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Urban Growth Prediction in Athens, Greece, Using Artificial Neural Networks

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***Abstract*—**Urban areas have been expanded throughout the globe. Monitoring and modelling urban growth have become a necessity for a sustainable urban planning and decision making. Urban prediction models are important tools for analyzing the causes and consequences of urban land use dynamics. The objective of this research paper is to analyze and model the urban change, which has been occurred from 1990 to 2000 using CORINE land cover maps. The model was developed using drivers of urban changes (such as road distance, slope, etc.) under an Artificial Neural Network modelling approach. Validation was achieved using a prediction map for 2006 which was compared with a real map of Urban Atlas of 2006. The accuracy produced a Kappa index of agreement of 0,639 and a value of Cramer's V of 0,648. These encouraging results indicate the importance of the developed urban growth prediction model which using a set of available common biophysical drivers could serve as a management tool for the assessment of urban change.

***Keywords*—**Artificial Neural Networks, CORINE, Urban Atlas, Urban Growth Prediction.

I. Introduction

URBAN areas have significantly increased over the last decades, in our age of globalization. Many scholars have hailed that urban growth is an indicator of progress [1]. Although it seems that urbanization is promoting economic prosperity, there is no evidence that urbanization affect economic growth rate [2]. Because of its accelerating rate, urban growth should be a primary issue in urban planning. One of the negative impacts of urban growth is sprawl, an undesirable urban expansion.

Urban sprawl is a consequence of the huge urbanization (50% of the total world population lives in urban centers in 2008). It has one or more of the following characteristics: non-compact growth, low density suburban development, scattered, leapfrog or ribbon structure [3]. The sprawl has a negative effect in urban centers due to the high and unsustainable energy consumption, extensive use of the car and heating needs, the reduced level of transport means in the suburbs and the fragmentation of urban development [4], [5]. The decrease of urban sprawl does not necessarily imply a reduction of urban growth, but puts some rules in order to make it more functional. Moreover, not everyone agrees that urban sprawl has negative impacts on residents, because it is associated with a better quality of life away from the city center and close to open and green spaces [6].

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There is no doubt that urban growth modelling is a subject of great importance. A thorough review papers in the literature describe different modelling approaches as well as advantages and disadvantages of collaboration between modelling and planning communities [7]-[11]. Reference [11] found that there is a strong recognition of the model's potential in urban planning, but unfortunately it is difficult to reach that potential in practice.

Nowadays there is a plethora of models dealing with urban growth. Moreover, many factors seem to be responsible for that change. These factors can be categorized to four types: biophysical, socio-economic, cultural and institutional. Although the importance of these factors, it is impossible to include all of them in a model. Except the availability of the data, the main reason for non-inclusion of all factors is that the less complex a model is, the faster and more understandable the process become.

Artificial Neural Networks (ANNs) are powerful tools that use a machine learning algorithm in order to model complex behaviour. Unlike most multi-variate modeling techniques, ANNs are independent from input data relationships and therefore there is no need to make any assumptions concerning in spatial autocorrelation and multi-collinearity of the data. The most common ANN is the multi-layer- perceptron (MLP) neural network, produced by [12]. Some applications in urban growth include: ART-MMAP [13], SLUETH [14], [15], etc. Furthermore, other ANNs have used fuzzy set theory [16], multivariate analysis [17] and self- organizing maps [18] in their algorithms.

The objective of this paper is threefold: First, to examine how extensive the urban growth is during 1990 and 2000. Second, to model the urban growth in order to make predictions in the future. Third, to propose a user friendly model in planning community of Athens metropolitan area. The contribution of this research in urban growth modeling aspires to provide a useful tool in urban planning and support appropriate decision making initiatives.

II. Materials and Methods

A. Study Area

The study area includes the metropolitan area of Athens, Greece. Athens is a multicultural capital in the crossroad of Mediterranean region and its specific location allow a mixture of European, African and Middle East influences. The city center has been rebuilt and expanded after 2nd World War but nowadays new conditions as the lack of new parcels in the city center, the expansion of railway roads, the population density (included non-registered immigrants), the development of new facilities outside the tradition center such airport and shopping centers and finally the construction of new peri-urban roads (“Attiki road”) have led to the compulsory expansion of Athens.

