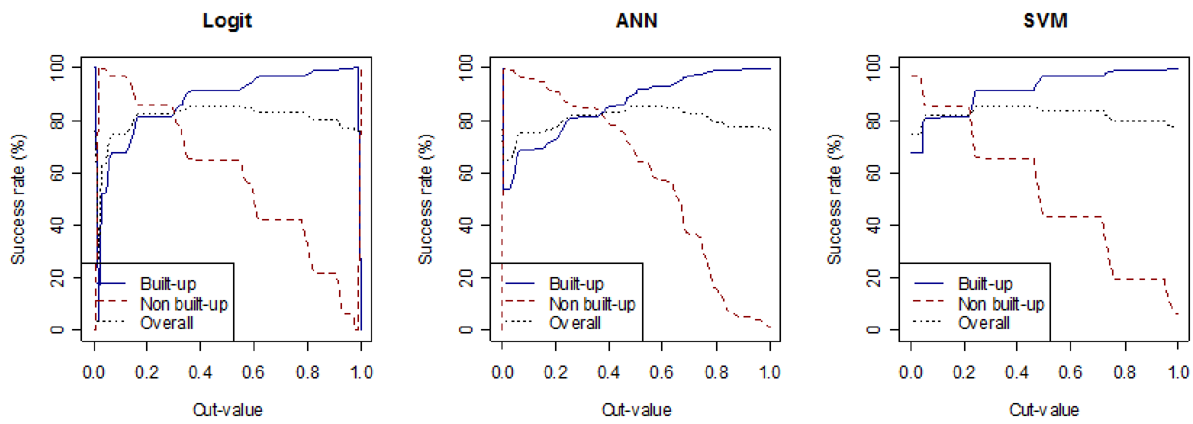

Figure 6: Prediction accuracy (success rate) as a function of the cut-off value for classifications using Logit, ANN-MLP and SVM-RBF.

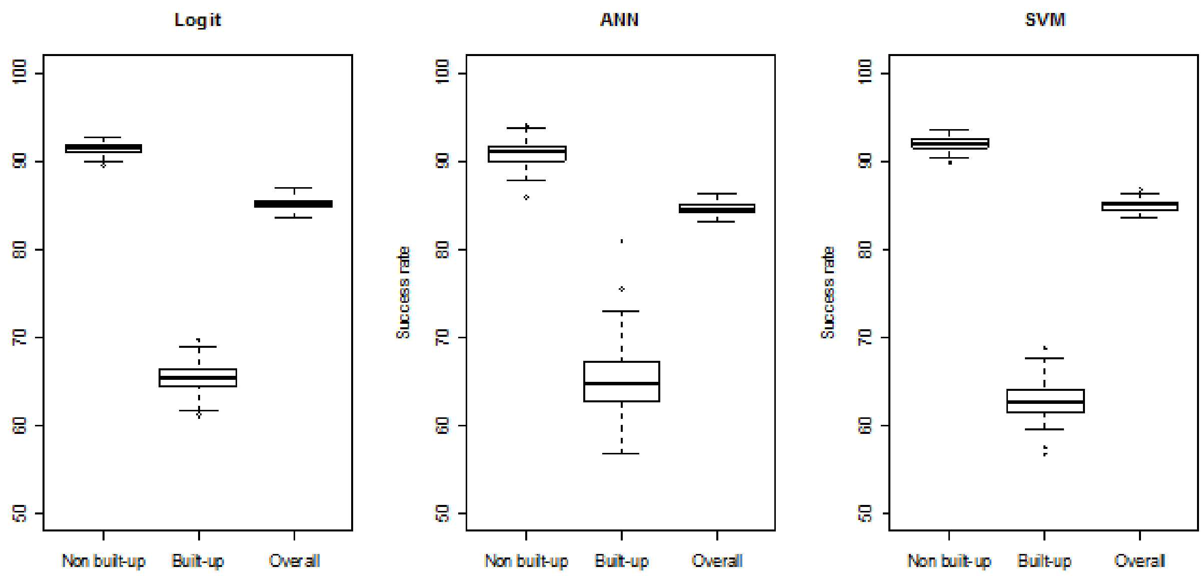

Figure 7: Boxplots of the success rate of Logit, ANN-MLP and SVM-RBF with cross-validation ($K = 100$ replications).

Table 5 summarizes the different results by giving a comparative analysis of alternative models tested in this paper. We compared the performance of all models to Logit as the baseline model. Based on the result, we support the ANN-MLP model for land use modelling because of its promising performance. Figure 9 presents land use changes of the study area in 2000, 2050 and 2100 using ANN-MLP model. The evolution of built-up cells and not built-up cells from 1990 to 2100 are shown in Fig.10. It can be observed in Fig. 9 that the southern part

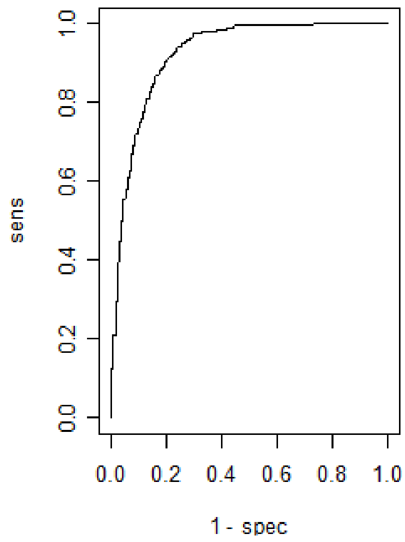

Figure 8: ROC curve analysis from ANN-MLP (1-specificity and sensitivity measures).

of the study area is more dynamic than the northern part. This situation can be explained by the more intensive relief (steep slope, Fig. 3) and higher density of urban cells.

