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Research Paper

Evidence-bases environmental planning: CA-Markov in the analysis of land use change in a Taiwanese town

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ABSTRACT

Urbanization is a global phenomenon and expanding gradually into rural areas, creating transportation problems, consumption of resources and destruction of open spaces. Changes to our land are another irreversible impact caused by urbanization, affecting our environment and landscape and creating an impact on the ecological system that cannot be overlooked. A simulation model is built in this study according to the characteristics of spatial changes of the study area as well as, the CA-Markov theory. The impact factors for spatial changes in the study area are investigated and identified in the model. Then, a potential case of spatial changes in the study area is presented through quantitative results to investigate how the set-up for the model structure affects the results. Finally, the landscape metrics is used for calculation and analysis to review the development of the study area through landscape ecology theory. Overall, the CA-Markov model is effective in simulating and predicting spatial changes. The results complemented by landscape metrics analysis are proven to be able to provide more information to interpret the results of spatial change and evaluate the ecological quality.

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INTRODUCTION

According to statistics from the United Nations, more than half of the world's human population was expected to reside in urban areas by 2002, with this rate set to increase over time (Seto and Fragkias, 2005). These social and environmental impacts, together with the expansion of urban space, will be one of the main challenges that urban planners face in the 21st century (Aguilera et al., 2011) (Ji et al., 2006). Thus, many scholars have continued to study the issue of land changes from different perspectives. Relying on computer technology to assist in planning has become increasingly important in order to understand the complex dynamics involved in land planning (He, 2006). The development of geographical information system (GIS) has been beneficial to landscape planners.

The emergence of many landscape simulation tools brought about by GIS has indirectly led to the development of many new planning support models, including the cellular automata (CA) theory. This theory has a simple model structure with a method of cell calculation naturally compatible to GIS. The advantage of CA theory is its ability to clearly illustrate activities in a certain area, providing good dynamic information that is beneficial to planning (Silva et al., 2008). Furthermore, planning decisions made from the perspective of a dynamic model often result in a bottom-up approach as compared to the traditional top-down approach. Zimmerer (1994) mentioned that ecologically oriented developments should incorporate more of a bottom-up approach. Theories such as the CA theory start from a localized position, slowly spreading to the overall body, satisfying the bottom-up approach idea. In recent years, many academics have used the CA theory as a basis to conduct research on land planning.

Brown and Corry (2011) mentioned two important points for landscape planning strategy. First, the most effective

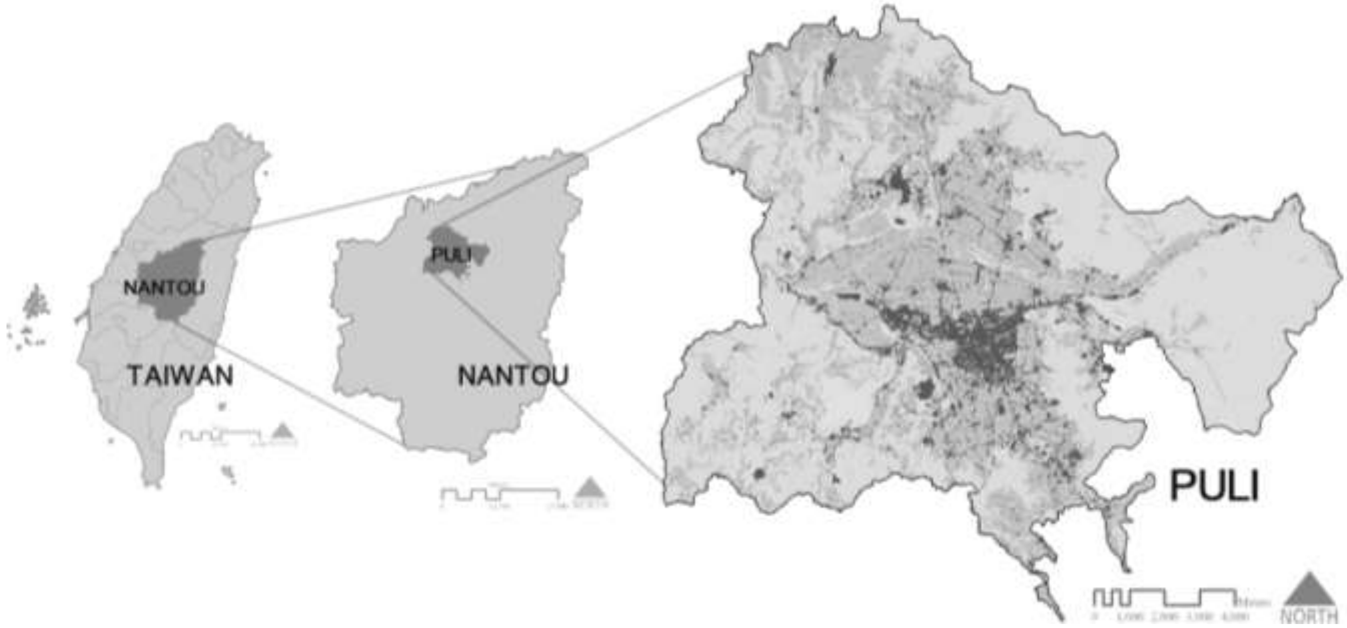

Figure 1: Study area.

planning and design strategy is to separate known facts and information from future results that are still uncertain. Second, current studies on landscape architecture lack evidence-based planning and design, hindering the quest to build a credible and leading position in land planning. In this connection, landscape ecology offers an effective data- and evidence-based foundation. The study of landscape ecology began in 1950 and focuses on landscape and spatial structure in order to understand and analyze the impact and changes caused to landscape structure by ecological changes (Forman, 1995). Studies on landscape ecology can provide sufficient information to the planner due to the ability to obtain quantitative information through landscape metrics calculations and its capacity to provide proofs regarding spatial dimensions. This allows it to combine theory and practical application and fully apply them in practical planning (Aguilera et al., 2011).

From the aforementioned, we realize the importance of computer technology in assisting planning, as well as, the possibility of using landscape ecology to apply on the actual planning. In recent years, researchers have combined those two into one. For example, researchers presented three proposals based on the CA model in the metropolitan area of Granada, Spain. The advantages of the proposals were then investigated through the landscape metrics before new policies and directions for current development and planning were proposed. This led to a fine evaluation for the results of the dynamic model and more objective data for future land planning, reducing the impact done to the environment by future development. That said, there are both merits and drawbacks for the various theories when conducting simulation scenarios. For example, the traditional Markov chain theory cannot predict the spatial structure changes caused by land changes, despite its current widespread usage and even though CA theory is effective and systematic for spatial calculations, there is a lack of demand for its usage in regard to land changes (Sang et al., 2011). Nevertheless, researchers have proposed that the two theories can complement each other. Li and Reynolds (1997) reported that the cellular automata-Markov chain (CA-Markov) model is effective and self-complementing. This combination improves the accuracy and the ability to explain simulation models, providing researchers with the ability to simulate the spatial structure in land changes more effectively.