B. CORINE and Urban Atlas Land Cover Maps

The land use data used include the CORINE land cover maps for 1990 and 2000 as well as the Urban Atlas for 2006 (Fig. 1). All the data are accessible through European Environmental Agency. The scale of CORINE maps is 1:100.000 and the minimum mapping unit is 25 ha. The scale of Urban atlas is 1:10.000 and the minimum mapping unit is 0.25 ha for the artificial surfaces and 1 ha for the other surfaces. It is obvious that the difference is not negligible and therefore the CORINE maps are neither always detailed nor compatible with Urban Atlas [19], [20]. These spatial discrepancies were overcome adopting a spatial resolution for the analysis of 100m x 100m, which is sufficient for detecting the urban changes in three land use maps.

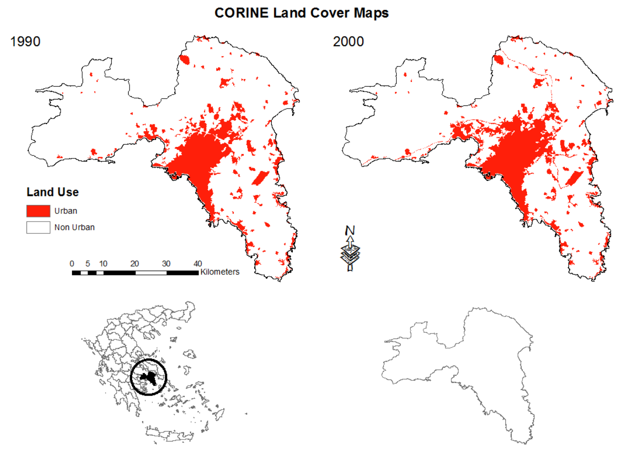

Fig. 1 CORINE land cover maps for 1990 and 2000 consisting only two classes: urban and non-urban areas

The CORINE land cover map contains 44 class nomenclatures on the third detail level. In the first level (five classes), the land use map contains the main categories of the land cover/land use (artificial areas, agricultural land, forests and semi-natural areas, wetlands, water surfaces). In the second level (15 classes), physical and physiognomic entities (urban zones, lakes, etc.) are included and finally in level 3, 44 classes are contained [21]. For the requirements of the present study, only two classes were considered: urban areas and non-urban areas (all the other classes except urban). Although the official classification accuracy of CORINE land cover map is 87%, [22] revealed lower accuracy.

The Urban Atlas land cover map considers in total 20 classes of which the 17 are urban classes. The urban fabric (CORINE LC classes 1.1.1 and 1.1.2) is included in different classes using different degree of imperviousness [20]. All the classes with different degree of imperviousness were reclassified to urban areas, while the remaining classes were considered as non-urban areas.

C. Urban Land Use Drivers

The urban land use drivers which were included into the ANN model were: elevation, slope, distance to roads and distance to urban areas (Fig. 2).

Elevation data were provided by Aster Global Digital Elevation Map (version 2), freely available from NASA. Because the spatial resolution was 30m x 30m, the dataset was resampled to working spatial resolution of 100m x 100m. From these elevation data, the slope map was also derived.

Euclidean distance was used in order to produce the datasets of distance to roads and distance to urban areas. These drivers can be considered as socio-economic, because the distance to these geographic entities express the accessibility to human activities.

