Modelling of land cover change using support vector machine

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ABSTRACT

Spatially explicit modeling approaches have been successfully applied to analysis of land use and cover change (LUCC). Theories and methods of LUCC modelling include economic theories, spatial interactions, cellular automata, statistical analysis, optimisation techniques, rule-based simulation or multi-agent models (Koomen, Stillwell, 2007). The aim of this study is to introduce the methodology which combines a relatively new method in LUCC modelling – support vector machine (SVM) – and frequently used geographical cellular automata (GCA; Ménard, Marceau, 2007) for developing scenarios of land cover change. The GCA-SVM methodology is implemented to simulate the land cover dynamics in the Carpathians between 2006 and 2056.

Geographical cellular automata (GCA) models are a combination of the original cellular automata (CA) and multiple transformations required for the modeling of the geographical space (Ménard, Marceau, 2007). In general, a simulation environment in the CA models is a space of grids, in which a set of transition rules determines the attributes which are assigned to each cell. Typically, a linear type of the rules like multi-criteria evaluation is used in the models (Yang et al. 2008). However, linear transition rules cannot suitably hold nonlinear characteristics of complex land use or land cover dynamics. Recently, the nonlinear transition rules based on artificial neural networks (ANN) have been tested but it was found that ANN are not well-controlled learning machines (Vapnik, 1998, Li and Yeh, 2004, Ostapowicz and Kozak 2009). In this study, the transition rules are based on SVM. SVM is a data mining method (for more details see Vapnik 1998) which operates by projecting input vectors to a Hilbert space in which they can be linearly classified by a hyperplane. The hyperplane is generated by applying a kernel function to given support vector (Vapnik, 1998, Yang et al., 2008).

Our GCA-SVM model calibration and accuracy assessment is based on the information of LUCC between 1987, 2000 and 2006 and its driving forces. The analysis concerns five land cover classes: built-up areas, agriculture, forest, semi-natural areas non-forested areas, and water. The source of information about past land cover were satellite land cover maps with spatial resolution 30 m obtained from Landsat TM and +ETM (SVM classification). The driving forces were estimated on a basis of the Shuttle Radar Topography Mission digital elevation model (the SRTM DEM; elevation and slope), topographic vector data (roads and railway network – the Digital Atlas of the Małopolska Region; forest ownership – the Polish State Forest data), socio-economic statistical survey data from the Polish Central Statistical Office (NUTS 5 level; level of migration, employment in industrial, agricultural or service sector).

The proposed GCA-SVM model was implemented using SML in Erdas Imagine and imagesSVM in IDL (www.hu-geomatics.de). The SVM allowed to build the non-linear transition rules for the GCA simulation. The results of simulation were probabilities of different types of land cover change. We modelled, based on our knowledge about study area, six types of changes (and six transition functions): (1) increase of built-up areas, (2) decrease of forests, (3) increase of forests, (4) decrease of agricultural areas, (5) increase of semi-natural areas, (6) decrease of semi-natural areas. For each type of change and for each cell the probability of transformation was estimated and assigned. The decision about a change of cell was based on probability values: transformation type with the highest probability of change was selected. To control the area of land cover changes and construct alternative scenarios, various probability thresholds were used. Generally, the cell with probability

lower than 0.75 were assumed to be stable. Scenarios were generated using the calibrated models until 2056 (five 10-year iterations). Three types of scenarios were implemented: (A) extrapolation of the current LUCC processes, (B) cultural landscape conservation, (C) significant increase of forest cover. We inserted also to our model some additional assumptions derived from e.g. existing development plans – particularly to outline the areas where changes are unlikely (e.g. within the State Forest property or in the national parks).

The results suggest that coupling the two different modeling techniques – CGA and SVM provide new insights into spatial patterns and underlying processes of land cover change. In three scenarios, two processes were dominated; increase of built-up areas and forest cover but with different intensities.

ACKNOWLEDGEMENTS

This research is supported by national budget funds for science, 2008-2010. Project N N306 050034

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