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Modeling urban evolution using neural networks, fuzzy logic and GIS: The case of the Athens metropolitan area

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ABSTRACT

This paper presents an artificial intelligence approach integrated with geographical information systems (GISs) for modeling urban evolution. Fuzzy logic and neural networks are used to provide a synthetic spatiotemporal methodology for the analysis, prediction and interpretation of urban growth. The proposed urban model takes into account the changes over time in population and building use patterns. A GIS is used for handling the spatial and temporal data, performing contingency analysis and mapping the results. Spatial entities with similar characteristics are grouped together in clusters by the use of a fuzzy c-means algorithm. Each cluster represents a specific level of urban growth and development. A two-layer feed-forward multilayer perceptron artificial neural network is then used to predict urban growth. The model, applied to the prefecture of Attica, Greece, delineates the current and future evolution trends of the Athens metropolitan area, which are illustrated by maps of the urban growth dynamics. The proposed methodology aims to assist planners and decision makers in gaining insight into the transition from rural to urban.

Introduction

Although the developed world and developing countries differ in the percentage of people living in cities, as well as in the way in which urbanization is occurring, there is a global trend of urban population growth. The United Nations Population Fund has estimated that by 2030 the urban population of the developing world will have increased from 2.048 billion in 2000 to 3.991 billion, while the urban population of the developed world is expected to increase relatively little, from 870 million to 1.01 billion (United Nations Population Fund, 2007). As a result, the spatial patterns of urban areas, by means of their limits and borders, are changing in a complex way. Urban areas continue to expand at the expense of rural areas, intensifying among others, urban sprawl. Because of consistent changes in their structure and shape, urban areas are continuously at the epicenter of a wider scientific interest as the problems arising are complex and exceed the pure urban aspect.

As contemporary cities are polycentric and avoid the classic monocentric model of the past, understanding their evolution is becoming constantly more complicated. The quantitative and spatial demographic changes in urban regions are accompanied by perpetual transformations that are manifested by urban sprawl and land use changes. Metropolitan areas have come under pressure, and problems such as congestion and the loss of open space are negatively affecting urban and transportation planning as well as the quality of life and the environment (Waddell, 2000).

Modeling and simulation of complex dynamic systems such as urban areas could greatly benefit from the synergy of the methods and techniques of geographical information science with artificial intelligence techniques such as fuzzy logic and neural networks. For example, artificial intelligence algorithms are very capable of capturing urban land use and land change patterns in a non-parametric approach and handle to a higher degree spatial heterogeneity well (McDonald & Urban, 2006; Wang & Mountrakis, 2011). Additionally, the main advantage of fuzzy clustering is that objects can be associated with multiple clusters to different degrees, whereas in common clustering, each object corresponds to one cluster only. Because administrative boundaries do not divide people into totally different groups, fuzzy boundaries are more appropriate than fixed boundaries to represent spatial clusters (See & Openshaw, 2001). With fuzzy clustering, we delineate a better profile for each spatial unit and avoid aggregating our results to the level of only one cluster (Grekousis & Hatzichristos, 2012). Additionally, neural networks do not depend on fixed functional relationships and do not require any a priori knowledge of the variable relationships (Cheng, 2003). This independence is a major advantage of neural networks because they can be used as powerful predictive tools when modeling complex nonlinear problems (Olden & Jackson, 2001). Neural networks are robust to noise and exhibit a high degree of automation (Openshaw,

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1997). Furthermore, they do not make any assumptions regarding the nature of the distribution of the data (Grekousis & Hatzichristos, 2012).

In this paper, a prototype methodology is proposed for the development of an urban model from a geodemographic perspective. Methods and techniques from artificial intelligence are used for the spatiotemporal analysis, the prediction of future trends and the development of urban regions. More specifically, we propose a method estimating future urban growth using neural nets, fuzzy clustering and geographical information systems (GISs).

First, fuzzy clustering is used to group the spatial units into clusters. Clustering is based on data from the national census, such as population, number of buildings and building's usage. With fuzzy clustering, each spatial unit will be assigned a factor of evolution and urbanism. Based on demographic time-series data, a neural network is used to predict the future urbanism state of each spatial unit. The proposed approach is applied to the Athens metropolitan area of Greece.

The remainder of the paper is organized according to the following outline: Section 2 presents a literature review of urban growth models and artificial intelligence, primarily focused on neural networks; Section 3 describes the proposed methodology; Section 4 presents the case study; and finally, Section 5 presents the conclusions of this research.

