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Generating a Future Land Use Change Scenario with a Modified Population-Coupled Markov Cellular Automata Model

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ABSTRACT. With the population increasing and land use patterns changing, there will be environmental consequences. To solve these impending problems, information on the future land use pattern is needed. This study attempted to develop an enhanced land use model, capable of predicting future conditions. The traditional Markov model was modified by incorporating a Cellular Automata (CA) and a population variable to depict the neighboring effects and the impacts of population growth on urbanization. The performance of this new model was quantitatively assessed by generating the 2001 land use patterns of the East Fork Little Miami River watershed in southwest Ohio with and without the CA and the population variable and compared with the actual 2001 land use imagery. From the comparison, it was apparent that the land use map generated with the CA and population variable was more accurate. To further ascertain its applicability in a larger watershed, the same procedure was used to model the entire Little Miami River watershed. The validation results demonstrated that the performance of the modified CA-Markov model at both watershed scales was acceptable, and the inclusion of the CA and population variable could markedly improve model predictability. Based on these findings, the 2030 land use scenario for the LMR watershed was postulated. The resultant map showed much urban expansion in the western and southern portions of the basin. This information can be useful to planners and resource managers, enhancing their efforts in generating more sustainable future development strategies.

Keywords: Markov, CA-Markov, population growth, land use modeling, urbanization, multi-criteria evaluation

1. Introduction

Our world is changing rapidly in land use patterns; never in our history had we witnessed such a rate or magnitude of change. With the economic development, population growth, and in-migration, many places are experiencing expeditious urban expansion and sub-urban sprawl, which can cause significant environmental consequences, such as changes in surface runoff and water quality (Tong et al., 2011). Moreover, future climate changes may further interact with these physical and socio-economic factors, exacerbating the transformation of landscape and degrading environmental qualities (Lambin et al., 2001). With the anticipation of these changes and the associated environmental problems, it is of paramount importance to be able to postulate the future land use conditions so that we can better plan for sustainable future developments. However, the prediction of future land use is often complicated as there are many intrinsic, inter-dependent, and interrelated socio-economic and biophysical drivers controlling the process of land use change (Parker et al., 2003).

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This paper attempted to develop an enhanced Markov-based spatial dynamic modeling procedure to predict the prospective land use conditions. The goal was to improve the prediction accuracy of the original Markov land use model by coupling it with a Cellular Automata (CA) and the trend of population growth through Multi-Criteria Evaluation (MCE). The integration of a CA with Markov will take into account the neighboring effects in calculating the transition probabilities (Eastman, 2006). Additionally, since population growth is often an important socio-economic factor driving urban growth (Li et al., 2003, Liu et al., 2005), it is hoped that by considering population density in the study area, this modified Markov Cellular Automata Land Use Change Model (CA-Markov) could explicitly simulate the tendency of urbanization and suburban sprawl. Through the validation process, the efficacy of this enhanced population-coupled CA-Markov land use model in simulating urban expansion and in making realistic predictions of the future land use conditions was explored.

2. Methodology

2.1. Study Areas

This research used the East Fork Little Miami River (EFLMR) watershed, a sub-watershed of the Little Miami River (LMR) in southwest Ohio, as a pilot study to first develop an enhanced land use model. After the model was developed

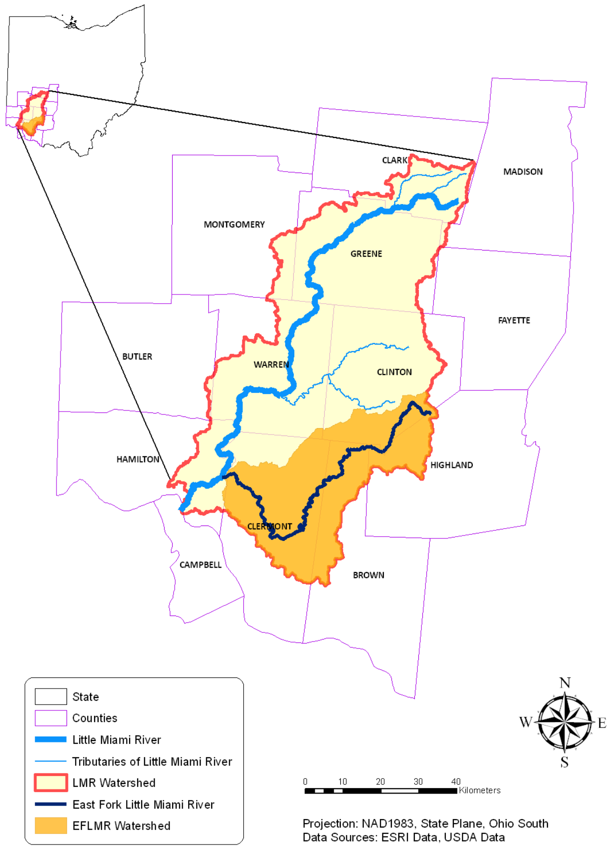

Figure 1. The East Fork Little Miami River and Little Miami River watersheds.

and validated, it was extended to the whole LMR watershed to ascertain its applicability and effectiveness in a larger watershed. Figure 1 shows the geographic locations of the EFLMR and LMR watersheds in southwest Ohio.

2.1.1. Rationale for Choosing the EFLMR and LMR Watersheds

Originating at the southeast of Springfield in Clark County, Ohio, the LMR flows 169.78 km to join the Ohio River at the confluence near the eastern side of Cincinnati, draining an area of 4,550.6 km^2. Within the LMR watershed is a sub-basin of the EFLMR, which only covers 1,295 km^2. Because of its small size, EFLMR watershed is an ideal area for a pilot study as it will enable easier and simpler model development and validation. Besides, if the modeling results are promising in this small and predominantly agricultural sub-watershed with a moderate population density, it is likely that the model will be able to generate a relatively accurate future land use pattern for a larger watershed with a higher population density and a faster rate of urbanization.