Summarizing the aforementioned, Puli town, the center county of Taiwan geographically, needs to be evaluated and tracked (Figure 1). It has earned the nickname of “Little Luoyang” because of its lavish agriculture products and heavenly landscape. However, due to recent developments in the commercial, industrial and agriculture economies, Puli has witnessed the construction of roads and widening of urban areas as part of the government’s plan to create a new look for Puli in its quest to develop leisure, tourism, culture, religion and arts. There are also expectations that Puli can continue to protect its natural ecology and maintain its pleasant environment, in order to pass on the natural landscape and cultural assets of Puli to the next generation (Puli Town Office, 2011). It can be seen from past government data and comprehensive development plans that Puli is heading towards a future that emphasizes leisure, tourism and the maintenance of its natural ecology. This research aims to study the impact of such a development to the landscape and ecology changes of Puli through the discussion and analysis of a dynamic simulation model.

In response to the points mentioned by Brown and Corry

(2011) that need to be made up for in landscape planning, modeling land changes from a dynamic perspective can predict future results and the landscape metrics can provide objective data for planning purposes. This shows the importance of such a combination to the application of computer technology in future landscape planning (Zhang, 2006). Improved understanding of how dynamic settings affect simulation results would lessen the deficiencies in prediction and evaluation, benefit the future discussion of the causes and effects of landscape changes and have the potential to be fully utilized in land planning policies. The objectives of this research are as follows:

(1) Construct a simulation model to evaluate and predict the environmental change of Puli town;
(2) Assess weights of factors and explain reasons behind their impacts;
(3) Analyze the ecological quality and landscape changes to Puli town through the application of landscape metrics and dynamic simulation.

MATERIALS AND METHODS

Research process

A simulation model was built according to CA-Markov theory and characteristics of the empirical site and the impact factors for landscape changes in the empirical site identified in the model are investigated (Figure 2). The predicted landscape change of the empirical site in the future is presented through quantitative results to investigate how the model structure setting affects the results. Finally, the landscape metrics is used for calculation and analysis to review the development of the empirical site through landscape ecology theory.

Study area and data

The study area of this research, Puli is located at Nantou County, the geographical center of Taiwan with co-ordinates of 23.973875°N/ 120.982024°E and is the only county in Taiwan which is not adjacent to the sea. Surrounded by mountains on all sides, Puli has a basin terrain with an altitude between 380 and 700 m. Due to its geographical location and terrain, Puli does not experience severe cold during winter or scorching heat during summer. It has abundant rainfall, often cloudy with high humidity and a low rate of evaporation with no strong winds, thus, giving it a pleasant climate suitable for living. It has gained many representative nicknames including heart of Taiwan, green lake, house of stars, flower town, wine country and the most livable place etc. The total area of the town is approximately 162.23 km^2, with hills occupying 74% of land area and flat basins occupying 26%. It has a population of 86,000 people, with a total of 23,417 households. Administratively, it is a mid-sized village separated into 33 neighborhoods with a rich cultural industry including winemaking, flowering, painting and papermaking.

Research tools and materials

Research materials were based on the results of the 1995 and 1996 land use surveys done by the National Land Surveying and Mapping Center of the Ministry of the Interior. The rest of the data attributed to factors affecting landscape changes was built up through various means. Due to differences in the classification of diagram data in the surveys from 1995 and 1996, the different diagram data had to be sorted and categorized again for the present study.

Land use map data in 1995 were categorized into nine classes of agriculture, transportation, leisure, waterworks, construction, industrial, mining and military etc respectively; data in 2006 encompassed nine classes of agriculture, forest, waterworks, transportation, construction, public usage, leisure and rock salt mining etc. Due to the difference in classification and considering that the primary objective of this research is to build a dynamic model structure to investigate how landscape changes affect our landscape ecology, this research re-sorted the different classifications from the available documents and re-classed them into the eight classes of agriculture, forest, transportation, water bodies, grasslands, build land and bare land (Table 1). Further discussion was then conducted based on the changes to these eight classes.

Based on the concept of landscape changes, the dynamic model in this research considered the various factors affecting nature and the social economy. The causes of landscape changes can be divided into two classes, limitations (or constraints) and impact factors. As per relevant research done in the past, this research primarily considered the various factors and limitations, including those due to gradient, existing buildings, existing roads and river course, while impact factors included accessibility to existing buildings, roads, the city center, tourist attractions, government agencies and population growth. The data for various factors would go through fuzzy standardization when undergoing spatial evaluation with multi-criteria. The respective weights were decided based on Cramer's V method. The simulation results were used to test the data repeatedly to improve the weighting coefficients and choice of factors so as to better understand the relationship between the landscape changes and its impact factors in the study area.

CA-Markov model structure

This research studied the construction and operation of the dynamical model of CA-Markov. Firstly, the land use data

