LAND-USE SUITABILITY ANALYSIS OF BELGRADE CITY SUBURBS USING MACHINE LEARNING ALGORITHM

Uroš, DJURIĆ[1], Miloš, MARJANOVIĆ[1,2], Vladimir, ŠUŠIĆ[1], Rastko, PETROVIĆ[3], Biljana, ABOLMASOV[1], Snežana, ZEČEVIĆ[1], Irena, BASARIĆ[1]

[1] Department of Geotechnics, Faculty of Mining and Geology, University of Belgrade, Djušina 7, 11000, Belgrade, Republic of Serbia

[2] Department of Geoinformatics, Faculty of Science, Palacky University, Olomouc, Tr. Svobody 26, 77146, Czech Republic

[3] Department of Hydrogeology, Faculty of Mining and Geology, University of Belgrade, Djušina 7, 11000, Belgrade, Republic of Serbia

djuric@rgf.bg.ac.rs; milos.marjanovic@rgf.bg.ac.rs; vladimir.susic@rgf.rs; rastko.petrovic@rgf.bg.ac.rs; biljana@rgf.bg.ac.rs; snezana.zecevic@rgf.rs; irenabasaric@yahoo.com

Abstract

This paper treats development issues of the suburban areas of Belgrade city. A considerable growth that the city had experienced has led to excessive consumption of land and also to degradation of the landscape and loss of the natural biodiversity. This is why an augmentation of the current Master Plan within the administrative extents of the city is considered to be vital for consistent planning of suburban areas development. Model used in this paper considered defining land-use suitability, relying on available thematic data, including the following sources: topography, land-cover, geology, protected areas and some synthetic maps derived from these sources in a GIS environment. For this purpose Support Vector Machines (SVM) algorithm has been implemented in a typical supervised classification learning task. Two modelling schemes have been involved (since the main problem of the study was the unavailability of the land-use suitability in the testing area): MODEL1 has been built in the extents of the training area having only two land-use suitability classes at disposal (Unsuitable and Very Unsuitable) and extrapolated to the testing area within which the same two classes were known (thus available for model performance evaluation), while MODEL2 has been trained on all four land-use suitability classes, and extrapolated to the testing area, with unknown land-use classes. The second model was then correlated with the first one in order to estimate its otherwise disputable performance. Results of MODEL1 were satisfactory, with high overall accuracy (85%). MODEL2 visually shows a good tendency, and since it has at least 85% accuracy for those coincident two classes (Unsuitable and Very Unsuitable) with MODEL1, it is justified to assume that remaining two classes match similar accuracy rates. The model could be improved by more thorough optimization of the classifier parameters, which will require much longer experimenting costs.

Keywords: land-use, suitability, machine learning, GIS, Belgrade

INTRODUCTION

Land-use suitability (LUS) analysis is a tool used to define future land uses or their potential. Suitability techniques enable environmental managers, planners and engineers to analyze the interactions among various factors. Analysts are then able to map these interactions in a variety of ways. Public officials and developers can use these maps to set policies and make decisions regarding the use of land. Contemporary environmental managers and planners are aware of the technological advancements in land-use allocation and suitability modelling. New methods of spatial analysis are now commonly used in the development of land-use plans, environmental impact reviews, and site selection studies for many different land uses and public and private facilities (Collins, 2001). One of the state-of-the-art methods involve machine learning techniques implemented hereinafter. Conventional methods on the other hand, are still needed to validate the outcomes and to calibrate these methods, which are still to be developed and perfected.

The main objective of this study is to use available public data and process them in a GIS environment for estimating a model of LUS. There was a strong motif supporting this research, since in-charged City's government services have shown interest in extending the Master Plan (MP) to the Belgrade suburb areas, thus needing a sound LUS assessment.

Belgrade has a long history of development under MP framework. First MP was *The Plan of Borough in the trench* by Emilijan Josimović from 1867 and last one (in power) is *Master Plan of Belgrade 2021* (adopted in 2003). The first pro-European Town Plan of Belgrade was introduced by Alban Chambon, a French architect, in 1912[1]. Since then, MPs had been published and adopted successively in 15–20 years intervals.