The main reason for choosing the LMR basin in this study is because it is an important growth area in southwest Ohio (Ohio Department of Development, 2010). The LMR watershed was once predominately agricultural, but in recent decades, there have been rapid population growth and land use changes. The good transportation systems offered by the rivers, highways, railroads, and regional airports; the mild climate; as well as the abundant supply of water from its aquifer help to facilitate urbanization and economic development. As shown in Table 1, the agricultural land use in the LMR watershed has experienced a drastic decrease from 80.3% in 1976 to 56.2% in 2001, whereas the urban land has increased by 6.8%. In the same period, population from the ten counties in the basin has grown from 2,371,943 in 1980 to 2,558,509 in 2000, an increase of 7.87% of the population (US Census Bureau, 2010). These rates of changes in land use and population are among the highest in Ohio. Similar situations, though in a lesser magnitude, are found in the sub-watershed of the EFLMR; in 1976, almost 70% of the land was agricultural, 12% forests, and 7% urban. But, the amount of agricultural land has been decreasing, and it is now accounting for only 57% of the total area in the EFLMR basin (East Fork LMR Watershed Collaborative, 2007), and much of the former agricultural lands are now encroached by urban development. Any further demographic and land use changes in the EFLMR and LMR watersheds will certainly have major environmental consequences. Earlier studies by Tong (1990), Wang (2001), Tong and Chen (2002), Tong and Naramngam (2007), and Tong et al. (2008; 2011) had demonstrated that changes in land use patterns in the LMR basin have caused significant hydrologic and water quality impacts on the downstream receiving water bodies.

Table 1. Land Use Categories in the LMR Watershed in 1976, 1992, and 2001 by Percentages

Land use types	1976	1992	2001
Water body	0.6%	0.9%	1%
Urban area	11%	17%	17.8%
Forests	7.6%	24.1%	23.7%
Agriculture	80.3%	56.7%	56.2%
Others	0.4%	1.3%	1.4%

2.1.2. Physical Geography of the LMR Basin

The LMR watershed has a cool temperate climate; summers are warm and humid with an average high temperature of 30 °C and low temperature of 15 °C, whereas winters are moderately cold with few annual winter frosts and snowfalls. Winter temperature highs are mostly around 0 °C and lows about -10 °C. Average annual air temperature ranges from 10°C in the north to 13 °C in the south. Average snowfall in the watershed is 50 to 76 cm per year, and the average annual precipitation ranges from 90 to 110 cm, approximately one-third of which becomes surface runoff (Debrewer et al., 2000).

The entire LMR basin lies within the clay-rich Till Plains comprising mainly of glacial till and loess irregularly overlying limestone and shale. At the bedrock valley are outwash deposits composed of sand and gravel. These bed rock deposits exert considerable impacts on surface water by absorbing large quantities of rainfall, releasing it throughout the year, especially during the low-flow seasons (Schneider, 1957).

The soils in the region belong to the deep, moderately well drained, and highly productive Genesse-Williamsburg Association. They were formed from the silts, alluvial, and residual materials from the glacial drifts, outwash, and tills (Lerch et al., 1975). Soils on the older till plain in the southeast exhibit more drainage problems and have been less extensively cultivated than the younger till-derived soils in the northwest.

2.2. Approaches to Generate Future Land Use Scenarios

Despite the fact that there are existing future land use plans from different administrative offices (such as county offices) comprising the LMR basin, which can be processed to produce future land use scenarios, there are several drawbacks in this approach. The most notable one is that since the administrative boundaries may not necessarily coincide with the physical boundaries of a watershed, there will be a need for multiple future land use maps from various administrative offices, which often are not consistent, differing in terms of spatial and temporal scales and the degree of details. Due to this shortcoming, some researchers resolve in using statistical analyses, such as correlation and regression analyses, to generate future land use scenarios. By employing the socio-economic determinants and physical drivers as independent variables, regression equations can be derived to predict future land use changes. But due to the dynamic nature and uncertainty of the land use change process, these techniques are often inadequate to predict future changes. This is mainly because most statistical methods can only characterize simple and uniform changes in the form of linear, polynomial, exponential, or power functions, but not complicated processes driven by a multitude of spatial and temporal factors and multi-directional change patterns (Parker et al., 2003).

The other method is to employ a spatially explicit and dynamic land use model to quantitatively describe the underlying system attributes and their interrelations, as well as to postulate the future land use pattern. This is a more common method as it is convenient and can allow the researcher to examine the spatial and temporal drivers for land use change and to predict the future conditions under certain known assumptions (Li and Yeh, 2002). Thus, this approach often provides more realistic results. As pointed out by Silva and Clarke (2002), the use of spatial explicit modeling, coupled with remote sensing and geographic information systems (GIS), offer an alternative means of research, enabling an efficient characterization of the current conditions, the detection and monitoring of spatial and temporal changes, and the prediction of future land use patterns. In this research, the method of land use modeling was adopted to characterize the existing land use pattern and to generate future land use scenarios.

2.3. Selection of the Land Use Model

A literature search had been conducted to identify an appropriate model for use in this study. The criteria for choosing the land use model were: theoretical suitability, predictive power, requirement of data inputs, ease of use, and compatibility with the commonly used GIS systems, such as ArcView and ArcGIS, as well as feedbacks from other users. In this study, the traditional stochastic Markov chain model was first selected because it is a dynamic, spatial, and stochastic model. A dynamic model is preferred over a static model since it is capable to simulate land use change over time. The fact that the Markov model is a spatial model is also desirable as it can produce spatial maps. Moreover, being a stochastic model instead of a deterministic model is beneficial, as there is often a certain degree of randomness and uncertainty in the land use change process, and a stochastic model will be more effective in simulating these changes. Many researchers, including Bell (1974) and Tang et al. (2007), had employed Markov-based models to explain land use change.

Markov chain is a stochastic process that simulates the changes from a current state to the next state using a transition probability matrix. In Markov chain, there is a series of random values; the probability of each of these values at a certain time interval is dependent on its value at the previous time period. When used in land use change analysis, Markov chain relies on two sets of historical land cover images to analyze past land cover changes. By using the earlier land use patterns as the basis to project future conditions and assuming that land use change is a stochastic process, Markov chain describes land use change from one period to another. The changes in each land use category between these two time periods are calculated, transition probability matrices and a group of transitional probability images are generated to represent all the multidirectional land use changes between land use categories, and the potential for future changes is modeled. Thus, in the Markov analysis, the predictive modeling of the future land use is based on the changes in land use patterns between these two periods through a probabilistic process.