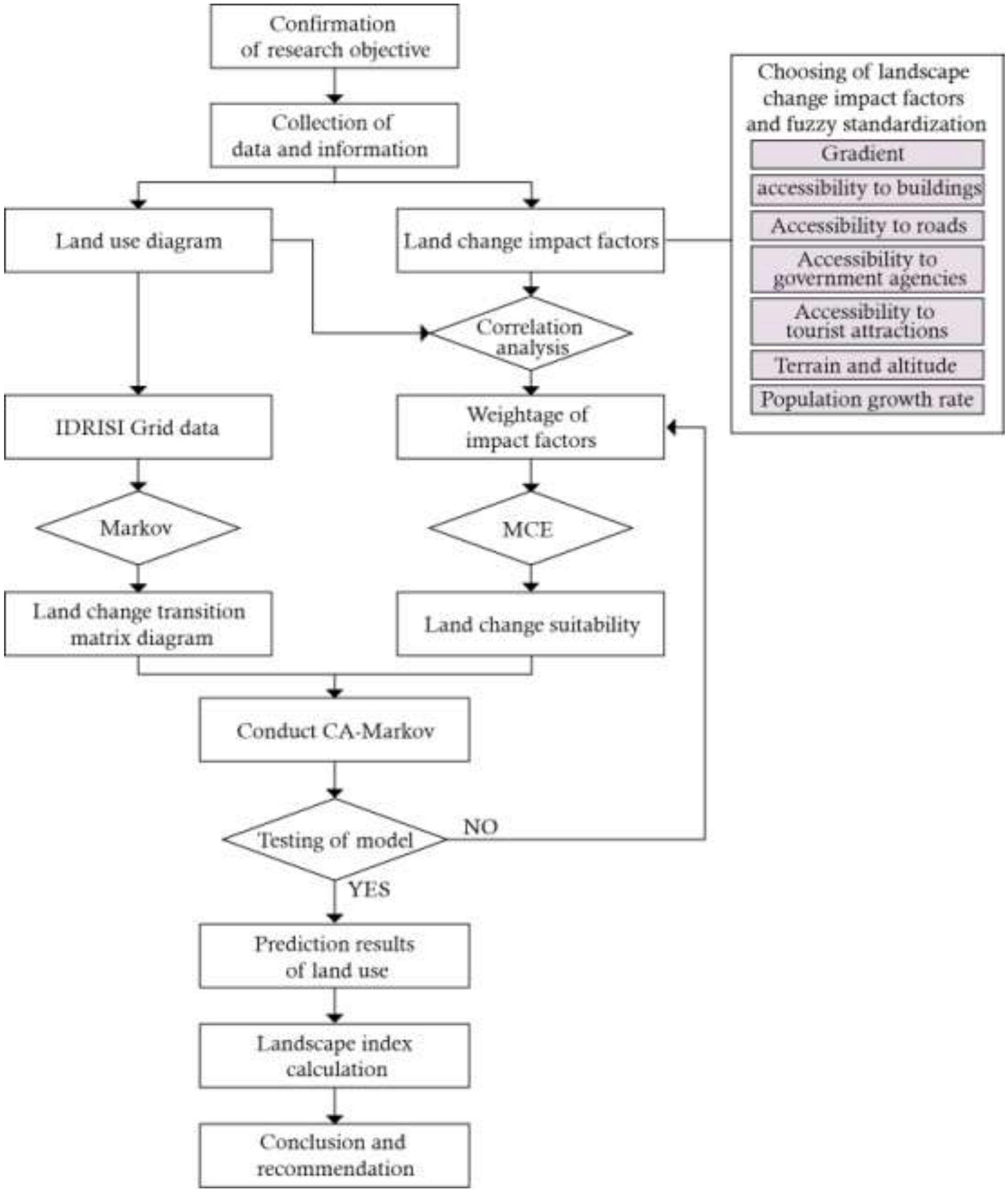

Figure 2: Research process.

from the two periods were re-sorted respectively and converted into a raster format, calculating the transition probabilities and transition area through the Markov-Chain theory. In addition, considerations were made as to whether testing limitations and impact factors should be included in this model after relevant analysis and if included, its suitable weights. Next, the potential for land development was evaluated after fuzzy standardization, before combining the data with the transition area obtained through Markov-Chain to conduct cellular automata. The final result was then tested using Kappa values to predict the accuracy of the model.

Establishment of image files

Many GIS spatial analysis and simulation are usually conducted based on the raster data structure as the basic spatial system. Therefore, it is essential to convert the image file data into gridded format, meaning to perform file

Table 1: Categorization of research on land use.

Number	Land use class	Sub-classes
01	Agriculture	Rice Farming, Dry Farming, Fruit Trees, Arable waste land, Animal Husbandry, Agricultural ancillary facilities.
02	Forest	Natural Forest, Artificial Forest, Other Forest usage, Forestry
03	Transportation	Normal Road, National Highway, Provincial Highway, Railroads, road-related facilities
04	Water Bodies	Watercourse, Canal, Reservoir, low-lying wetland, Flood-prevention roads, Water conservation structures.
05	Built land	Commercial, Residential, Industrial, Other construction uses, Amusement Parks, Sport Venues, Government Agencies, Schools, Healthcare, Social Welfare, Public Facilities, Environmental Conservation Facilities, Military Facilities.
06	Grass land	Wasteland, Grassland, Garden Greenery.
07	Others	Mining, Earth and Rock, Salt industrial use, Unused land, Land undergoing artificial change.
08	Bare land	Bare Land, Landslides.

Source: Compiled by this research.

conversion for vector format data. Based on past research, the size of the grid would depend on the various research objectives and scale of the research base. Huang (2007) investigated the impact on analysis materials by the different grid sizes. Through a level diagram and ANOVA analysis, it was found that the smaller the grid resolution, the higher the possibility of significant differences in land use diagram data. Such differences can also be divided into various classes. For example, the land use grid data for the 1 × 1 meters size is totally different from the rest. The 10 × 10 m to 14 × 14 m grid size is similar to each other, with differences surfacing again starting from the 15 × 15 m size, showing that the grid size is correlated to its homogeneity. In order to conform to a unit grid and resolution, this research carried out grid conversion on the diagram data based on a 10 × 10 m grid size.

Establishment of impact factors data

Impact factors for landscape changes include those of natural and social-economic. After all image data of impact factors have been gridded, this research then adopted the Fuzzy standardization to facilitate future comparisons and calculations with the various impact factors.

Setting of the degree of impact analysis and weight

After the various impact factors of landscape changes have undergone fuzzy standardization, this research adopted a multi-criterion evaluation to calculate the sum of the various weight linear combinations of the impact factors after standardization to obtain the final land-development potential diagram. In the calculation of weight linear combination, researchers need to decide on the weights between the various impact factors. To prevent an overly subjective perspective of impact factors of landscape changes due to human conditions, this research adopted the Cramer's V method to calculate the relationship between landscape changes and its impact factor, before deciding on their respective weights. Cramer's V is a measure based on the Chi-Square theory with the following formula (Rees, 2008):

$$\mathrm{V} = \sqrt{x^2/(N)(\text{minimum of } \mathrm{r}-1, \mathrm{c}}$$

In the aforesaid formula, x^2 represents the chi-square value, while represents the total sum, $\text{minmum of } \mathrm{r}-1, \mathrm{c}$ represents the smaller value between (the number of rows – 1) and (the number of columns – 1). The value V obtained varies between 0 and 1 and is proportionate to the chi-square value.

Evaluation of potential land development

This research adopted a multi-criterion principle in evaluating the weight linear combination. Weight linear combination is the most common procedure used to merge overlapping data. It multiplies the standardized impact factors with their respective weights and add up their total sum before dividing by the individual values of the factors. Calculating the average weight of each unit grid and multiplying by the constraints calculated by Boolean's method would produce the final value, which would be used in the CA-Markov land development process. The weight linear combination method provides more flexibility as compared to the Boolean calculation of restrictions and

Table 2: Landscape Index selection.

Name	Abbreviation	Concept	Formula	Explanation
Landscape percentage	PLAND	The percentage of the landscape occupied by a certain land type	$P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} \times 100$	P_i =PLAND, a_{ij} =*ij* patch area (m^2), A=total landscape area (m^2), range of values is from 0 till 100, unit: not scalable.

provides sufficient tradeoff and averaging of risks (Liu, 2003).

CA-Markov

The CA-Markov model can be classified into three parts, including using Markov chain to calculate demand for land usage, cellular automata settings and prediction of test results. Within the framework of the cellular automata model with Markov chain as its basis, the purpose of the latter is to calculate from the conditions of land usage of the past two periods, the transition probability matrix and transition area matrix from the first period of land usage to the second period, so as to provide reliable data for the demand of space due to various changes in land under the cellular automata calculation model.

For empirical study purposes, this research classified eight types of land usage data, before inputting them into the IDRIDI software for Markov chain analysis. The purpose of the analysis is to understand the transition conditions for the various land uses between 1995 and 2006 and to obtain the transition probability matrix for future calculation purposes.

Settings of the cellular automata model include deciding upon the cell types, cell evolution rules and the spatial filter within the cellular automata. For the decision of cell types, this research requires the cell to be converted into square grid.

