Integrating the Multi-Label Land Use Concept and Cellular Automata with the ANN-based Land Transformation Model

Hichem Omrani[1], Amin Tayyebi[2] and Bryan Pijanowski[3]

[1]Urban Development and Mobility Department, LISER, Luxembourg
Telephone: (+352) 585855-313
Email: hichem.omrani@liser.lu

[2]Center for Conservation Biology, University of California-Riverside, USA
Telephone: (765) 412-1591
Email: amin.tayyebi@gmail.com

[2] Department of Forestry and Natural Resources, Purdue University, USA
Telephone: (765) 496.2215
Email: bpijanow@purdue.edu

Abstract

Cellular automata (CA) and artificial neural networks (ANNs) have been used by researchers over the last three decades to simulate land use change. Conventional CA and ANN models assign a cell to only one elementary land-use class. However, in reality, a cell may belong to several land-use classes simultaneously. The recently developed multi-label concept overcomes this limitation. Although this concept is a new paradigm with non-exclusive classes and has shown considerable merit in several applications, very few studies have applied it in land change science. Finding transition rules in conventional CA is difficult when the number of drivers is large. ANNs models, on the other hand, are limited to considering neighborhood effects in the modeling process. Using an integrated CA with ANN model to overcome these limitations and combine the strengths of both CA and ANN, we extend the land transformation model (LTM), which is an ANN model, with both a CA based-model and the multi-label concept. The ANN used for multi-label learning determines CA land use transition rules. Results show that the new land-use change model, called multi-label cellular automata land transformation model (MLCA-LTM) performs well using several evaluation measures, compared to the standard LTM, in capturing land change patterns in details and complexity.

Keywords: Artificial neural networks, Cellular automata, Land use change, Multi-label concept, Non-exclusive classes.

1. Introduction

Land use is known for being a complex spatial and temporal system (Clarke et al., 1997). This complexity can be explained by the fact that different endogenous factors (e.g., neighbourhood effect and interaction among factors as well as land use classes) and exogenous factors (e.g., slope and transport systems, human behaviour, socio-economic and cultural factors) are involved in model development (Pijanowski et al., 2014). Prior the computation of all explaining factors, land use changes (LUC) can be formulated as a prediction problem in which land use classes of cells are classified as a function of the computed explaining factors (i.e., variables also called features or driving factors).

Experts and scientists from various disciplines such as computer science, geography, cartography and environmental engineering have contributed to land change science field. Machine learning techniques have been used (Tayyebi et al., 2014c) to model LUC due to their approximation power. Machine learning techniques are able to learn spatial and temporal LUC patterns in data (Pijanowski et al., 2002). Machine learning techniques include various approaches such as artificial neural networks (ANN; Pijanowski et al., 2009), support vector machines (Jiang et al., 2011; Yang et al., 2008), genetic algorithm (Shan et al., 2010), classification and regression tree (Tayyebi and Pijanowski, 2014), multivariate adaptive regression spline (Tayyebi et al., 2014c) and others (Tayyebi et al., 2010). In the supervised framework of machine learning, the learning is performed on training data to define a function that predicts correctly the labels of cells. If the labeling of the training examples is categorical (discrete labels or classes), the learning task is called classification.

Land Transformation Model, which is ANN based model, is one of the well-known machine learning approaches that has been used and applied to various places across the globe, such as Asia (Pijanowski et al., 2009), Europe (Pijanowski et al., 2006), Africa (Tayyebi et al., 2014c) and United States (Tayyebi et al., 2014b). ANNs build a functional relationship to capture the pattern of the LUCs and mimicking the land-use evolution. There are also other studies that used other types of ANNs to study LUC (Grekousis et al., 2013; Mas et al., 2004; Basse et al., 2014).

Despite all the achievements in land-use modeling, the development of suitable LUC model that can simulate a mixed LUCs remains an active and exciting research topic (Couclelis, 2005; Batty, 2011).

The conventional CA, despite its success in land use science, assumes that land use classes are mutually exclusive which is not realistic to model mixed land use. A possible solution is the multi-label concept (ML) instead of single-class or mono-label concept (ml). In this paper, we integrated the CA model and the idea of ML into the well-known LTM. We specifically integrated the LTM with CA and the ML concept to simulated mixed LUCs. The multi-label artificial neural network (ML-ANN) is used to determine CA land use transition rules. We applied the developed model on rich datasets, from Luxembourg country, to study the mixed land use changes. We validated the developped model using the common goodness of fits measurements for ML learning such as sensitivity, specificity and F-measure. We also compared the proposed ML-CA-LTM model with the conventional LTM model, based on a set of measures carefully selected to demonstrate the added value of the proposed ML-CA-LTM methodology.

2. Conclusion

We come to the following conclusions:

1) The new LUC model, called ML-CA-LTM, performed well in capturing mixed land use patterns.
2) Integrating Land Transformation Model with cellular automata model and multi-label concept is an effective instrument to simulate mixed land use changes.
3) The differences between before and after integration for simulating multi-label land use change are substantial.

4) The ML-CA-LTM model offer to the wider community of researchers working on land use modelling a new research framework, to model such geographical phenomena that is intuitively more attractive and appealing.

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