Although Markov chain may produce accurate time transition probabilities for each category of land use, it does not provide any geographical element in its analysis. Consequently, even if the dynamic transition probabilities may be accurate on a per category basis, the analysis cannot portray an accurate spatial distribution of these land use categories, as such it is more functional as a descriptive tool in land use change analysis instead of a predictive tool in generating future land use patterns. Another weakness of Markov chain analysis is related to the fact that it assumes that the transition probabilities do not change over time, which may not be valid under some situations (Sun et al., 2007). Hence, Markov model often produces poorer predictions of land use change, especially if the geographic patterns are taken into account, and further modifications are required (Brown, 1970). To address these shortcomings, this study also developed another land use model by incorporating the traditional Markov model with a CA and a population variable through the MCE method to depict the spatial dimension and contiguity as well as to include suitability knowledge in the analysis.

CA is a simple and computationally efficient method capable of simulating spatial contiguity and temporal-spatial dynamics at high resolution. It was first used by Von Neumann for self-reproducible systems (Couclelis, 1989). Since then, it has been widely applied in modeling the growth of cities and the evolution of land use (Tobler, 1970). In a CA system, there are four basic elements: the cells, states, neighborhoods, and rules. The cells are the smallest spatial units, and the states are the attributes of the cells at a given time step. For each neighborhood, there is a set of well-defined relationships between the cells, and there are rules to define the states of the cells in each time step (Thapa and Murayama, 2011).

As a discrete and dynamic system, CA studies each grid cell, assuming that the geographical space and cell states are discrete. Additionally, it examines the dynamic behaviors of the state in each cell over time (Wolfram, 1984), thereby capturing the dynamic nature of land use change. In land use modeling, the geographical space of the CA is represented by grid cells, and their states are denoted by finite, integer numbers. The state of each cell is governed by the local relationship between the cell and its neighbors (Abdalla et al., 2006), as such it not only influences its neighbors, but it is also influenced by its neighbors. The contiguity rule embedded in a CA ensures that a pixel located at the proximity of a specific land use category will have a higher probability to become that category. For this reason, the suitability value of each pixel is dependent on whether there are pixels of the same category in the neighborhood. Since time is progressing in uniform steps in a CA, the state of each cell is evolved in discrete time steps across the geographic space according to its own state, the configuration of its neighborhood, as well as some pre-defined local transition rules (White and Engelen, 1993). With the neighborhood functionalities and contiguity rule, CA can therefore simulate the complicated land use change process over time and space (Wolfram, 1984) and provide a more accurate simulation of the spatial characters (Eastman, 2006). As contended by Tobler (1970), it is important to consider the neighboring effects and spatial contiguity in land use change modeling. In this research, we integrated a CA and a population variable into the Markov model through MCE.

MCE was first developed in regional economics as a decision support method for structuring and aiding complex decision making processes (Proctor, 2001). In the last two decades, the technique is becoming popular, and its application has been greatly expanded. Some researchers have integrated it with GIS (Carver, 1991) and applied it to land suitability analyses (see, for example, the work of Pereira and Duckstein, 1993).

MCE uses a variety of user-defined criteria, either as a factor or a constraint, which can be represented as map layers in a GIS (Eastman, 2006). In this study, the factor used in MCE was a population variable, represented as a population density map showing the changes in population distribution. Using mathematical functions, map algebra, and spatial overlay, MCE integrates these criteria, calculates the suitability of each land cover category, supervises the spatial allocation of the predicted time transition probabilities, and displays the results as suitability maps. When used with the CA-Markov model, MCE has the ability to incorporate the impacts of various spatial or temporal variables under the complex hierarchical transition rules (Zhang et al., 2008). Furthermore, by enabling a spatially explicit weighting factor, CA-Markov with MCE method considers both the factors causing land use change and the probabilistic randomness. Consequently, MCE can be used to define transition rules and to determine the parameter values of a CA model (Wu, 2002). The ability of parameterization in MCE is ideal because it provides a certain degree of transparency and flexibility in the modeling exercise, allowing the balance of different processes and factors to be addressed explicitly. As a result, the model can generate more realistic changes in different cells, improving the simulation of the patterns and spatial structure of land use and land cover. Indeed, the CA-Markov model is a combined Cellular Automata/Markov chain/Multi-criteria/Multi-objective land allocation land cover prediction procedure that adds an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to the traditional Markov chain analysis. By aggregating the automatic Markov chain analysis which computes land cover time transition probabilities with the geographic supervised CA analysis of spatial contiguity and land cover suitability, the CA-Markov can predict any transition among any number of land use categories. As a result, it can generate a better spatial pattern of the land use categories and can be used for more accurate future land use prediction. Many researchers, including Ward et al. (2000), Pontius and Malanson (2005), Paegelow and Olmedo (2005), Cabral and Zamyatin (2006), Sun et al. (2007), and Ye and Bai (2008) found the CA-Markov model to be valuable in land use predictions. For example, by using Markov chain, MCE, and CA in their land cover modeling of Garrotxes in France and Alta Alpujarra Granadina in Spain, Paegelow and Olmedo (2005) found that the accuracy of their prediction results had greatly improved.

Both the Markov and CA-Markov models used in this research are available in the IDRISI Andes software (IDRISI, 2008), an integrated GIS and image processing software for displaying and analyzing spatial information. IDRISI provides not only good facilities for map display, map composition, 3D visualization, and other common GIS and image processing functions, but also a suite of tools and models for cartographic and spatial analyses, land use planning, decision support, risk analysis, spatial statistical analysis, time-series analysis, and surface analysis. The software can be used to predict future land use and land cover changes through the Markov stochastic model or the CA-Markov modules. Moreover, the validation criteria, such as the Relative Operating Characteristics (ROC) and the Kappa index of agreement, are available in the software, facilitating easy assessment of model accuracy.

2.4. Development of the EFLMR Watershed Land Use Model

As a pilot study, a Markov land use model for the EFLMR basin was developed first. A polygon of the study area was obtained from the National Resources Conservation Service (NRCS, 2008). Using the polygon as a mask and the extraction function in ArcGIS, the environmental data, such as land use, topography, and river reaches, for the watershed were extracted from meta-datasets. The data were clipped, merged, and managed in a GIS.