This is due to consideration that cellular model of square grids has a similar structure to that of the gridded GIS data structure and such a requirement would facilitate future references for planners and designers (White et al., 2003).

Cell evolution rules are based on the relevant coefficients and weights in Cramer's V calculation, obtaining the potential for land development based on multi-criterion evaluation of weight linear combination. Other than the diagram for land development potential, the inter-relationship between neighboring cells are also important determinants of cell evolution rules. This means that once a range is set by the spatial filter, then its potential value will increase should there be an increasing number of homogenous cells within that range. Initial settings for the spatial filter in the IDRISI geographical information software would be a 5 × 5 grid. Eastman (2009) mentioned that under most circumstances, such a setting would produce a favorable yet realistic result. This research would adopt this setting to define the spatial definition between neighboring cells.

The completion of the model calculation would give us the diagram for the prediction of land use. This research then tested out the predicted results to ensure that they can be defined and are accurate; the effect on the prediction results due to different impact factors was also investigated. This research adopted the Kappa series index to evaluate the accuracy of the model prediction.

Landscape metrics analysis

Landscape level selection

Patch level is mainly a description of the various patches and is rarely applied directly. Most of the class level indices can be viewed as an important indicator for fragmentation. Landscape level can be broadly defined as an indicator for landscape heterogeneity (Wu et al., 2011).

The objective of this step is to make use of the landscape data index to review and improve land planning. Sorrell (1998) mentioned that the loss of natural habitats and fragmentation is the greatest threat to biodiversity, similar to the theme of this research which is to investigate the effect on our eco-system due to urbanization. Based on the aforementioned research objective and the various definitions of landscape levels, the class level index is viewed as an important indicator for fragmentation. Thus, we adopted class levels primarily for this research.

Landscape metrics selection

It is quite difficult to use all landscape indices in one planning or research, as there are many types of them with most being inter-related to each other. Thus, it is necessary to simplify the selection of landscape metrics based on the research objective. Thus, due to the aforementioned landscape level selection, past documents such as the ten core indices by Wu et al. (2011) and also considering what Aguilera (2011) mentioned about landscape metrics supporting spatial planning, this research therefore selected six landscape indices to predict the simulation results (Table 2).

Table 2: Landscape Index selection.

Name	Abbreviation	Concept	Formula	Explanation
Patch quantity	PN	Total sum of patches	$\sum_{i=1}^{n} P_i$	P_i represents *i* type of patch, range of values are from 1 to infinity (depends on total value of grids from research data), unit: NA.
Mean patch size	AREA_MN	The mean size of a patch of a certain land type	$\frac{\sum_{j=1}^{n} a_{ij}}{n_i}$	a_{ij} = area of patch *ij* (m^2), n_i = total patch quantity of *I*, unit: hectares.
Mean shape index	SHAPE_MN	A measurement of the complexity of the patch	$\frac{\sum_{j=1}^{n} p_{ij}/\min p_{ij}}{n_i}$	n_i = Patch quantity of *i* type of land, p_{ij} = parameter of patch *ij*, $\min p_{ij}$ = smallest perimeter of patch *ij*, range of values = 1 to infinity, Unit: NA.
Gyration radius index	GYRATE	Represents the mean distance between each grid and the center point within a patch	$\sum_{r=1}^{z'} \frac{h_{ijr}}{z}$	h_{ijr} = distance from the patch center *ij* to the unit grid *ijr* (m), *z* = total grid quantity of patch *ij*, range of values ≥ 0 till infinity, Unit: Meters.
Mean nearest neighboring distance	ENN_MN	The nearest distance between neighboring patches on the same type of land	$\frac{\sum_{j=1}^{n'} h_{ij}}{n_i}$	h_{ij} = nearest distance between neighboring patches *j* within land type *i*, based on nearest distance between edges of patches (McGarigal et al., 1995), range of values$\geq$0 till infinity, Unit: Meters.

RESULTS AAND DISCUSSION

Data presentation

Correction of basic data

This research used the numerical data results of the National Land Use Investigation survey done by the National Land Surveying and Mapping Center in 1995 and 2006. The classification of land use would be as previously described, using GIS to classify them into the eight classes of agriculture, forest, transportation, water bodies, built land, grassland and bare land etc (Figures 3 and 4). This research conducted comparisons using the aerial photographs capturing current conditions.

Analysis of the change in land use

After sorting out and reclassifying the land use data between 1995 and 2006, this research did an initial calculation of area of the eight classes of land using the Calculate Geometry method of GIS to understand the various land use changes of Puli Township, Nantou County during these 11 years. The results show that from 1995 to 2006, decrease in land use area includes agriculture from 66.07 to 55.9 km^2 with a 15.39% decrease, water bodies from 5.53 to 4.17 km^2 with a 24.59%, forest from 87.01 to 85.58 km^2 with a 1.64% decrease; increase in land use area is topped by other land use from 1.06 to 5.79 km^2 followed by developed land from 7.67 to 10.77 km^2 with a 40.42% increase.

From the various land use area data, it can be seen that between 1995 and 2006, Puli Township underwent increased development (increased in other land usage, built land and transportation land). Such changes are typical urbanization processes that imply a changing landscape. Therefore, it is essential to investigate the impact done in the environment due to landscape changes. Relying solely on the area data, however, is difficult to understand the landscape composition and configuration of the various land types and the overall development trend. This makes it difficult to propose recommendations and improvements. Thus, this research would use the dynamic model and landscape metrics to conduct further investigation and