Urban growth models and artificial intelligence

There are several multifaceted efforts investigating the question of how urban space changes. Various models have been devised to analyze urbanization along with the physical and socio-economic factors impacting urban development (Liu, 2008). Urban growth is a very complex process because it involves multiple actors with differing patterns of behavior at various spatial and temporal scales (Cheng, 2003). Furthermore, it is not easy to define urban. For example, the United Nations Population Fund defines urban as "settlements or localities defined as 'urban' by national statistical agencies" (United Nations Population Fund, 2007). As a result, definitions vary based on the standards of national statistical agencies, and there is not a global definition. Since the 1960s, several theories have been developed for the analysis and simulation of the evolution of cities, and the mathematical equations that have resulted have led to the creation of several models simulating urban phenomena (Batty & Xie, 1994; Chapin & Weiss, 1968; Laurence & Edward, 1981; Tobler, 1970). The liaison between the theories and the models was often not very strong. Furthermore, the initially limited computing capability did not always lead to widely known and applicable tools. Urban growth modeling is an interdisciplinary field as it involves numerous scientific areas, such as GIS, remote sensing, urban geography and complexity theory (Cheng, 2003). GIS and remote sensing have proven to be very powerful tools for managing spatial information and extracting valuable knowledge concerning urbanization and its dynamics (Hasse, 2007; Kumar, Garg, & Khare, 2008; Masser, 2001). Agent-based modeling (Benenson, 1998; Kerridge, Hine, & Wigan, 2001), fractal-based modeling (Batty & Longley, 1994; Shen, 2002) and decision trees (Triantakonstantis, Mountrakis, & Wang, 2011) have also been used in urban growth modeling.

Artificial intelligence tools including, but not limited to, neural networks and cellular automata are gaining popularity in modeling urban growth. Cellular automata are dynamic, discrete-space and discrete-time systems that are widely used in urban modeling. For example, Batty, Couclelis, and Eichen (1997), Batty (1998), and Batty, Xie, and Sun (1999) studied urban systems and urban dynamics with cellular automata, and Clarke, Hoppen, and Gaydos (1997) studied the urban development of San Francisco based on historical data. Almeida, Batty, and Monteiro (2003) designed an urban model for estimating land-use transitions that used cellular automata and elementary probabilistic methods.

Neural networks are widely used in geographical analysis (Hewitson & Crane, 1994; Openshaw, 1997; Pradhan & Lee, 2010). Some applications in urban studies include telecommunication traffic flows (Fischer & Gopal, 1994), transport planning (Shmueli, 1998), land cover classification (Foody, 2002; Lula, 2010; Mas & Flores, 2008) and spatial housing market structure (Kauko, 2004). There are many studies in urban growth modeling using neural networks. For example, Liu and Lathrop (2002) used neural networks to detect newly urbanized areas in satellite sensor images. Their results highlight the practical value of neural networks in detecting changes. Using GIS and neural networks, Pijanowski, Brown, Shellito, and Manik (2002) developed a land transformation model based on social, political and environmental factors to predict land use changes and urbanization. Lin, Lu, Espey, and Allen (2005) explored the applicability of neural networks in urban growth modeling. A regression model was used to compare the results, and neural networks proved better in terms of prediction accuracy.

Maithani, Jain, and Arora (2007) developed a three-layer back-propagation neural network for simulating urban spatial growth. Remote-sensing temporal data were used to provide empirical inputs related to urban growth and other spatial information. The model results were evaluated using Moran's spatial autocorrelation index to predict the urban spatial pattern. In a later study, Maithani (2009) improved his method using a faster version of the back-propagation algorithm, the Levenberg–Marquardt algorithm. Liu and Seto (2008) presented a spatiotemporal neural network method to predict urban evolution based on transportation routes, land use and topography. Pijanowski, Tayyebi, Delavar, and Yazdanpanah (2009) adopted an urban expansion model (UEM) based on GIS, neural networks and remote sensing. They used a multilayer perceptron neural network, satellite imagery from 1988 and 2000 and socio-economic and environmental variables to estimate urban expansion for the Tehran metropolitan area in Iran for the year 2012.

Wang and Mountrakis (2011) developed the multi-network urbanization (MuNU) model for studying urban growth. In this very interesting work, the MuNU model integrates multiple neural networks to capture spatial heterogeneity. The input space is split into segments, and each input pattern is reallocated to the appropriate neural network. Their model is tested in a case study of Denver, Colorado, based on satellite imagery datasets of land use and land cover. The method was compared to two single-step algorithms, stepwise logistic regression and a single neural network, and several improvements were suggested by the authors.

In many applications, the combined use of cellular automata, neural networks and fuzzy logic gives better results than heuristic, probabilistic or statistical techniques (Kanungo, Arora, Sarkar, & Gupta, 2006; Melchiorre, Matteucci, Azzoni, & Zanchi, 2008; Pradhan & Pirasteh, 2010; Yeh & Li, 2002). For example, Guan and Clarke (2005) used a constrained cellular automata model based on a two-layer back-propagation neural network to simulate and forecast urban growth in Beijing. The model estimates demand for urban space in the future based on socio-economic data. Mantelas, Hatzichristos, and Prastacos (2007) presented a methodological framework for modeling urban growth based on fuzzy systems and cellular automata. First, a set of fuzzy systems processes the data and calculates certain thematic indices regarding urban evolution. Then, empirical rules are used in a cellular automata model to predict urban growth. Their method was applied to Mesogeia, which is part of the Athens metropolitan area, for the year 2004. Liu (2008) used a fuzzy-constrained cellular automata model in a GIS environment to simulate urban development in Sydney, Aus-