The earliest applications of suitability analysis conducted by engineering geologists and civil engineers for Belgrade MP area, in form of hand-drawn sieve mapping overlays was done by Šutić *et al.* (1972). Later, numerous researchers performed similar suitability analysis for different purposes (urban planning, defining best/optimal road routes etc), but first work involving suitability analysis in GIS environment has been done in 2009/2010 (Marjanović, 2009; Djurić, 2010) but none for Belgrade area.

CASE STUDY AREA

The study area includes the territory of Belgrade City, the capital of the Republic of Serbia. For the purpose of machine learning, study area has been divided into the following splits: training and testing area (Fig. 1). The training area included the territory of Belgrade MP, while the remaining part of the Belgrade City territory (which is herein considered as suburban area) was adopted as the testing area. The basic descriptions of these areas are given in Table 1. Geographic extents of Case Study Area are: 4994905N; 4902405S; 7419130E and 7488830W (ArcGIS predefined spatial reference system: MGI_Transverse_Mercator/Zone 7)

Table 1. Basic data about Case Study Area[2]

Case Study Area	Area (km^2)	Population (2011)
Training	776	1 373 000
Testing	2446	266 121

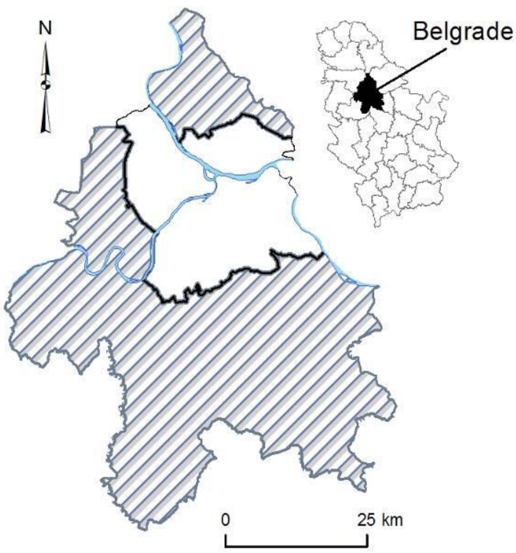

Fig. 1. Geographic location of the study area (blank=training, hatched=testing area).

[1] Institute of Urbanism - Belgrade (http://www.urbel.com)
[2] Republic of Serbia population Census 2011 - First Results (www.stat.gov.rs)

DATASET

The dataset has been assembled from different resources, and required different pre-processing manipulations, dependent on the model requirements. It has been established as a set of featured raster layers in a GIS environment.

COMPRESSIBILITY raster was made by reclassifying geological units. Basic Geological Maps in 1:100 000 scale (sheets: Belgrade, Pančevo, Obrenovac and Smederevo) were digitized and then reclassified by using ground compressibility as a criterion. Five categories were defined by the degree of ground compressibility (Jovanović et. al, 1977; F.G. Bell, 2007): Very high, High, Medium, Low and Very low. Very high degree of compressibility was considered as very unsuitable for urbanization, and vice-versa (Fig. 2-a). The reclassification was done because original geological units were very diverse and complex for the analysis since they counted more than 50 classes.

The *LAND COVER* project is a part of the Corine[3] program and is intended to provide consistent localized geographical information on the land cover of all European countries. Corine methodology implies visual interpretation of false color composites (4, 3, 2) of Landsat TM images (30 m resolution), which turned as a very convenient resource for this research. The Corine land cover classes comprise of three levels, and herein, the third level has been used at 1:100 000 scale. New (intermediate) classification was formed, because the second level of Corine classes was too simple and third was too complex (Fig. 2-b). Land cover classes were modified (reclassified) into five classes (Table 2).