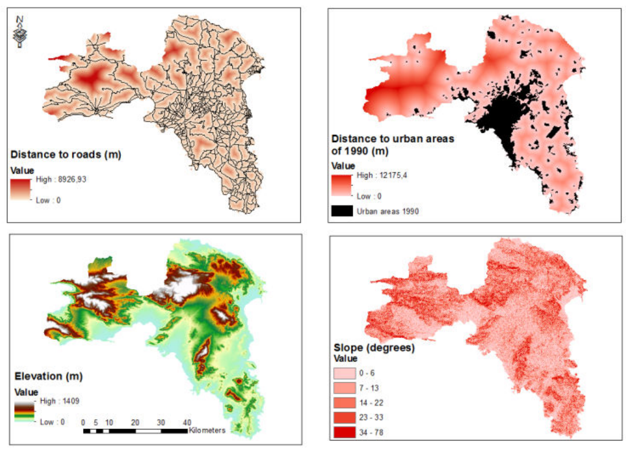

Fig. 2 Drivers used for urban growth predictionmodelling (distance to urban areas of 1990, distance to roads, elevation and slope)

D.Methodology

Datasets were masked using the clip boundary of Athens metropolitan area. Datasets were first stored in an ESRI geodatabase and they were further imported to IDRIS Selva software, where the Land Change Modeller extension was used for applying the urban growth prediction modelling.

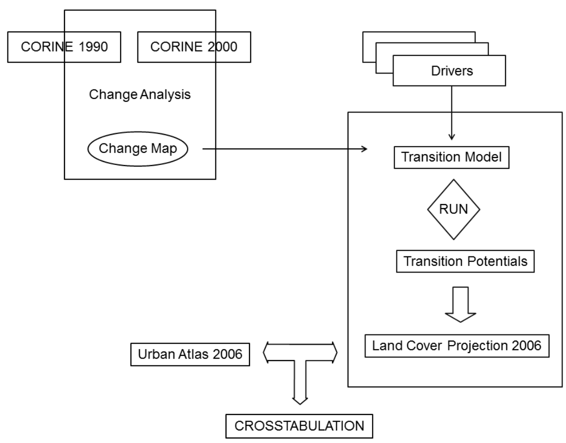

Fig. 3 Flowchart of the applied urban land use prediction model

The land cover transitions in years 1990–2000 were identified. Next, transition potential of urban land was modelled. After obtaining the transition potential, a prediction scenario was applied using historical rates of change. MLP neural networks method was applied in order to predict urban land use map in 2006. 2006 Urban Atlas land cover map was used for validating the model. The flowchart of urban land use prediction is presented in Fig. 3.

E. Change Analysis

In this step, changes between two CORINE maps from 1990 and 2000 are assessed. More specifically, the change between non-urban areas to urban areas was calculated and the percentage of urban growth reached 2,8% of the total study area. Although this percentage seems to be low, the actual urban growth close to city center as well in nearest surrounding is quite larger, taking into account that much of study area consists of forests, wetlands and protected areas. More specifically, the non-urban areas which were converted to urban were forests and agricultural areas. 17,8% of forests and 82,2% of agricultural areas were urbanized.

F. Transition Modelling

Transition model provides the transition potential from non-urban to urban land use using a MLP neural network. After having provided the driver variables, a transitional potential map was created. An excluded layer was also considered, containing NATURA areas, national parks, national wildlife sanctuaries, protected mountain areas of Penteli, Parnitha, Egaleo and protected areas of Laurio.

The model relies on neural networks, operating in automatic mode. The model itself decides how the drivers change in order to achieve a better representation of the data modelled. The model reaches the maximum accuracy under an iterating framework process [23].

III. Results

A. Population Dynamics

The Athens metropolitan area is subdivided into four administrative prefectures: Prefecture of Athens, Prefecture of Pireaus, Prefecture of West Attika and Prefecture of East Attika. The population from 1991 to 2011 is provided by Hellenic Statistical Authority (www.statistics.gr) and it is referred to resident population (Greek and foreign residents who have their usual residence in each administrative division). Fig. 4 presents the resident population growth between 1991-2001 and 2001-2011.

The population growth in Athens and Pireaus is low in 1991-2001, while it has a negative sign in 2001-2011. This trend can be explained by the highly urbanized areas of these regions, with no many chances for further urban development. On the contrary, areas outside the dense urban fabric, located in West and East Attika have increased their percentage of urban growth and as a consequence their resident population. Especially in East Attika the higher population and urban growth are observed due to construction of accessibility facilities (road network, transportation, airport, etc.).