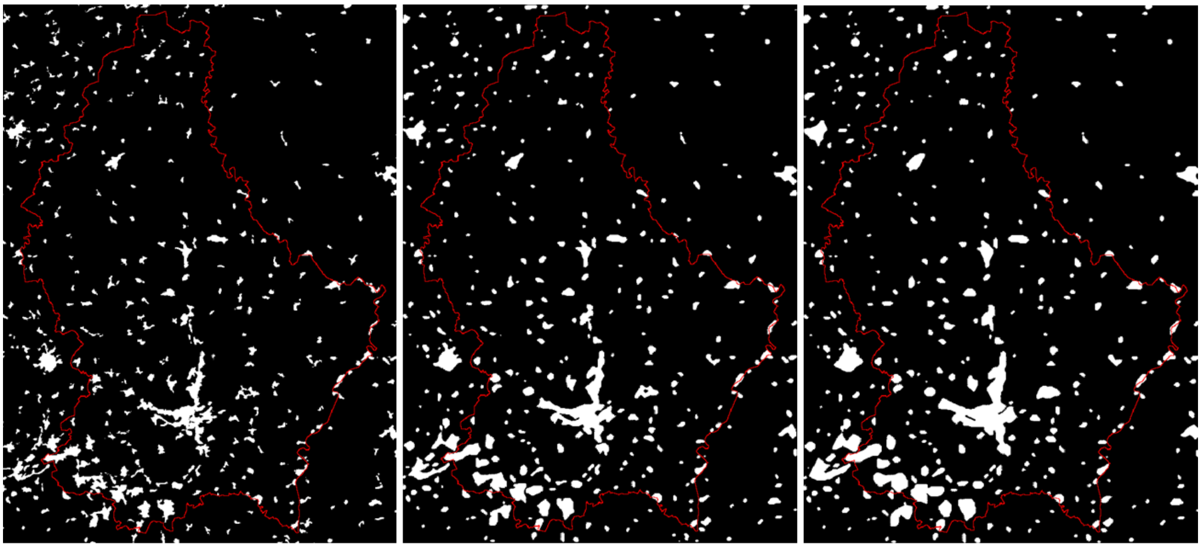

Figure 9: Land use changes of the study area in 2000, 2050 and 2100 using ANN-MLP. Not Built-up area, built-up area and administrative limit are displayed respectively in black, white and red colour.

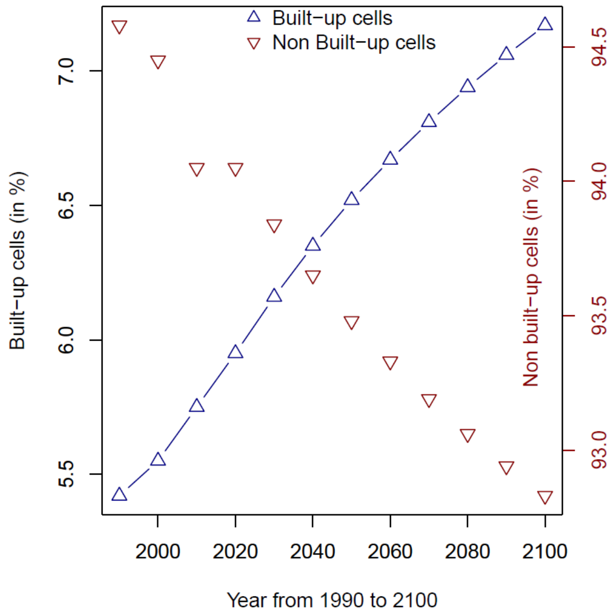

Figure 10: Evolution of Built-up and not built-up cells from 1990 to 2100 using ANN-MLP.

4 Conclusion, discussion and perspectives

Several modelling approaches have been applied in the study of land use changes (section 2). The problem of using conventional statistical methods in spatial land use analysis (like logistic regression: logit), is that these methods assume the data to be statistically independant and identically distributed (iid). But spatial land use data have tendency to be dependant, a phenomenon know as spatial autocorrelation [46]. However, a number of papers recently published [18, 22, 28, 33] used Logit model even with non mutually exclusive alternatives (e.g. the transition of urban cell to non urban cell is not possible). For this reason, we choose in the application two mutually exclusive states (built-up and not built-up cell). In this paper, we presented land use changes using ANN as a core of CA transition rule for Luxembourg and its cross-border region. The application of ANN was motivated by its universal approximation capabilities and its high performance in a wide range of scientific fields. The results of the applied methods were assessed by success rate using cross-validation.

The comparison of different techniques is influenced by the structure of data. This is due to the separability of classes and also to the limited spatial representation of classes. (e.g. in the given application: 75.84% of not built-up cells and 24.16% for built-up cells).

The results show that the ANN-MLP is superior to the studied alternatives (ANN-RBF, SVM and Logit). In addition, ANN-MLP was able to classify built-up land from not built-up land (72.68% as success rate), compared to the three techniques (ANN-RBF, SVM and Logit: having respectively as succes rates: 47.60%, 64.80% and 65.56%). All the applied techniques were able to classify not built-up from built-up land (success rate: 90%). The results are in accord with [31]. The added value of this paper is the use of ANN in CA and cross-validation technique for extended validation. Our next challenge is to integrate various cell states (urban, industrial, agriculture, forest, water) and additional inputs (Luxembourg urban planning) into the model. In addition, a dynamic neighbourhood shall be analysed to improve the CA based land use model for an extended study area (the Greater Region). We plan to apply the developed technique based on ANN model with Dempster-Shafer theory [17] for simulating future suitable land use in Luxembourg and its Greater Region.

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CEPS
INSTEAD

3, avenue de la Fonte
L-4364 Esch-sur-Alzette
Tél.: +352 58.58.55-801
www.ceps.lu