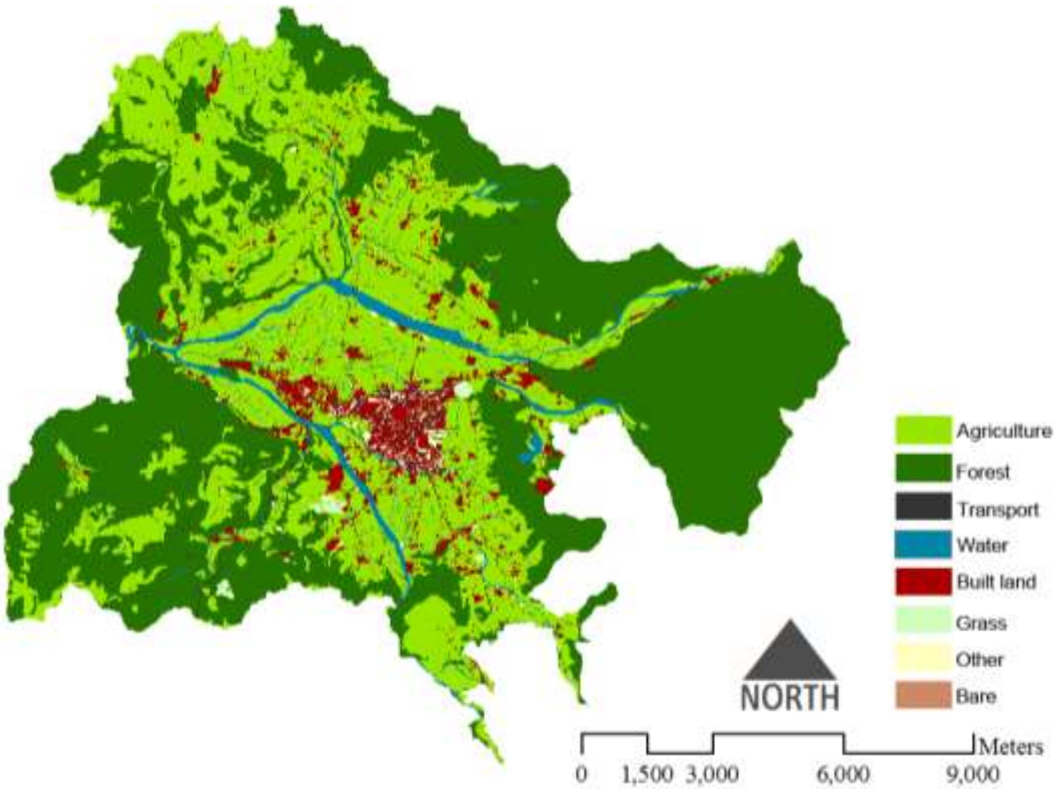

Figure 3: Land use diagram of Puli in 1995.

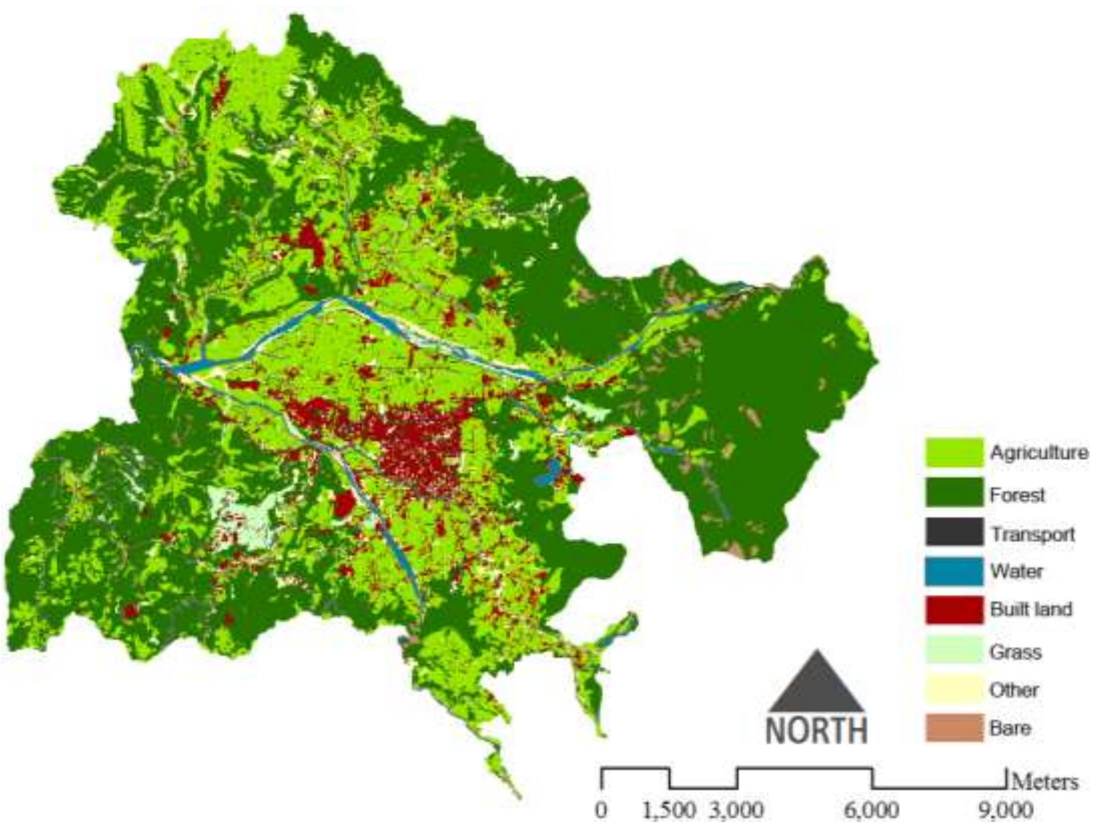

Figure 4: Land use diagram of Puli in 2006.

Table 3: Land use transition probability of Puli from 1995 to 2006.

Type of land use	Transition probability							
	Agricultural	Forest	Transport	Water bodies	Developed land	Grass land	Others	Bare land
Agricultural	0.5630	0.2234	0.0351	0.0198	0.0751	0.0188	0.0641	0.0007
Forest	0.1799	0.7064	0.0145	0.0117	0.0112	0.0211	0.0196	0.0357
Transport	0.1941	0.1395	0.3836	0.0255	0.1748	0.0180	0.0617	0.0029
Water bodies	0.2596	0.0914	0.0588	0.3763	0.0249	0.0663	0.1204	0.0023
Developed land	0.1712	0.0950	0.0727	0.0038	0.5723	0.0050	0.0795	0.0006
Grass land	0.0889	0.5606	0.0492	0.0266	0.1555	0.0487	0.0703	0.0000
Others	0.1295	0.0829	0.0761	0.0033	0.4760	0.0339	0.1984	0.0000
Bare LAND	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000

Note: Shading denotes the same type of land use.

analysis.

Establishment of landscape change impact factors

Both the land use image data during the aforementioned period of time and the building of landscape changes impact factors image data are needed to conduct a CA-Markov simulation. Impact factors of landscape changes can be attributed to limiting factors comprising of gradient above 30%, existing built land, existing water bodies and roads; impact factors would comprise of accessibility to existing built land, accessibility to existing roads, accessibility to the urban center, accessibility to tourist attractions, accessibility to government agencies and population growth etc.

CA-Markov model prediction

Markov-chain analysis

This research used the land use data in 1995 and 2006 to reclassify them into eight classes namely agriculture, forest, transportation, water bodies, built land, grassland, other land use and bare land, before converting them into 10 × 10 grid format data. Markov-chain analysis was then conducted through the Chang/Time Series in IDRISI software to obtain the transition probability and transition area matrix (Table 3) during this period for the eight classes of land use.

Correlation analysis of landscape change impact factors

It is essential to adopt a multi-criterion evaluation for the aforementioned limiting factors and impact factors to obtain the most suitable diagram when conducting CA-Markov model prediction. This serves as an evolution rule for model calculations. Other than limiting conditions, impact factors are also partly continuous and therefore need to undergo fuzzy standardization to obtain the final numerical values of the various factors prior to assignment of weighting parameters and calculation overlay. To avoid subjective influence and human bias, this research used Cramer's V coefficient to analyze the various Fuzzy standards and weightage parameters of the impact factors before conducting a CA-Markov model prediction and investigating the relationship between landscape changes and its impact factors. Cramer's V analysis was conducted using the land use data from 1995 to 2006 as a basis to compare with the various impact factors that have undergone the Fuzzy standardization process (Table 4); the results show the numerical values after standardization and the relevant indices of landscape changes.