Table 2. Land cover raster classification

Corine Classes (Level 3)	**Reclassification**
Continuous urban fabric	Class 1 (Built-up area)
Discontinuous urban fabric	
Industrial or commercial units	
Port areas	
Airports	
Construction sites	
Pastures	Class 2 (Suitable for the urbanization)
Natural grasslands	
Non-irrigated arable land	Class 3 (Conditionally suitable for the urbanization)
Complex cultivation patterns	
Land principally occupied by agriculture, with significant areas of natural vegetation	
Beaches, dunes, sands	
Green urban areas	Class 4 (Unsuitable for the urbanization)
Sport and leisure facilities	
Vineyards, Fruit trees and berry plantations	
Broad-leaved forest	
Coniferous forest	
Mixed forest	
Transitional woodland-shrub	
Road and rail networks and associated land	
Mineral extraction sites	Class 5 (Very unsuitable for the urbanization)
Dump sites	
Inland marshes	
Water courses, Water bodies	

[3] European Environment Agency (www.eea.europa.eu)

When analyzing an area for urban development relief characteristics in generally play a major role (Tošković, 2006). Therefore, initial computations considered generating 50 m resolution *DIGITAL ELEVATION MODEL* (DEM) (Hutchinson, 1996), by digitized 2.5 m equidistance contours, using *Topo to raster* interpolation method (Hutchinson, 1988, 1999, 2000) of the *Spatial Analyst* extension in the ArcGIS 10. DEM has been further used to generate *SLOPE* and *ASPECT* rasters (Burrough, 1998).

Urban planners consider *ASPECT* to be a significant attribute when projecting urban development (Tošković, 2006), since it is necessary to calculate the solar illumination for each location/cell/pixel (Daniels, 1997). Criteria used for this model is that the most suitable for building are the flat and westward exposed terrains. Vice-versa, the least suitable is a terrain exposed to the north (Fig. 2-c). However, for the basic experimenting design, non-classified (continual numeric) *ASPECT* has been used.

