Chapter 78
A Neural Network for Modeling Multicategorical Parcel Use Change

Kang Shou Lu
Towson University, USA

John Morgan III
Towson University, USA

Jeffery Allen
Clemson University, USA

ABSTRACT

This paper presents an artificial neural network (ANN) for modeling multicategorical land use changes. Compared to conventional statistical models and cellular automata models, ANNs have both the architecture appropriate for addressing complex problems and the power for spatio-temporal prediction. The model consists of two layers with multiple input and output units. Bayesian regularization was used for network training in order to select an optimal model that avoids over-fitting problem. When trained and applied to predict changes in parcel use in a coastal county from 1990 to 2008, the ANN model performed well as measured by high prediction accuracy (82.0-98.5%) and high Kappa coefficient (81.4-97.5%) with only slight variation across five different land use categories. ANN also outperformed the benchmark multinomial logistic regression by average 17.5 percentage points in categorical accuracy and by 9.2 percentage points in overall accuracy. The authors used the ANN model to predict future parcel use change from 2007 to 2030.

INTRODUCTION

Land use change has been a major cause of many environmental problems. Changes are often necessary to accommodate population growth and economic development. Degraded environments, however, threaten sustainable development. As more states and local governments are willing to create and implement smart growth strategies, planners and policy makers need to know the impacts of future land use change and related

DOI: 10.4018/978-1-4666-2038-4.ch078

regulatory decisions. Predictive modeling is not only a learning tool to understand causal factors and dynamic changes of a land use system, but also an important mechanism to predict future changes and simulate the potential effects under different growth scenarios (Pijanowski et al., 2002).

Despite the emergence of numerous predictive models over the last half-century, our ability to accurately predict land use change remains limited. Recently, 18 scientists jointly conducted an evaluation of the performance of nine land cover/land use models applied in 13 regions (Pontius et al., 2008). These models included conventional logistic regression (McConnell, Sweeney, & Mulley, 2004), cellular automata based SLEUTH (Dietzel & Clarke, 2004; Silva & Clarke, 2002), multiple agent based SAMMBA (Boissau & Castella, 2003; Castella, Trung & Boissau, 2005), multistage model CLUE and its variant CLUE-S (Duan et al., 2004; Verburg et al., 2002; Veldkamp & Fresco, 1996; Verburg & Veldkamp, 2004), and multifunctional LTM (Pijanowski et al., 2005), multiple objective GEOMOD (Pontius, Cornell & Hall, 2001; Pontius & Malanson, 2005; Pontius & Spencer, 2005). It was found that prediction accuracy, as measured in percent of the correctly predicted against the observed, falls within a range of 1-73 percent, falling below 30 percent in seven cases and above 50 percent only in three cases. Some of the assessments were against the sample datasets used for model calibration or training. But judging on these results, how much can we trust the predictions of the models?

Pontius et al. (2008) point out that something must be wrong with the mechanics of these models. We attribute the poor performances more to the oversimplification of complex land use systems in both semantics and syntax. Semantically, most models, particularly cellular automata models, tend to overemphasize “parsimony” and use too few predictive variables to truly represent complex reality. It may not be a coincident that SLEUTH, constructed with only three effective predictive variables, is the worst performer among all the models examined by Pontius et al. (2008). Although there is no suggested threshold for how many predictive variables are deemed appropriate, a good model should include variables that measure key drivers of changes in land use such as population, economy, and technology (Turner & Meyer, 1994). More importantly, the model should be able to generate meaningful predictions, and pass the reality test.

From the syntax perspective, most existing models, particularly conventional statistical models, lack the multilayered, hierarchical, interconnected structure needed for modeling complex land use systems as Batty and Torrens (2005) have suggested. Multiple layers mimic the processes of land use changes that involve land transaction, speculation, and development; whereas interconnections through these layers capture the interrelationships and interactions between dependent and independent variables, whether they are observable, quantifiable or comprehensible. The CLUE (-S) model is to some degree structured in this way and thus performed relatively well (Pontius et al., 2008). Batty and Torrens (2005) did not provide specific suggestions about what algorithms to use and how to derive them in order to describe such interrelationships and implement the framework. The structure of the conceptual model, however, implicitly points to an artificial neural network (ANN) approach which does offer such capabilities.

This paper presents an artificial neural network (ANN) for modeling multi-categorical parcel use changes. We intended to improve the model by: 1) incorporating more effective predictor variables for a better semantic representation; 2) expanding the model structure for a multiclass land use system; 3) using a multilayer neural network to enhance predictive power; and 4) applying a Bayesian regularization (BR) training algorithm to avoid the over-fit problem. We applied the model in Beaufort County, South Carolina, to predict and simulate future land use changes from 2000 to 2030 under different growth scenarios.

Related Content

Creativity with Building Information Modelling Tools
A.M. Ahmad, P. Demianand A.D.F. Price (2013). *International Journal of 3-D Information Modeling (pp. 1-10).*
www.irma-international.org/article/creativity-building-information-modelling-tools/77812

Unified Rule Approach and the Semantic Enrichment of Economic Movement Data
Werner Scheltjensand Kurt Dopfer (2012). *Universal Ontology of Geographic Space: Semantic Enrichment for Spatial Data (pp. 229-247).*
www.irma-international.org/chapter/unified-rule-approach-semantic-enrichment/64002

Scalability and Sustainability of M-Government Projects Implementation in Developing Countries
Olalekan Samuel Ogunleyeand Jean-Paul Van Belle (2016). *Geospatial Research: Concepts, Methodologies, Tools, and Applications (pp. 1371-1394).*
www.irma-international.org/chapter/scalability-and-sustainability-of-m-government-projects-implementation-in-developing-countries/149554

Characterization of Fire Regime Descriptors in Botswana Using Remotely Sensed Data
John Isaac Molefe (2018). *Handbook of Research on Geospatial Science and Technologies (pp. 86-100).*
www.irma-international.org/chapter/characterization-of-fire-regime-descriptors-in-botswana-using-remotely-sensed-data/187718

A Review of Geospatial Information Technology for Natural Disaster Management in Developing Countries
Sam Heroldand Michael C. Sawada (2013). *Geographic Information Systems: Concepts, Methodologies, Tools, and Applications (pp. 175-215).*
www.irma-international.org/chapter/review-geospatial-information-technology-natural/70442