CA-Markov model prediction and testing

Testing of impact factors settings

Part of the CA-Markov model prediction adopts the 1995 prediction as a basis to predict the 2006 landscape change situation before comparing with the actual situation to ensure prediction accuracy. The Markov-chain analysis used in the CA-Markov dynamic model conducts its analysis and obtains the transitions probability and transition area based on past land changes, thus, the data would not deviate due to research objectives and methods. The analysis of cellular automata would need the input of the transition potential map. Due to the difference in settings and method for impact factors in the various researches, the results for dynamic simulation would be affected. This research now tested the impact on the simulation results caused by different sets of impact factor settings using the aforementioned relevant analysis results. The purpose is to obtain the most accurate and easily explainable result for the simulation prediction of Puli Township before going on further to analyze and simulate future land use.

There are three main tests for the impact factor settings in

Table 4: Cramer's V indices table for landscape changes.

Variable	Distance (m)	150	300	450	600	750	900	Distance (m)	1050	1200	1350	1500	To Border
Cramer's V coefficient	Accessibility to buildings	0.1326	0.1283	0.1283	0.1283	0.1283	0.1135	Accessibility to buildings	0.1096	0.1079	0.1067	0.0799	0.1096
	Accessibility to roads	0.1318	0.1152	0.1154	0.1147	0.1125	0.1110	Accessibility to roads	0.1086	0.1073	0.1063	0.1054	0.0878

	Distance (m)	300	600	900	1200	1500	2000	Distance (m)	3000	4000	5000	To Border
Cramer's V coefficient	Accessibility to government organizations	0.0873	0.0898	0.0914	0.092	0.0936	0.0976	Accessibility to government organizations	0.1017	0.0999	0.0991	0.0916
	Accessibility to tourist attractions	0.0706	0.0736	0.0751	0.0747	0.0734	0.0705	Accessibility to tourist attractions	0.0658	0.0626	0.0614	0.0589
	Accessibility to City Center	0.0237	0.043	0.0591	0.0662	0.0701	0.0752	Accessibility to City Center	0.0865	0.0957	0.0998	0.1036

this research. The first test is based on the highest correlation from Cramer's V accessibility distance testing done as the impact factor settings. The second test is to set the accessibility distance from the base boundary for the various impact factors. The third test is to remove impact factors with a lower correlation and further explore if such factors can be excluded from the dynamic model. The aforementioned tests aim to understand which kind of settings would be better in predicting landscape changes in Puli Township.

Content settings for test one: 150 m accessibility to buildings, 300 m accessibility to roads, 3000 m accessibility to government organizations, 900 m accessibility to tourist attractions, accessibility to the city center till the border, population growth rate, gradient limitations, existing buildings limitations, existing roads limitations, and existing water bodies limitations. We can obtain the land use potential diagram (Figure 5A) from the aforementioned settings. The Kappa value after comparing results of test one (Figure 5B) and the actual land usage in 2006 is 0.8114. Although test one results are accurate to a certain degree (Kappa 0.75), it is not in line with urban development. Considering the various land use conditions from the test results, land changes occur around the impact factors due to distance settings. Such a simulation result in other areas having a low transition probability and therefore no changes. Thus, this research does not view this test result as being ideal.

Content settings for test two: Buildings, roads, government organizations, tourist attractions and city center accessibility to border, population growth rate, gradient limitations, existing buildings limitations, existing road limitations and existing water bodies limitations. We can obtain the land use potential diagram (Figure 5C) from the aforementioned settings. Content settings for test two is on one hand, based on past relevant documents about distance settings to the border (Kamusoko et al., 2009; Mitsovaa et al., 2011) and on the other hand, using such a setting to explore the difference in results with test one. Kappa value after comparing results for test two (Figure 5D and the actual land usage in 2006 is 0.8222, even better than test one results, with K_{loc} rising to 0.7940. From the results diagram of test two, the spread of land use is also reasonably more even as compared to test one. This shows that for the empirical base of Puli Township, setting of impact factors distance actually causes the simulation to be out of line with the actual landscape-changing situation. ◦

Judging from the correlation between the various impact factors and landscape changes in Puli between 1995 and 2006, the impact factors actually displayed a low correlation. The highest being accessibility to the city center (0.1036) and population growth rate (0.1125). Their Cramer's V coefficient of 0.1 can only be viewed as having a weak correlation, while the other four impact factors had a coefficient of less than 0.1. To test the effect on simulation results by impact factors with low correlation, this research conducted Test Three by excluding accessibility to tourist attractions (0.0589), the factor with the lowest correlation, while keeping the rest of the settings the same as test two to serve as test three. From test three results, we can obtain the land use potential diagram as (Figure 5E) and simulation results diagram (Figure 5F). The Kappa coefficient after comparison with the actual land use condition in Puli during 2006 is 0.8290. To further confirm the test results and study the effects on simulation by impact factors with a low correlation, accessibility to buildings (0.0799) is also excluded, with the new Kappa coefficient being 0.8301. If the impact factor with the next lowest correlation, accessibility to roads (0.0878) is excluded, the Kappa coefficient would