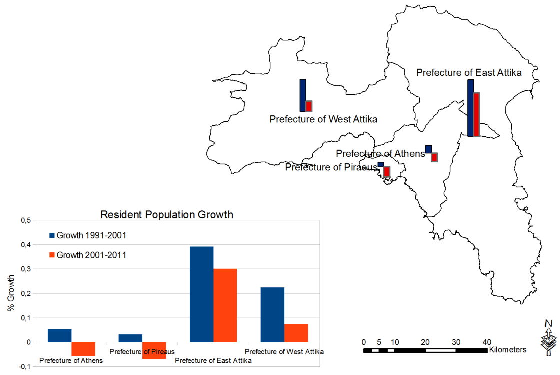

Fig. 4 Resident population growth between 1991-2001 and 2001-2011 in the administrative divisions of Athens metropolitan area

B. Urban Growth Prediction Modelling

A key task of urban growth prediction modelling is to determine the drivers responsible for the transition from non-urban to urban areas between 1990 and 2000. The drivers used, as they were already explained are: elevation, slope, distance to roads and distance to urban areas of 1990. For every variable a natural log transformation was performed. This procedure was adopted because the natural log transformation is effective in linearizing distance decay variables and therefore, modelling becomes easier [23]. For each variable as well as for their natural log transformation an explanatory power testing was also achieved. The Cramer's V was used for the evaluation of the association of a variable with the land use classes of the later image (2000 urban land use map). High values of Cramer's V indicate a good explanatory value of the variable. The results of Cramer's V testing are given in Table I. The final variables included into the urban growth model were: elevation, slope, distance to roads and distance to urban areas 1990 (ln). Because the Cramer's V of distance to urban areas 1990 (ln) improved after natural log transformation of the initial image, then this transformed variable continued to modelling.

In order to predict urban growth, a potential map was created through transition from non-urban to urban areas between 1990 and 2000. Thus, a transition sub-model was produced using a MLP neural network. The implementation of MLP for LCM is preset with parameters that work quite satisfactory in most cases. Generally, the two most critical parameters are the number of hidden layer nodes and the learning rate, which were preset by an automatic algorithm of MLP.

TABLE I
Cramer's V Values for the Drivers and Their Natural Log Transformations

Drivers	Cramer's V
Elevation	0,23
Elevation (ln)	0,23
Slope	0,24
Slope (ln)	0,01
Distance to roads	0,22
Distance to roads (ln)	0,22
Distance to urban areas 1990	0,58
Distance to urban areas 1990 (ln)	0,65

C. Validation

A Markov Chain prediction process was used in order to estimate the urban prediction map of 2006. Markov Chain determines the amount of change using the earlier (1990) and later (2000) maps along with the future date (2006). The transition from 2000 to 2006 based on a projection of the transition potential map. The prediction map of 2006 with the real map of Urban Atlas (2006) is presented in Fig. 5.

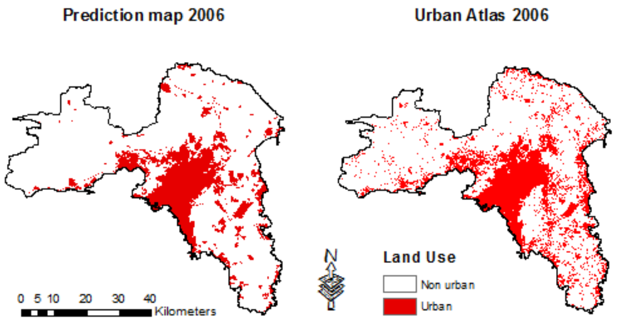

Fig. 5 Comparison between prediction map for 2006 derived by the urban growth model and the Urban Atlas real map of 2006

Cross-tabulation was performed in these two images in order to validate the results. Finally, the Kappa statistic and Cramer's V value were calculated from the cross-tabulation table. Kappa statistic assigns a value of 0,639, while Cramer's V value is 0,648. We cannot expect that a model will have a perfect fit, but this is the key point for a model. The above statistic values are high and therefore a strong association between projected and real map is revealed.