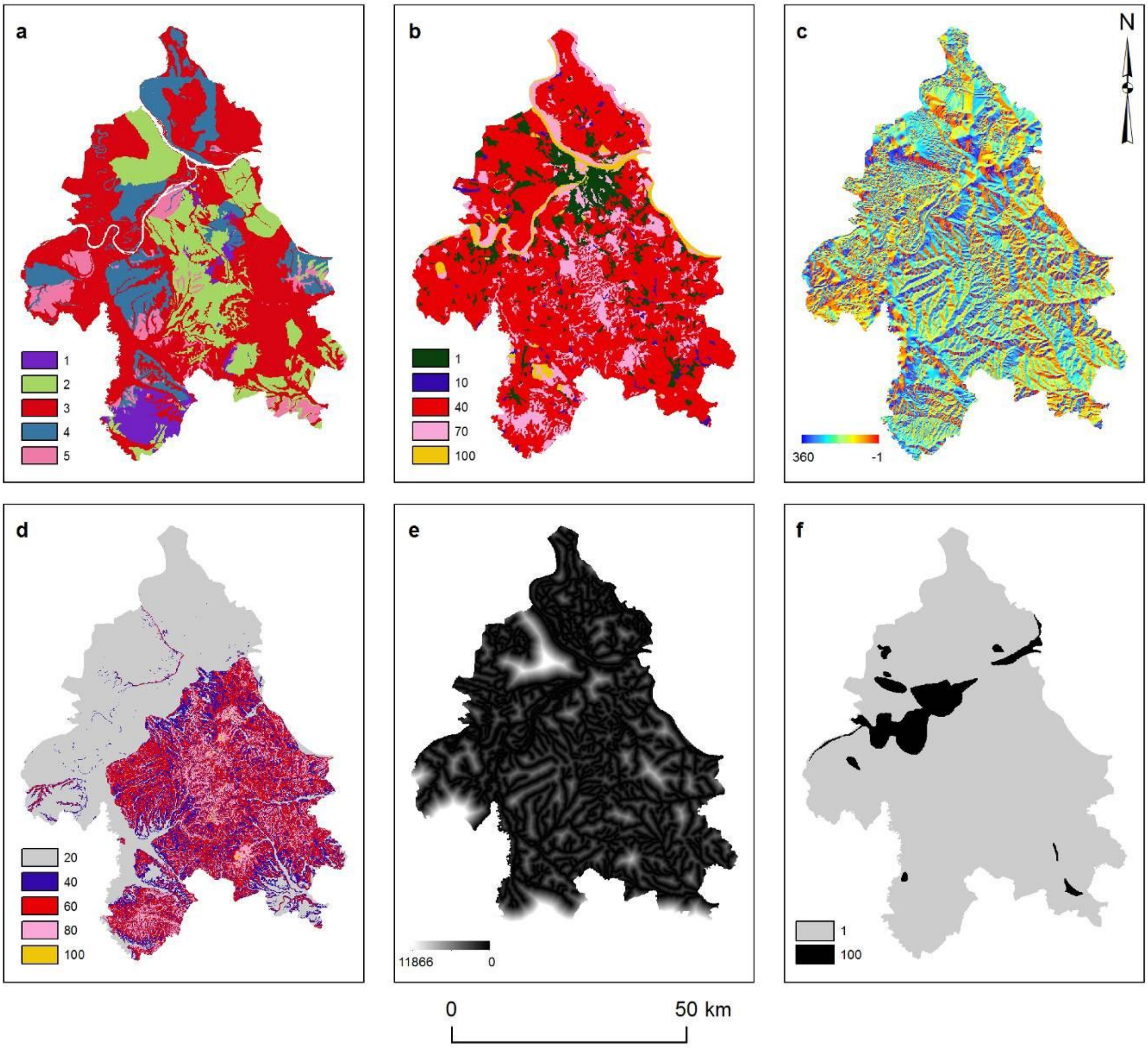

Fig. 2. Dataset: a) Ground compressibility (1=Very Low, 2=Low, 3=Medium, 4=Very High, 5=High); b) Land Cover (1=Built-up area, 10=Suitable for the urbanization, 40=Conditionally suitable for the urbanization, 70=Unsuitable for the urbanization, 100=Very unsuitable for the urbanization); c) Aspect (scale in degrees); d) Slope (20=Very Low, 40=Low, 60=Medium, 80=Very High, 100=High)
e) Hydrology (distance in meters) f) Protected areas (1=Non-protected, 100=Protected)

SLOPE raster is found significant for the model since all of the landslides on the territory of the City of Belgrade are formed on slopes greater than 7° (Djurić, 2011). Therefore, lower slope values as well as flat terrain were considered to be more suitable for building and vice versa (Fig. 2-d).

HYDROLOGY raster was made by buffering (*Euclidian distance* module in ArcGIS 10) digitized occasional and permanent stream flows, (Fig. 2-e). Streams were digitalized from Topographic maps of Belgrade (scale 1:100 000).

PROTECTED AREAS is an attribute raster resulting from compiling two maps: Zones of Sanitary Protection of Fresh Water Sources and Swamp Habitat, both on the administrative territory of the City of Belgrade. Extents of registered features are digitized from existing maps. According to the current legislation and Rule Book for defining and maintaining zones of sanitary protection of sources for water supplying, "zone of sanitary protection is an area around water supplying object, where building and activities of built objects as well as the conducting of any other activity is being surveyed". Swamp habitat is considered to be an area either protected by the decree of Institute of Nature Conservation of Serbia in order to protect biodiversity or simply not suitable for building because of its geotechnical characteristics. Therefore, marked territories from both maps were considered as areas where building is forbidden, hence evaluated as not suitable (Fig. 2-f).

METHODS

Support Vector Machines (SVM) algorithm is a sub-branch of Neural Network algorithms, which has been proven successful in various applications, including different types of spatial modelling (Brenning, 2005). Herein, this state-of-the-art machine learning algorithm has been implemented in a typical supervised classification learning task, which could be briefly described as follows.