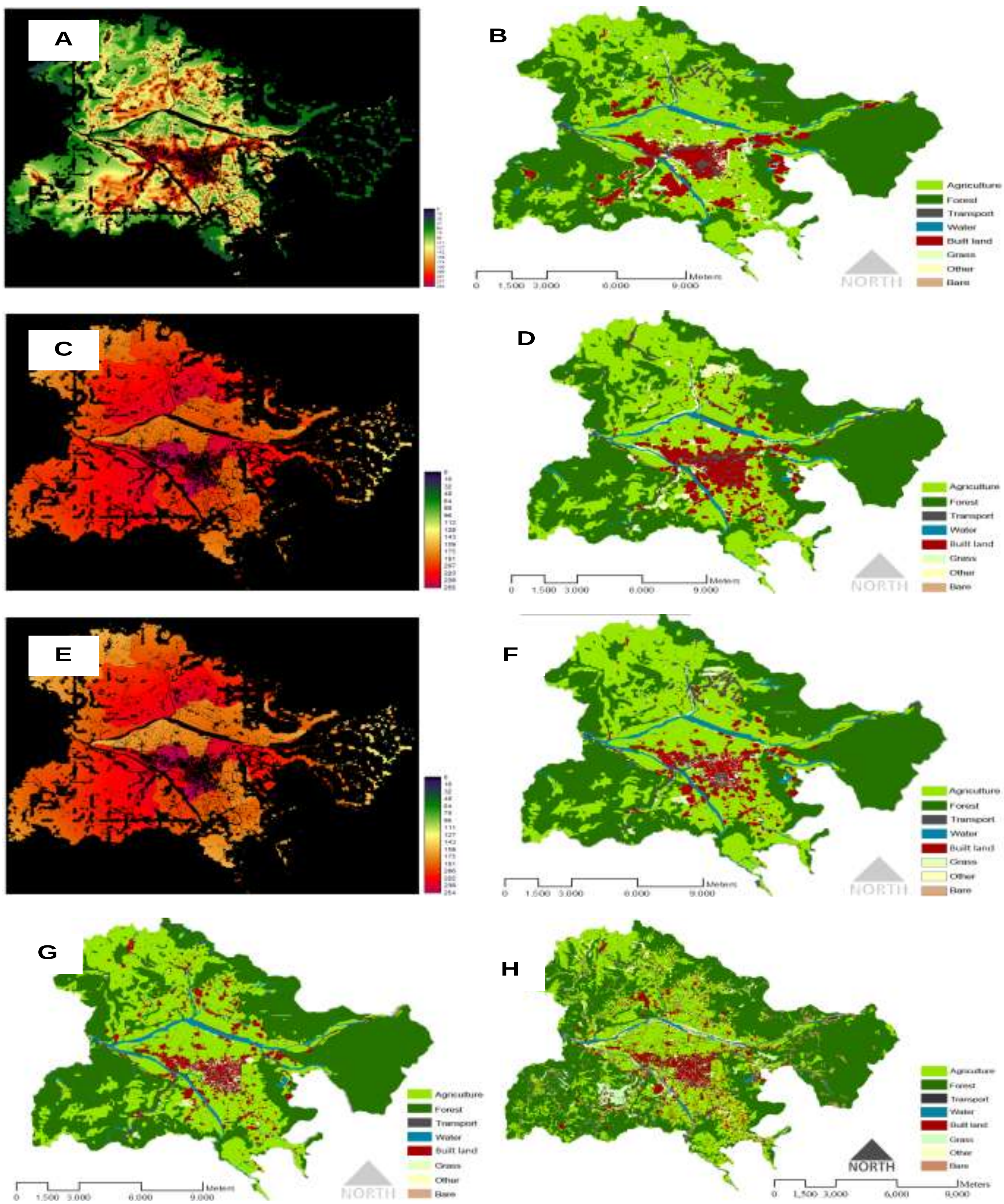

Figure 5: Simulation results of the various tests A) Land use potential, test one; B) Simulation results, test one; C) Land use potential, test two; D)Simulation results, test two; E) Land use potential, test three; F) Simulation results, test three; G) Land use potential, test four; H) Simulation results, test four.

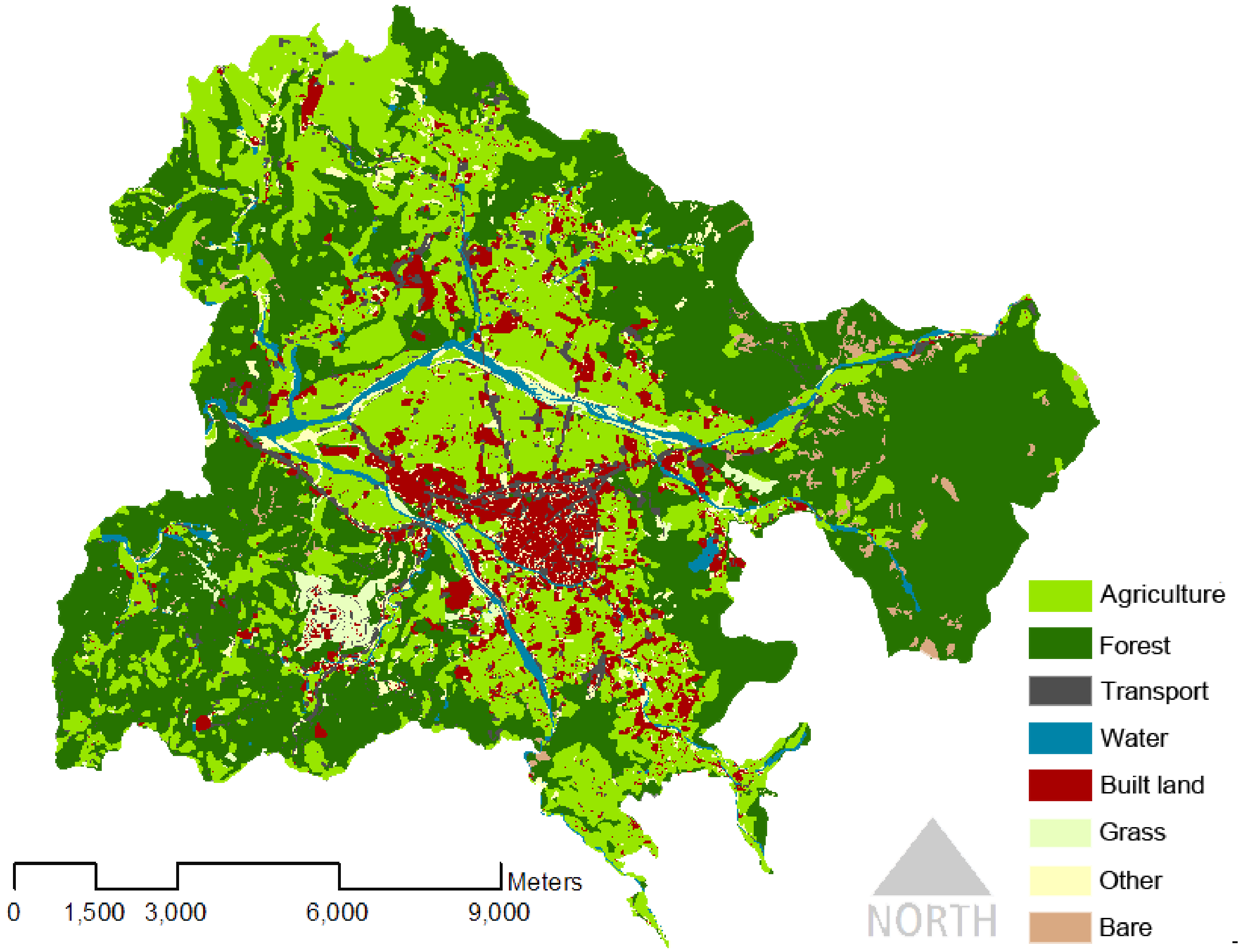

Figure 6: Simulation results of landscape changes in 2017.

become 0.8357. Excluding impact factors with low correlation would result in an increasing trend from the Kappa coefficient showing that increased consideration for impact factors might not affect the simulation result positively.

As the results from test three show that impact factors with low correlation can be excluded from the model, this research changed the content settings further to form test four: solely consider the four limitations of gradient limitations, existing buildings limitation, existing road limitations and existing water bodies limitations to see if it can affect the CA-Markov prediction results of landscape changes in Puli positively. Figure 5G and H shows the simulation results of test four. The Kappa coefficient after comparison with the actual land use in 2006 is 0.8360, the best result among all the various tests.

CA-Markov model prediction

The impact factor settings test shows that test four produced the best simulation result for the landscape changes in Puli Township. Therefore, this research adopted Test Four settings as a basis and land use diagram of 2006 as the 1st period to conduct CA-Markov prediction for landscape changes in Puli Township for 2017 (Figure 6).