Spatial modelling and simulation don't have as a primary objective to create models with a perfect fit on future projections. Modellers should keep in mind that it is impossible. Nevertheless, our efforts should go towards to this target [21].

IV. Discussion

In Athens, the phenomenon of uncontrolled urban growth in peri-urban area does not appear as a consequence of a post-urbanization, as in western metropolises but a particular way of development was taken place. The urban development of Athens metropolitan area was unplanned and unregulated [24], [25]. Thus, for example, in the postwar period (1950-1970) which is characterized by massive waves of internal migration, urbanization of the western districts was occurred. This will gradually decrease after 1980 (decrease of the rate of internal migration). During the last period (1981 to date) the life standards have changed significantly leading to greater consumption of space by moving to less densely populated suburban neighborhoods and urban expansion in off-plan building areas and areas in the east part due to the airport. Some convergence towards western standards gradually appeared, which is accompanied by better housing conditions and quality of life. Thus, the spatial development of the Athens metropolitan area took place in remote locations scattered broken with considerable difficult planning organization. It should also be noted the irregular building which played an important role in urban development, a characteristic feature of the Mediterranean [26].

Each of the successive phases of development was characterized by different dynamics of urban growth. It is of great importance the weakness of the official design to control the urban development trends. This is recorded both at the macro level (planning of urban and metropolitan infrastructure expansions), and the micro level (arbitrary demolition, off-plan building). In the recent period the policy framework has changed radically with the development objectives towards promotion of urban competitiveness. The Olympics played a key role in initiating this development.

After having considered the irregular building which is strongly occurred in Athens metropolitan area it can easily be implied that no-one urban growth model could detect these changes. Many modelling techniques can be applied in urban changes. In [11], after a review of a plethora of urban growth models, the following are the most familiar (in hierarchical order from the most to the least familiar): cellular automata, logistic regression, ANNs, fractals, agent-based models, linear regression and decision trees. ANNs, which is used in this research are incorporated in urban growth models due to their modeling capabilities. Unlike most multi-variate modeling techniques, ANNs are independent from input data relationships, therefore no assumptions about spatial autocorrelation and multi-collinearity need to be taken into account.

It is out of the authors' expectations to consider this study as another one which added to the bibliography of urban growth models with a controversial practical importance. Our aim is to highlight the planning problems of the Greek capital and to propose a methodology of predicting urban growth in order to be used by administrative planners and decision makers. It is well known the gap between urban modellers and urban planners. In [11] there is a thorough discussion of the causes of this gap, such as data availability, prediction quality, clear expectations, communication, usage support, etc.

V. Conclusions

An ANN urban growth model was developed in order to simulate the urban changes in Athens metropolitan area. Our effort was to produce a model as simple as possible so as to be easily used for non-experts. Therefore, the drivers used to describe the changes were as few as possible and all the data (urban land use maps, drivers) were open-source data. Urban changes from 1990 and 2000 were used for model simulation. Prediction for 2006 was achieved and the results were validated using a reference map of 2006. The accuracy was satisfactory and therefore the proposed methodology is highly recommended. Urban planners in Athens should be the recipients of this urban growth model because as it has been already mentioned; only a good communication and cooperation between urban modellers and urban planners could lead to a sustainable urban development.

In this context models have high explanatory power but some disadvantages appear. The basis for the model simulation is the past. But the past is not always the best driver to predict future transitions. Urban changes between one time period may be different from those in the future. Many times, political reasons are more dominant in urban change. Actually, in urban growth modelling interdisciplinary research should be adopted. Apart from being a tool for describing system dynamics, urban growth models are important in predicting future scenarios. These exploratory and predictive capacities allow models to be useful tools in local stakeholders involved in urban change decision making.

Finally, the urban growth in Athens metropolitan area in the future will depend on the available funds, accessibility improvement (railway and metro networks), land speculation and lack of land use control.

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