To build the Markov land use model for the EFLMR basin, three sets of historical land use records were required: two would be used to determine the pattern of land use change and to "train" the Markov iteration process, and the other set was used for validation. A search in the database had found a few

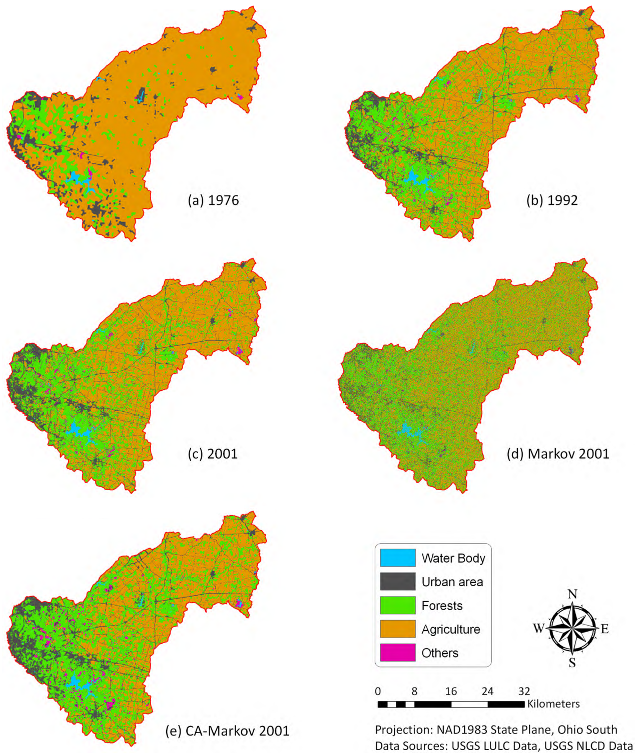

Figure 2. EFLMR watershed land use maps from USGS: (a) 1976 LULC, (b) 1992 NLCD, (c) 2001 NLCD; and projected 2001 land use maps for the EFLMR watershed: (d) from Markov, (e) from CA-Markov with the population variable.

Table 2. Reclassification of the Land Use Categories

Land Use Reclassification*	Descriptions
Water body	Streams, Lakes, Reservoirs
Urban area	Industrial, Residential, Commercial, Transportation, Mixed Urban or Built-up Land
Forests	Deciduous forest, Evergreen forest, Mixed forest
Agriculture	Crops, Pasture
Others	Wetlands, Barren

* The original land use datasets were reclassified to five land use categories using Anderson Level I classification system: “Water body”, “Urban area”, “Forests”, “Agriculture”, and “Others”.

comprehensive and compatible datasets available for the EFLMR area: the 1976 Land Use and Land Cover (LULC) and the 1992 and 2001 National Land Cover Data (NLCD) from the U.S. Geological Survey (USGS). The data from LULC were derived from aerial photographs from the Geographic Information Retrieval and Analysis System (GIRAS), whereas the data for the NLCD were derived from the 30-m resolution satellite imageries from the Multi-Resolution Land Characteristics Consortium (MRLC). The 1992 and 2001 land use data were the retrofit data recently published by USGS, which had been reclassified using Anderson I supervised classification and rectified for changes in elevation. Nevertheless, the resolution and the amount of details in the LULC and NLCD imageries were different. There was also a dataset from the U.S. Environmental Protection Agency for the study area, but it was collected by a low-flying airplane with hyper-spectral sensors, and it was only for the year of 2002.

With these constraints, we had decided to use the USGS LULC 1976 and the NLCD 1992 land use maps (Figures 2a, b) as the training maps and the NLCD 2001 map (Figure 2c) for model validation. Although this choice was less than ideal, it was the best option available for this stage of model development.

Since the LULC and NLCD datasets were different, the land use classes for all three imageries were re-sampled and reclassified into five categories in ArcGIS: (1) Water body, (2) Urban area, (3) Forests, (4) Agriculture, and (5) Others (see Table 2). The original data were in grid format; so the maps were converted to 'TIFF' images. Moreover, they were projected into NAD 1983 State Plane Ohio South FIPS 3402 coordinate system and were resized to assure conformity in size and dimension with other data sets.

2.4.1. Markov Stochastic Land Use Simulation

The first land use scenario for the EFLMR study area was generated using the Markov stochastic method. The 1976 and 1992 historical land use maps were imported into the IDRISI Markov as the training maps to generate the transition probability matrix as well as the probability maps for each land use category, which were used later as suitability maps to simulate the final prediction.

To verify model predictability, one can adopt a visual assessment method (Pontius et al., 2008). However, since it is a qualitative approach, it is vulnerable to subjective bias. Another method is to examine the percentage of correctly classified pixels of the model output as it is compared to a reference map. Notwithstanding its simplicity, the method has some inherent problems because this method only compares two images pixel by pixel, and it does not consider the spatial patterns of these pixels, regardless of whether the correct pixel is found near a neighboring pixel or somewhere else in the map. Accordingly, a high number of correctly classified pixels may not imply that it has a good predictive power (Pontius, 2002). In this research, we used ROC to measure the degree of certainty for the suitability maps. As a method to assess the validity of a scenario, ROC compares and measures the degree of agreement between the predicted location of an occurrence, which is usually represented as a suitability map of a certain land use category, with a Boolean image showing where that occurrence actually exists. According to Pontius and Schneider (2001), a ROC value higher than 0.5 means that there are no statistical significant differences between the two compared objects. The only differences are due to randomness. In this model simulation, the ROC validation was performed by comparing the 2001 suitability map for the urban area (Figure 3a) with the Boolean image derived from the actual 2001 NLCD map of the urban area (Figure 3b).