The main objective is to exploit the possibility of automating the process of mapping, i.e. making a plausible prediction of spatial distribution of land-use suitability (LUS) classes $C=\{c_1, c_2,\ldots,c_l\}$, where l stands for the number of LUC classes. The procedure assumes that there is a reliable interpretation of LUS classes in one representative region, called training region. Let $P=\{\mathbf{x}|\mathbf{x}\in R^n\}$ be the set of all possible pixels extracted from the raster representation of a given area, then each pixel instance $\mathbf{x}$ is represented by n-dimensional vector $\mathbf{x}=\{x_1, x_2,\ldots,x_n\}$, where each x_i represents one of the n attributes (geology, land cover, stream buffer, slope, aspect and protected areas). A function f_c which maps $P\rightarrow C$ is called a classification if for each $\mathbf{x}\in P$ it holds that $f_c(\mathbf{x})=c_j$ whenever a pixel $\mathbf{x}$ belongs to the LUS class c_j. For a given training area, there is a limited set of m examples $(\mathbf{x}_i, c_j)$, $\mathbf{x}_i\in R^n$, $c_j\in C$; $i=1,\ldots,m$. The machine learning approach tries to find a function f_c' which is a good approximation of unknown function f_c, using only the examples from the training set.

Originally, SVM is a linear binary classifier, but one can easily transform l-classes problem (multinomial classes) into a sequence of l (one-versus-all) or $l(l-1)/2$ (one-versus-one) binary classification tasks, where using different voting schemes leads to a final decision (Belousov et al, 2002; Witten et al, 2011). For the simplicity, let a binary training set $(\mathbf{x}_i,c_j)$, $\mathbf{x}_i\in R^n$, $c_j\in\{-1,1\}$ be considered. SVM algorithm attempts to generate a separating hyper-plane in the original space of n coordinates between two distinct classes (Fig. 3). During the training stage the algorithm seeks for a hyper-plane which best separates the samples of binary classes (classes 1 and –1). Let h_1: $\mathbf{wx}+b=1$ and h_{-1}: $\mathbf{wx}+b=-1$ ($\mathbf{w},\mathbf{x}\in R^n$, $b\in R$) be the possible hyper-planes such that majority of 1 class instances lie above h_1 ($\mathbf{wx}+b>1$) and majority of –1 class fall below h_{-1} ($\mathbf{wx}+b<-1$), whereas the elements belonging to either h_1, h_{-1} are defined as Support Vectors (Fig. 3). Finding another hyper-plane h: $\mathbf{wx}+b=0$ as the best separation assumes calculating $\mathbf{w}$ and b, i.e. solving the nonlinear convex programming problem. The best separation can be formulated by defining the maximum margin M between the two classes. Since $M = 2\|\mathbf{w}\|^{-1}$, maximizing the margin leads to the constrained optimization problem and obtaining optimal $\mathbf{w}^*$. Despite of having some instances misclassified it is still possible to balance between the incorrectly classified instances and the width of the separating margin by introducing the positive slack variables ε_i and the penalty parameter C, representing (i) the distances of misclassified points to the initial hyper-plane and (ii) the penalty for misclassified training points, that trades-off the margin size for the number of erroneous classifications, respectively. The goal is to find a hyper-plane that minimizes misclassification errors while maximizing the margin between classes, which is done by solving the optimization problem (in its dual form). Support Vectors for which $C>\alpha_i>0$ condition holds, belong either to h_1 or h_{-1} (their **w*** is a non-zero value). Let x_a and x_b be two Support Vectors ($C>\alpha_a,\alpha_b>0$) for which c_a=1 and c_b=–1, such that b could be calculated from $b^*=-0.5\mathbf{w}^*(\mathbf{x}_a+\mathbf{x}_b)$, so that:

$$f_c^{'}(\mathbf{x}_i) = \operatorname{sgn}\sum_{i=1}^{g}\alpha_i c_i(\mathbf{x}_i \cdot \mathbf{x}) + b^* \quad \textbf{(1)}$$

It is desirable to further increase the dimensionality of R by introducing kernel function which maps $R^n \rightarrow R^d$, $n<<d$, i.e. $\mathbf{x}\rightarrow\phi(\mathbf{x})$, thus allowing the basic linear variant of the SVM classifier (Eq. 1) to be applied in the R^d space, and then retransformed back to the original R^n space. The most common are Radial-Basis Function kernels, with their dimensionality defined by the kernel width γ (Witten et al, 2011). Thus, it is possible to model the function by optimizing only two parameters C and γ (hypothetically, on a significantly smaller training sets sizes).