Evaluation and discussion of prediction results

From the series of test results and the decision to simulate the land use situation of Puli in 2017, this research made a few preliminary conclusions. Firstly, during the dynamic simulation of land /landscape change, the consideration for impact factors should be based upon the geographical characteristics of the research or planning base and environment. It is not true that more impact factors in the simulation model will lead to a more favorable result. Although not able to provide a quick solution to understanding the impact factors at the base, Cramer's V coefficient nevertheless provides a good source of reference data. Secondly, the dynamic model cannot simulate special

Table 5: Analysis results of landscape metrics.

Type	Year	Forest	Agric	Built	Water	Transport	Others	Grass	Bare
PLAND	1995	25.5735	19.4159	2.2288	1.6295	1.0519	0.3093	0.1519	0.0002
PLAND	2006	25.1415	16.4096	3.1567	1.2257	1.4529	1.7015	0.7330	0.5428
	2017	23.9416	16.2738	3.9241	1.3639	1.9333	1.7015	0.7330	0.5428
NP	1995	273	410	1585	1783	4005	721	39	1
	2006	837	1207	3192	1669	12237	1821	159	186
NP	2017	443	714	2088	590	5577	1821	159	186
AREA_MN	1995	31.8558	16.104	0.4782	0.3108	0.0893	0.1459	1.3243	0.0700
	2006	10.2147	4.6233	0.3363	0.2497	0.0404	0.3177	1.5677	0.9924
	2017	18.3785	7.7509	0.6391	0.7861	0.1179	0.3177	1.5677	0.9924
GYRATE_MN	1995	87.6071	74.4735	22.1065	19.8960	14.0551	13.1989	37.816	24.2457
	2006	42.7419	49.2131	18.1406	19.0331	8.5575	21.3681	37.7502	40.2367
	2017	55.7533	69.5779	20.4550	30.5397	10.5664	21.3681	37.7502	40.2367
SHAPE_MN	1995	1.6621	1.7938	1.3800	1.4377	1.4181	1.2620	1.5559	2.3333
	2006	1.5864	1.7021	1.3533	1.3741	1.1998	1.4255	1.6244	1.6365
	2017	1.5315	1.6839	1.2413	1.4534	1.1955	1.4255	1.6244	1.6365
ENN_MN	1995	63.4014	53.2473	56.9620	27.7317	24.2648	61.1411	505.4443	N/A
	2006	57.9108	43.1356	44.8123	44.8090	26.8976	58.5435	191.1733	188.5166
	2017	82.3049	60.6491	56.3172	82.7367	34.9552	58.5435	191.1734	188.5166

development situations, such as Chi Nan University and the Chung Tai Monastery, as it will result in a huge deviation between the simulation result and the actual situation. However, CA-Markov still has a certain degree of accuracy (Kappa 0.75) for prediction of urban development simulation and can be used for reference in land planning and policy making.

Analysis of landscape metrics

The aforementioned CA-Markov model has been proven to be effective in making predictions from the empirical base of Puli Township, but is unable to determine if its environment will be affected by changes in landscape. Therefore, this research conducted further investigation based on analysis of the landscape metrics. Using the six types of landscape metrics for this research, input the land use diagram of Puli Township in 1995, 2006 and the prediction of 2017 into the FRAGSTATS software and the data calculated would be as shown in Table 5.

It shows the various landscape changing conditions. Under the eight classes of land use in this research, forest has always had the highest percentage of land use in Puli. On the other hand, its PLAND value has been continuously declining between 1995 and 2006. This shows a gradual decrease in forests in Puli. Although the huge rise in NP from 1995 to 2006 represents an increase in patches, the decrease in PLAND and AREA_MN also means the fragmentation of forests. This can also be seen from the decrease in GYRATE_MN, a representation of the migration ability of the species within the habitats of the particular land type. A decrease in GYRATE_MN therefore implies an increase in land segmentation. Furthermore, PLAND for forests continues to decrease in 2017. Even though there is a decline in NP and increase in AREA_MN, we can see that forests continue to undergo disturbance by deducing from SHAPE_MN and ENN_MN.

Forman (1995) mentioned that landscape change is a process starting from perforation, segmentation, fragmentation before going through reduction and depletion. SHAPE_MN can be used to represent the degree of complexity of the shape of the land type. The SHAPE_MN coefficient of forests has continued to decrease from 1995 to 2017, showing that ever since undergoing segmentation and fragmentation in 2006, the patches of separated forests have been gradually isolated. Other land types have also replaced the sole remaining ones. Therefore, NP has decreased while AREA_MN has increased. SHAPE_MN has also decreased. The increase in ENN_MN also means that forests have been carved further away from each other, making it less conducive for species to migrate. Agriculture land PLAND and SHAPE_MN experienced continued decline from 1995 to 2017, NP increased till 2006 and decreased between 2006 and 2017. AREA_MN, GYRATE_MN and ENN_MN decreased before 2006 and increased between 2006 and 2017. Such readings are similar to that of forests as earlier mentioned, implying that agriculture land in Puli is also facing fragmentation.

Built land PLAND and AREA_MN increased from 1995 to 2017, pointing to continued urban development in Puli. On the other hand, built land NP increased between 1995 and 2006 and decreased between 2006 and 2017, implying concentrated development. GYRATE_MN experienced a decline before increasing again, implying that initial concentrated development started to spread outwards. Increasing development due to human factors can be seen from the indices of other lands and transport.

Conclusion

This research used CA-Markov and landscape metrics to conduct analysis on the results. Although CA-Markov cannot predict special circumstances, it is still able to effectively predict landscape changes after accurate evaluation. On the other hand, the most important impact factors in dynamic simulation depend on the characteristics of the study area. For example, Puli in this research might achieve a better result if other impact factors were included. From current research conditions, there is a preliminary proof to show that Cramer's V analysis can be adopted as reference for impact factors. This should be tried with different cases in the future to further confirm the value of Cramer's V analysis in a dynamic simulation model. Furthermore, the impact factors suggested by previous studies have a low correlation in Puli indicating that this town has had a different developing path. Researches in the future can conduct more interviews and analysis to further understand the elements and conditions of Puli's development, so as to provide specific suggestions for the town.

Analysis of landscape metrics shows that Puli's development has indeed caused damages to its forests, which are important habitats for ecological life. Fragmentation of forests will cause huge damage to the environment. From the data provided by Puli Household Registration Office, Puli's overall population decreased from 1995 to 2006. However, based on land use data and landscape metrics analysis, Puli's development has been rising. Such a result is undesirable. Puli's development can be attributed to tourism, but it is worth discussing whether it is necessary to initiate so much development to promote tourism.

Overall, the CA-Markov model is effective in simulating and predicting spatial/landscape changes. If the results were complemented by landscape metrics analysis, more data can then be provided to determine the results of landscape changes. In future studies, the dynamic model can be applied in different geographical areas to further explore its effectiveness and model settings, which will subsequently be helpful to building a more complete set of data for the dynamic model. Since landscape metrics provides specific data information and evidence, it should complement the dynamic model to improve convenience and effectiveness in land planning and policy review, helping policy makers to steer clear of mistaken decisions.

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