After ROC validation, the transition probability matrix was used in the Markov stochastic model to predict the 2001

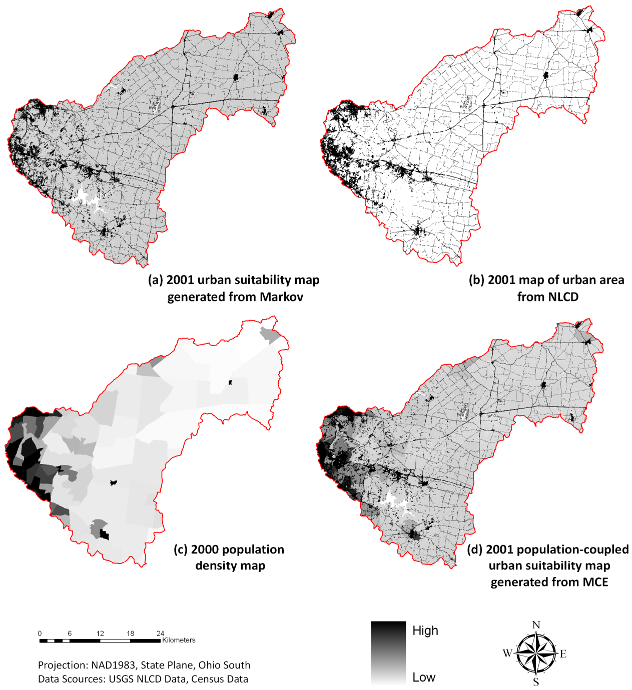

Figure 3. ROC validation for the EFLMR watershed: (a) the urban suitability map generated from Markov, (b) 2001 map of the urban area from NLCD; and development of the 2001 population variable for the EFLMR watershed: (c) 2000 population density map, (d) 2001 population-coupled urban suitability map generated from MCE.

land use of the EFLMR basin. The predicted 2001 land use pattern (Figure 2d) was compared to the 2001 USGS NLCD data (Figure 2c). Similarities between these two images were compared using an enhanced Kappa statistic, which discriminates both the errors of quantity and errors of location. It is more accurate than the original Kappa index of agreement, which only considers the errors of quantity. As a similarity index of agreement between two image pairs, Kappa provides a measurement of the overall accuracy between the predicted and the actual images. The possible values of the statistic range from 0 to 1, where 1 depicts perfect agreement, 0 means no agreement beyond that expected by chance, and the value below 0 represents complete disagreement (Pontius, 2000).

For this simulation, the training data sets were derived from different media with discordant scales. Nonetheless, the ROC value between the suitability map of the 2001 urban area and the actual urban area of NLCD imagery was 0.956, and the Kappa statistic between the predicted 2001 imagery of the EFLMR watershed and the NLCD imagery was 0.819 (see Table 3). Since both results are acceptable, it seems that the errors introduced by different sensors and resolutions may not be very significant.

2.4.2. CA-Markov Land Use Simulation with a Population Variable

From the aforementioned analysis, it is apparent that the Markov land use simulation can successfully predict a reasonable future land use pattern of the EFLMR watershed. However, since the Markov model did not simulate the neighborhood effects and geographical contiguity, a CA-Markov model was introduced to run the same set of data again. In this second simulation, suitability maps for each land use category derived from the Markov model were scaled from 0 to 255 using a linear fuzzy method available in IDRISI. The fuzzy method was used to standardize the dataset, recoding the original values to a suitability range stretching from 0 to 255 (Paegelow and Olmedo, 2005); a value of 0 indicated the lowest suitability and a value of 255 indicated the highest suitability. Moreover, a population variant was coupled in the CA-Markov model through the MCE method.

Driven by population growth, many human activities can substantially change the land use patterns. The trajectory of urban development is therefore affected by the future population. These effects of population growth in urbanization and suburban sprawl are well-documented in literature. As asserted by Li et al. (2003) and Liu et al. (2005), demographic change is one of the most significant internal factors of urban expansion. Tobler (1970) even argued that modelers should take into account the impacts of population growth in predicting future urbanization and land use change. de Almeida et al. (2003) demonstrated that by incorporating population density in the complex land use change analysis, it can improve the predictability of the land use model. It is therefore probable that by introducing a population variable into the CA-Markov model to portray the importance of population growth in urban growth and land use change, a more realistic suitability map for the urban area will be generated. Hence, in this research, a population variable was incorporated into the CA-Markov model, and its performance was assessed to determine the efficacy of such an inclusion.

2.4.3. Formulation of the Population Variable

To quantify the population variable, the 2000 population data were extracted from the census block groups; the year 2000 was selected to match with the 2001 land use map. The area of each census block group was calculated by using the "Calculate Geometry" function in ArcGIS, and the density for each census block group was computed and converted to a raster format. The EFLMR watershed mask was used to extract the population density map for the study area. The resultant population density map was then imported from ArcGIS to IDRISI through an ASCII file. Using the fuzzy method in IDRISI, the population data were scaled from the lowest population density (0) to the highest density (255) (Figure 3c). This was necessary because the density data were not normally distributed, and there was a wide range of values between different census block groups. In addition, for the purpose of conformity, all suitability maps derived from the Markov model were standardized to a scale from 0 to 255, using the same fuzzy method.

In order to incorporate the impacts of population growth and urban expansion on land use changes into the model as well as to compare the accuracy of land use projection, it was crucial to prepare another suitability map for the "Urban area" land use category with the population variant. To this end, this

Table 3. ROC Values and Kappa Statistics for Model Validation

Models	Comparisons	ROC	Kappa
EFLMR	Original suitability map for urban area from Markov without the population variable vs 2001 NLCD urban area	0.956	
	New suitability map for urban area from MCE with the population variable vs 2001 NLCD urban area	0.970	
	Projected 2001 land use using Markov model vs 2001 NLCD land use		0.819
	Projected 2001 land use using CA-Markov model with a population variable vs 2001 NLCD land use		0.929
LMR	Original suitability map for urban area from Markov without the population variable vs 2001 NLCD urban area	0.979	
	New suitability map for urban area from MCE with the population variable vs 2001 NLCD urban area	0.984	
	Projected 2001 land use using Markov model vs 2001 NLCD land use		0.812
	Projected 2001 land use using CA-Markov model with a population variable vs 2001 NLCD land use		0.913

research used the MCE method as a decision support tool to convert the population density layer to a new suitability map for the urban area and to depict the trend of population growth and urban development for input into the CA module. The weight of the population variable in MCE was determined using an Analytic Hierarchy Process (AHP) method developed by Saaty (1977). Initially, AHP was used to scale ratios based on pair-wise comparison, but it is now mainly used for complex decision making. In the AHP method, each variable is assigned with a value representing its degree of relative importance. Based on these values, the weight of each variable is calculated. In this research, two variables were considered: one was the urban suitability area, and the other was the population density. The values of each variable were assigned through trial and error. After numerous attempts, we had finally decided to assign the population variable with a weight of 16.67% and the urban area variable a weight of 83.33% in MCE because these weights seemed to produce the best results in the validation process. It was further assumed that there would be minimal changes in water bodies, and a constraint map was created to depict the water bodies. The Weighted Linear Combination (WLC) in MCE was used to generate a suitability map for the urban area scaling from 0 to 255 (Figure 3d). This was a spatially explicit weighting factor denoting the effects of population growth on urban development. The new suitability map for urban area became the population-coupled suitability map.