The SVM algorithm has been implemented in Weka 3.7. developer suite, with LibSVM extension package.

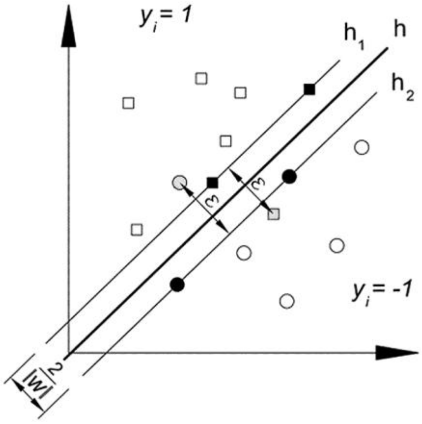

Fig. 3. General binary classification case. Shaded points represent misclassified instances

RESULTS AND DISCUSSION

The input data have had to be pre-processed to reduce the computational cost of the model. In this context, the following measures were undertaken: nominal data, such as *COMPRESSIBILITY* and *LAND COVER* have been binarized into the appropriate number of dummy variables (0 and 1 class), while ordinal data have been 0–1 normalized. The set finally contained 14 input attributes (4 original and 10 synthetic dummy attributes) derived from the original input set (Fig. 2) and the LUS class reference.

The SVM experiment has been designed so that approximately one third (292918 instances) of the total area has been used for training and the remaining two thirds (977097 instances) for testing of the algorithm. These splits were selected in accordance with the administrative extents of the city territory (MP territory and wider territory of the City of Belgrade), thus disabling strategies for balancing of the LUS classes in training/testing splits and limiting the possibilities for improving the training. The only optimization measure has thus been involved by adjusting the C, γ parameter pair during the optimization stage, done through a 5-fold cross-validation (for both models, MODEL1 and MODEL2 as proposed later) over the training split. This procedure has been involved in order to prevent the overfit problem, which causes overoptimistic training, while yielding poorer results in the test split. Due to the considerable time-consumption (in each cross-validation cycle the classifier building lasted for 10 h, while implementation took another 2 h on conventional machine with the following configuration: Intel i5 processor 3.3 GHz, 16GB RAM, 3GB of which were available for the Java emulation by the 64-bit OS Windows 7) the optimization of the parameters was also rather limited. Only four combinations of the following C, γ pairs were considered (100, 4) and (10, 0.1). Higher accuracies were achieved with the first pair, hence C=100 and γ=4 were the parameters of choice.

Since the model could have been evaluated in the testing area by the incomplete LUS reference, involving only Unsuitable and Very Unsuitable class, the model was first built on the modified training reference, wherein the Conditionally Suitable and Suitable classes (=0) were merged against Unsuitable and Very Unsuitable (=1), leading to a binary classification task. This model was labelled as MODEL1. Subsequently, MODEL2 was proposed as a hypothetic model of the original (all four) suitability classes mapped onto the testing area. The difference is thus that MODEL1 trained on only two classes while MODEL2 trained over all four LUS classes, but they bout could be evaluated by those two classes. The hypothesis implies that if MODEL1 yields a plausible result it is justified to assume MODEL2. MODEL2 thus relied on its ability to distinguish between *Conditionally Suitable* + *Suitable* class versus *Unsuitable* + *Very Unsuitable* class, while distinguishing among all four classes could not be properly validated due to the lack of a complete LUS reference for the testing area. However, if it shows a similar success as MODEL1 in distinguishing *Conditionally Suitable* + *Suitable* versus *Unsuitable* + *Very Unsuitable*, it is most certainly capable of distinguishing among all four suitability classes (*Very Unsuitable*, *Unsuitable*, *Conditionally Suitable* and *Suitable*), giving a complete, predictive model of LUS.