2.4.4. Performance of the Population-coupled CA-Markov Model

Similar to the earlier Markov analysis, the ROC was used to ascertain the effectiveness of the new population-coupled CA-Markov model. The agreement between the new population-coupled suitability map of the urban area and the actual 2001 urban map was evaluated. The results revealed that the ROC increased from 0.956 to 0.970 (see Table 3). The improvement in model performance demonstrated the benefits of incorporating the population variable and CA into the Markov land use projections for the mixed urban and rural areas of the EFLMR watershed. In light of this result, the new population-coupled suitability map of urban area, the CA-Markov model, together with the 1976 LULC and 1992 NLCD land use maps (Figures 2a, b), were employed to derive the projected land use map for 2001 for the EFLMR watershed (Figure 2e). This projected 2001 land use map was then compared with the 2001 USGS NLCD imagery (Figure 2c). The Kappa statistic was

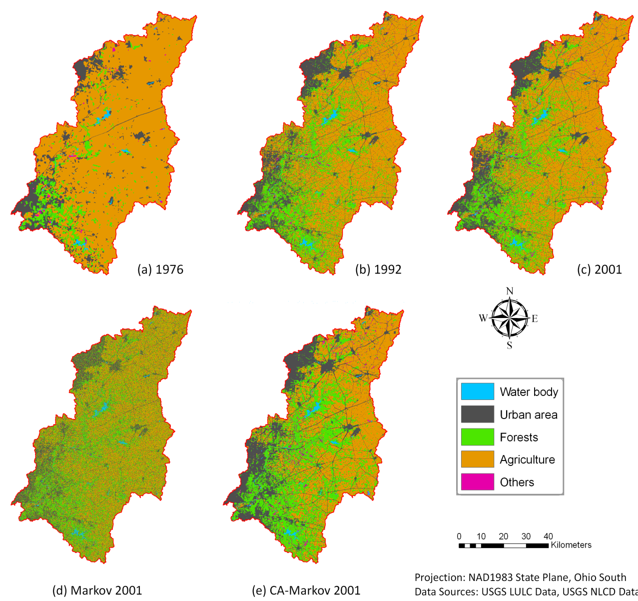

Figure 4. LMR watershed land use maps from USGS: (a) 1976 LULC, (b) 1992 NLCD, (c) 2001 NLCD; and projected 2001 land use maps for the LMR watershed: (d) from Markov, (e) from CA-Markov with the population variable.

used to compare the predicted 2001 land use map derived from the population-coupled CA-Markov with the actual 2001 land use map. The results in Table 3 showed a higher Kappa value (0.929) than that without the CA and population variable. Due to the improvement in model performance, it seems that the population-coupled CA-Markov model deserves further investigation.

2.5. Development of the LMR Watershed Land Use Model

The EFLMR watershed is a small sub-basin within the LMR watershed. Although the enhanced land use model seemed to be reliable, its appropriateness and applicability in a larger watershed needed to be assessed. To this end, the model was extended to the entire LMR watershed for further validation. Following the same procedure as outlined in the EFLMR pilot study, a Markov land use model for the LMR watershed was developed using the 1976, 1992, and 2001 land use maps (Figures 4a, b, and c).

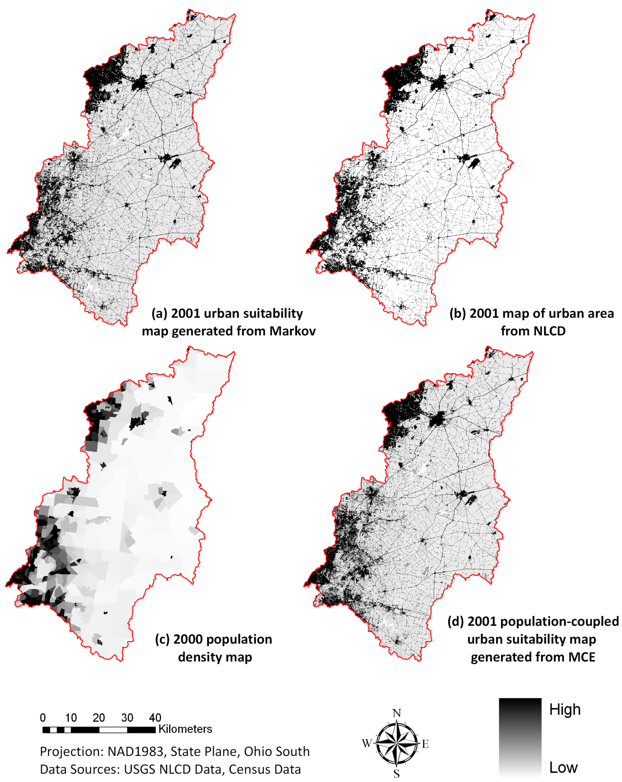

Figure 5. ROC validation for the LMR watershed: (a) the urban suitability map generated from Markov, (b) 2001 map of the urban area from NLCD; and development of the 2001 population variable for the LMR watershed: (c) 2000 population density map, (d) 2001 population-coupled urban suitability map generated from MCE.

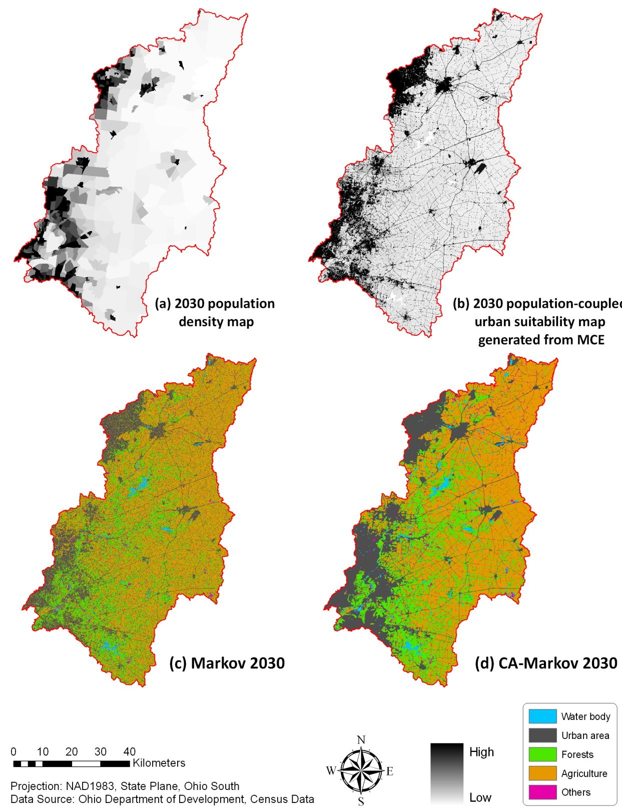

Figure 6. Development of the 2030 population variable for the LMR watershed: (a) 2030 population density map, (b) 2030 population-coupled urban suitability map generated from MCE; and projected 2030 land use map for the LMR watershed: (c) from Markov, (d) from CA-Markov with the population variable.