For the easier notation let class *Conditionally Suitable* + *Suitable* equal CLASS0 and *Unsuitable* + *Very Unsuitable* CLASS1. Results of the MODEL1, with 89.28% of accuracy, seemingly sound very convincing and go in favour of the model. Visually (Fig. 4) it is also a suggestive model, which manages to capture some regularity in the pattern distribution and follows the trends from the training area. However, the shear figures of the class-specific performance measurement are rather unbalanced (Table 3), because MODEL1 seems to map CLASS0 much more efficiently than CLASS1. Very high True Positives rate (TP rate) reaching 0.98 suggests solid precision for mapping CLASS0, while TP rate for CLASS1 reached only 0.04, yielding average of 0.89 for both classes. In the same time, False Positive rate (FP rate) was high in CLASS0 and low in CLASS1, which gave very poor performance considering some FP-TP rate trade-off measurement (such as ROC Area for instance), making the MODEL1 result plausible but disputable.

Table 3. Contingency Tables of MODEL1 and MODEL2

		LUS reference	
		true	false
MODEL1	positive (CLASS0)	868780	20013
	negative (CLASS1)	84737	3567

		LUS reference	
		true	false
MODEL2	positive (CLASS0)	829019	77251
	negative (CLASS1)	59545	11047

Nevertheless, a relieving circumstance is that the size of CLASS1 was much lower than that of CLASS0, which is a common case in the spatial prediction framework. Herein, the CLASS1 counted less than 10% in both, training and testing splits. This practically means that out of 88304 CLASS1 instances, only 3567 were correctly classified but the class size which it was working against (CLASS0) was much bigger, nearly 9 times as much. This aspect has been considered in MODEL2, and as expected, some improvements were noticed. Thus, the outcome of MODEL1 can be taken with certain reserve. Perhaps the best way to truly evaluate the performance would be with some fuzzyfied similarity approaches, such as Fuzzy Kappa statistics (Hagen, 2002).

MODEL 2 has been trained under the same experimenting design, i.e. using the same C, γ parameter pair (100, 4) after 5-fold cross-validation, and the same training/testing splits. As indicated above, the balance of the classes was slightly more convenient, and accordingly, the results have been improved (Figure 5). In MODEL2 overall accuracy reached 85% which is similar to MODEL1, but has significantly better TP/FP rates for CLASS0 and CLASS1 (0.91 and 0.84, respectively). Particularly encouraging are the trends and patterns which are extending from the referent LUS map (the bold contoured – training area in Fig. 5), which is evident from the visual inspection of the map (note the continuation of the units bordering the training area in Fig. 5).

The initial post-processing (filtering by 8x8 majority filter) did not resulted in higher precision, but the fact that there are some logical errors (class islands, pixelation and so forth) which should be exploited by some more advanced filtering scheme.

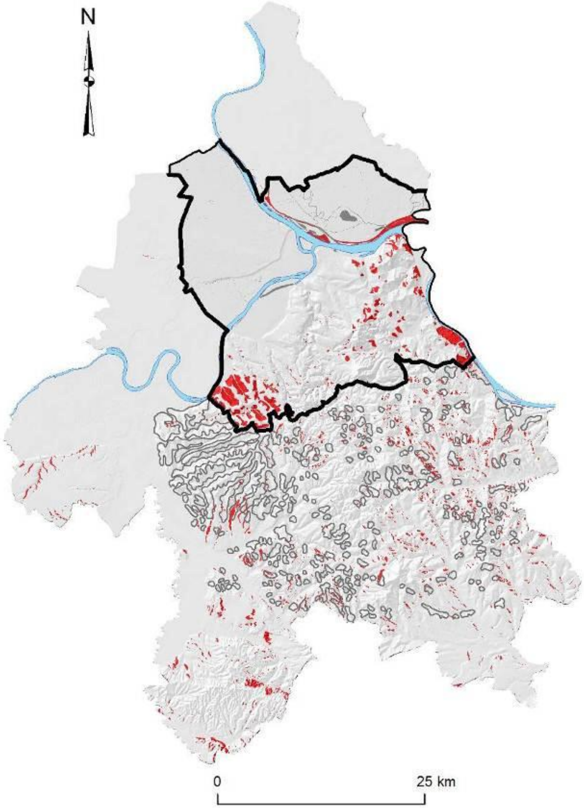

Fig. 4. SVM MODEL1. LUS CLASS1 of MODEL1 is shown red. Referent (testing) LUS CLASS1 (*Unsuitable* + *Very Unsuitable*) shown in black contours. Training area (MP area) is contoured bold black.

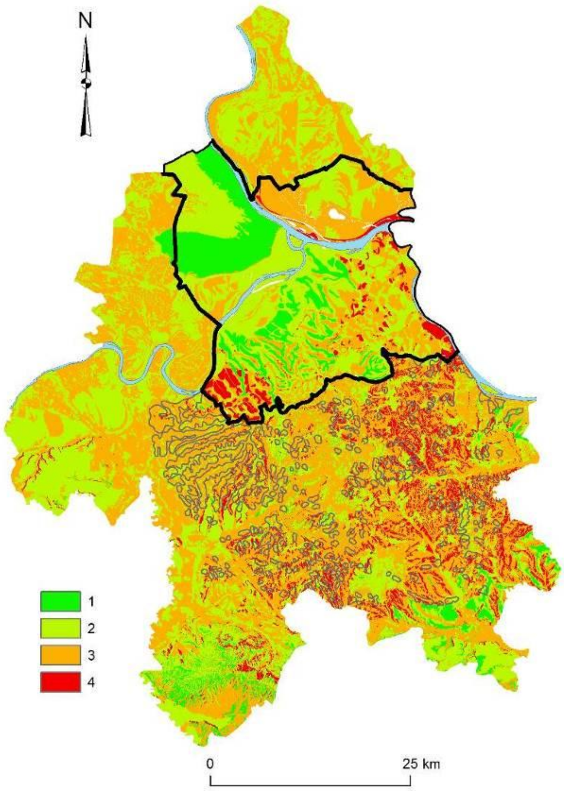

Fig. 5. SVM MODEL2. 1=*Suitable*, 2=*Conditionally Suitable*, 3=*Unsuitable*, 4=*Very Unsuitable*. Referent (testing) LUS CLASS1 is shown in black contours. Training area (contoured bold black) shows a present LUS map based on MP for the City of Belgrade.

CONCLUSION

The study completes a typical supervised machine-learning-based classification task, targeted at prediction of the spatial distribution of referent LUS classes on the area with unknown LUS. Modelling design followed a typical training/testing configuration by using the state-of-the-art SVM machine learning algorithm. The results prove convincing, reaching high accuracies for some classes, allowing a speculation on the actual application of the model (if the interest of the corresponding city service proves realistic). The biggest shortcoming of the model concerns the *Unsuitable + Very Unsuitable* class, which does not yield significant accuracy. In this context, some progress is evident in transiting form MODEL1 to MODEL2 which has to be related to the fact that class balance plays important role in the learning process, thus favoring the result of MODEL2 which has more classes than MODEL1, and therefore a better balance of the class populations available for learning. However, this is an on-going research and there are several directions to look for improvements. Firstly, more advanced post-processing schemes could be involved to eliminate logical errors and therefore raise the modelling performance. Secondly, input dataset could be enriched with some additional data, e.g. water table levels, or data from borehole sampling (if these become at disposal by the courtesy of corresponding city services). Finally, the model could be improved by more thorough optimization of the classifier parameters, which will require much longer experimenting costs (time-wise).

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