The 1976 and 1992 base maps of the LMR basin were imported into IDRISI to calculate the transition matrix between each land use class. After running the Markov model, a transition area file and a set of five probability images for each land use class were created for 2001. For validation purposes, the suitability map for the urban area (Figure 5a) was compared to the NLCD urban area (Figure 5b). The ROC result was 0.979. When the suitability maps for all land use classes were imported into the Markov model, a projected land use map for 2001 for the LMR basin was generated (Figure 4d), which was then compared with the NLCD 2001 land use image (Figure 4c). The Kappa statistic for the Markov model was 0.812.

The next step in the analysis was to incorporate the population variable into the CA-Markov model and to assess the performance of this new model. Using the same techniques as described earlier, the population density of the LMR watershed was calculated based on the 2000 census data, which was further converted into a standardized scaling map (Figure 5c) to impart the influence of population distribution and growth as a quantitative weight in urbanization.

The WLC method in MCE was employed again to generate a suitability map for the "Urban area" land use category, and the population variable was given the same weight as the one used in EFLMR pilot study. A new suitability map of the urban area for 2001 was generated and imported into the CA-Markov model. MCE was used once again to incorporate the population variable and to simulate a land use distribution map for 2001. Figure 5d shows the urban suitability map for the 2001 land use projection with the population variable. Figure 4e displays the projected land use map for 2001 with the population variable after using MCE and CA-Markov.

The accuracy of the land use projection generated from this enhanced model was validated using the ROC and Kappa statistics. As in the pilot study, both results showed good agreement between the predicted and the actual land use area in each category (Table 3). The projected 2001 land use with the population variant and the CA-Markov model displayed a better match with the actual 2001 land use than the projected 2001 land use without the population variable and the CA. With these results, we are confident that the population-coupled CA-Markov model is a reliable model. It should be able to predict the 2030 land use change in the LMR basin reasonably well.

2.6. Generation of the 2030 LMR Land Use Scenario

The model verification attested to the advantage of coupling a population variable with the CA-Markov model in land use projections. The findings of a 0.970 ROC and a 0.929 Kappa statistic for the EFLMR watershed and a 0.984 ROC and a 0.913 Kappa statistic for the LMR watershed indicated an improved model reliability and predictability. Based on these validation results, the land use scenario for the year 2030 in the LMR watershed was generated using the CA-Markov model in conjunction with the 2030 population variable generated from MCE. In order to be able to plan for the future, it is important to have a better knowledge of the future land use pattern. The year 2030 was used because water resources infrastructure often has a life-span of fifteen to twenty years; a prediction of the land use conditions for the year 2030 will be helpful to resource managers and city planners. Besides, this study was a part of a larger research project investigating the amalgamated impacts of global changes on water resources in which the horizon year was set to 2030. Furthermore, the 2030 population data could be derived from the official population projection of the Ohio Department of Development (2010).

Following similar procedures, the 2030 land use scenario for the LMR watershed was generated using the NLCD 1992 (Figure 4b) and 2001 (Figure 4c) land use maps as the training maps. Both of these datasets were extracted from the NLCD metadata sets; they had the same spatial resolution and were generated using the same image processing and classification methods. The 2030 population data from the Ohio Department of Development (2010) were used to calculate the population density (Figure 6a) and generate the population variable (Figure 6b), which was then incorporated into the CA-Markov using the MCE. Finally, the CA-Markov model was used in conjunction with the 2030 population variable to generate the 2030 land use scenario for the LMR watershed (Figure 6d). Accordingly, this scenario of land use change was based not only on the information of land cover change from 1992 and 2001, but also on the projected population growth from 2001 to 2030. Thus, this 2030 land use change scenario may be more useful to the local planning and management agencies since it also represents how population growth may affect urban land use change.

3. Results

Before generating the 2030 land use scenario for the LMR watershed, two models were examined: the Markov model and the CA-Markov model with a population variable. As a validation process, these two models were used to generate the 2001 land use maps for the EFLMR and LMR watersheds, and the results were compared with the 2001 NLCD maps. As shown in Table 3, the results from the CA-Markov model coupled with the population variable were better, with higher values for the Kappa and ROC statistics, revealing a higher degree of model performance and confidence level.

In the pilot study, the projected 2001 land use map of the EFLMR basin by Markov model was based on the transition probability matrix. Since it was generated by a stochastic process, it did not take into account the spatial distribution and contiguity of the land use categories. Consequently, the model output did not reflect the spatial characteristics of the land use nor the geographical relationships. As the main objective of this study was to postulate the future land use pattern of an urbanizing watershed, a better representation of the spatial pattern of urban growth was desirable. The CA-Markov model considered the spatial contiguity and the neighboring effects of each pixel in the land use map, generating a more geographically-based projection. By taking advantage of the CA, a spatially more explicit result was generated, enhancing the predictability of urban growth. Moreover, by coupling a population variable in the CA-Markov model through MCE, the effects of population growth on urbanization were modeled. The performance of this new model was quantitatively ascertained by comparing the simulated 2001 land use map with the data from the historical 2001 land use map. As evidenced by the Kappa and ROC values, the 2001 EFLMR land use map produced by the population-coupled CA-Markov model was more satisfactory; there was a marked improvement in model performance with ROC of 0.970 and Kappa statistic of 0.929. A visual comparison of the 2001 population-coupled CA-Markov model results with the 2001 NLCD imagery of the EFLMR revealed that the model was able to capture the urbanization process, even in this small predominately agricultural watershed.

Table 4. Projected Land Use Changes in the LMR Basin by Different Categories in 2030

Land use (sq km)	Year 1992	2001	2030
Water body	40.574	44.105	83.750
Urban area	775.039	809.582	1025.246
Forests	1098.124	1076.452	1048.795
Agriculture	2574.744	2555.441	2309.318
Others	60.196	63.096	81.680

When this enhanced land use model was extended to LMR basin, similar results were attained. The 2001 LMR land use map produced by the population-coupled CA-Markov model had a ROC of 0.984 and a Kappa of 0.913, which were higher than that without the population variable and the CA. These results confirmed that by incorporating the growth of population as a variant affecting urban area expansion into CA-Markov, the model performance had markedly improved. They also proved that this new population-coupled CA-Markov land use model was reliable even in a larger watershed. In terms of performance, this new model was certainly more advantageous than the traditional Markov chain, as it provided a more accurate land use prediction. These results also asserted that the adopted approach was appropriate in this study area where urban development is driven by population growth.

The simulated 2030 LMR land use scenario showed a substantial decrease in agricultural lands and an increase in urban areas. The change in the land use pattern was more evident than that projected by using the Markov stochastic model (Figure 6c), which depicted a smaller urban area. When GIS was employed to calculate the area extent of each land use category from the maps, it indicated that the new urban area would increase from 809.582 km^2 in 2001 to 1025.246 km^2 in 2030 (Table 4). A more extensive urban area was predicted to occur on the western and southern sides of the LMR watershed and

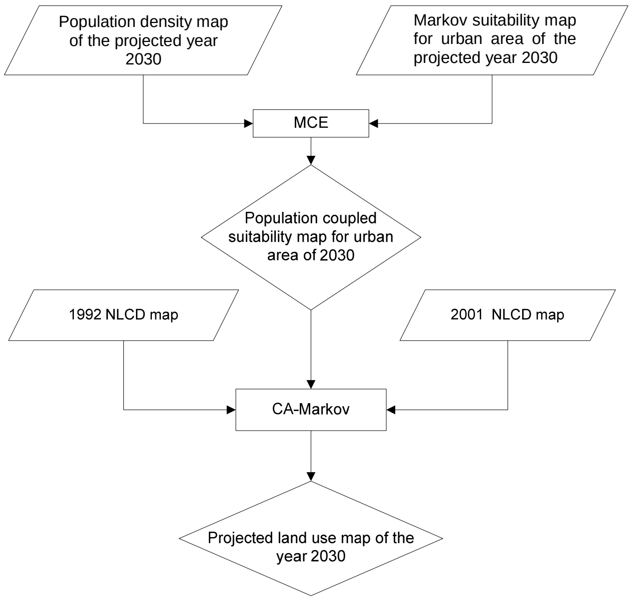

Figure 7. Schematic diagram showing the framework for building the modified population-coupled CA-Markov model to predict the 2030 land use pattern in the LMR basin.

along the major transportation thoroughfares (Figure 6d). Conversely, the agricultural land would decrease from 2555.441 km^2 to about 2309.318 km^2. These results were reasonable, concurring with our expectation based on the trend of recent developments.

4. Discussions and Conclusions

This study described a procedure used to develop a modified population-coupled CA-Markov model for generating a future land use change scenario for the LMR watershed. Although researchers, such as Paegelow and Olmedo (2005), Cabral and Zamyatin (2006), and Sun et al. (2007), had used CA-Markov in their land use modeling, they did not consider population growth as a socio-economic driving force of urban development and land use change. Ward et al. (2000) had used slope, distance from roads, and distance from population centers as constraints. de Almeida et al. (2003) had integrated various socio-economic and infrastructural factors in their land use modeling. However, both studies did not incorporate the population variant in their models as well. To address this gap, the modified CA-Markov model in this research was based on not only the stochastic change but also the neighboring effects of population growth, providing information on both the uncertainty and the geographic patterns of the future land use change. Quantitative assessment results through model validation from the 2001 land use data for both the EFLMR and LMR watersheds indicated that the use of this population-coupled CA-Markov model was appropriate, as it had enhanced the performance of the Markov model, increasing the predictability and the reliability of the model results.

Overall, the proposed modeling approach was effective in simulating land use changes. It was convenient to use, as it could operate in the commonly used GIS environment. Moreover, it was capable of GIS and spatial analyses. Additionally, since the methodology was based on an available GIS package, IDRISI, the approach could be easily adapted by other researchers to model other geographic areas. Therefore, this study had provided an easy and more accurate approach to land use prediction. The study also affirmed the advantage in considering the effects of spatial contiguity and population growth in land use modeling. These results may contribute to the scientific community in land use modeling, as other researchers and practitioners may find the tool and the concepts useful.

Nonetheless, one should note that this modeling exercise was based on historical processes of land use change and the predicted population change. It did not consider other factors, such as future climate change, extreme climate conditions, or city planning policy and development strategies fluctuations. One therefore has to use the simulation results with caution as they can only provide a future land use scenario.

Using the enhanced model, we also predicted the land use pattern for the year 2030 in the LMR watershed. For easy reference, the framework of the procedure used in developing the 2030 land use scenario is depicted in Figure 7. The 2030 land use map showed a more realistic land use pattern with more urban development in the western and southern portions of the watershed. This land use map can provide useful information to researchers. For instance, they can use the map in their studies of global changes. The 2030 land use map may also be used as an input parameter in hydrologic and water quality modeling to predict the future conditions in water resources. Moreover, the 2030 land use scenario can provide better information to facilitate government agencies, policy makers, and urban planners in their decision makings, enabling them to make appropriate sustainable development strategies, adaptation programs, and mitigation measures for environmental protection in the future. To cite an example, under the projected land use changes, there will be large aggregates of urban land use in the western portion of the LMR watershed. With these new urban developments, a series of environmental problems are likely to occur, including urban heat island effect and micro-climate change, non-point source pollutant loading, and increased water usage and wastewater discharges, which may pose new challenges to the future management of surface water quality and ecological functions in the watershed. To ensure sustainable development, new comprehensive planning and management schemes have to be derived (Pielke et al., 2007). The 2030 land use scenario generated from this study may be helpful in providing the necessary information for such an endeavor.

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