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Urban Growth Modeling in Kurunegala, Sri Lanka using Cellular Automata/Markov Chain Multi-criteria Analysis and Markov-Markovian Transition Estimator

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Summary

With accelerated global urbanization, the expansion of cities has become a pressing concern for urban planners and researchers. The growth and dynamics of urban encroachment are closely tied to changes in land use, especially in urbanized areas. This study seeks to evaluate the accuracy of the CA-Markov (Cellular Automata) model in predicting land use/land cover changes (LULCC) in the Kurunegala district, Sri Lanka as a result of urban expansion. The investigation employs secondary data, including 2007, 2012, 2017, and 2022 Landsat 05, 07, 08, and 09 images respectively. Using software applications such as ArcGIS 10.8, IDRISI 17.0, and MS-Excel 2019, diverse techniques including supervised classification, Markovian transition estimation, and CA-Markov chain analysis, this study attempts to analyze the Urban Growth Modeling for 2027 and 2037 using CA-Markov Chain Multi-criteria Analysis (MCA) under Markov-Markovian Transition Estimator. The study used 32 spatial variables for determining the LULCC. As per the derived results, from 2022 to 2027, urban areas have increased quite markedly. The vegetation cover area has reduced and the areas of water bodies have increased spatially. From 2027 to 2037, the urban area increment is 72.552%. Also, vegetation cover and water body distribution have reduced by 8.051% and 39.91% respectively.

Keywords: Urbanization, Urban Encroachment, Ca-Markov Model, Markovian Transition Estimation, Ca-Markov Chain Analysis, Multi-Criteria Analysis

1. Introduction

Researchers have paid a lot of attention to urban growth because cities around the world are growing rapidly [1]. Urbanization is an ongoing worldwide phenomenon that has resulted in significant shifts in land use trends and the accelerated growth of cities [2]. Urban sprawl is considered a phenomenon that deals with the expansion of auto-oriented development which has a considerable impact on the surrounding ecosystem [3]. As metropolitan areas continue to expand, urban expansion has emerged as a significant issue with far-reaching consequences for sustainable development, the preservation of the environment, and the overall standard of life [4-6]. Recognizing and precisely forecasting the land use changes resulting from urban sprawl is essential for successful urban planning and policymaking [7]. This growth has directly caused urban development to help spread within a city, which is especially clear in places like Sri Lanka, India, and China [8]. For example, between 1992 and 2013, the built-up areas of China's cities grew by an average of about 5.6% per year. Also, in 2014, the global rural population was surpassed by the global urban population which is currently identified as 54%, and this value is expected to reach up to 66% by the end of 2050 [9,10].

Numerous urban growth models were developed and extensively utilized to study the patterns of urban expansion also, how this could affect the urban ambient environment [11]. These models could be affiliated with urban policy-making or evaluation of the different development scenarios [12]. For analyzing urban growth various models such as Land use/ Transportation models, Cellular Automata (CA) models, Agent-based models…etc. are introduced [9]. Several methods of modeling have been devised for simulating and predicting the dynamics of urban development [13]. In urban growth modeling, the Markov-Markovian Transition Estimator and Cellular Automation/Markov Chain MCA are two common approaches [14]. These methods provide an understanding of both the temporal and spatial patterns of land use change, thereby assisting decision-makers in conceptualizing and controlling urban growth [15].

Recognizing how land use/land cover change (LULCC) fluctuates over time is important for achieving favorable urban growth and making cities more peaceful and less congested places to live [16]. LULCC interactions are all about how people change land for economic reasons [17]. In the last few decades, advances in technology like remote sensing and Geographic Information Systems (GIS) have made it easier to keep track of and evaluate the changes in LULCC by using high-resolution images [18]. For recognizing LULCC, various computational models, which include Markov models, cellular models, hybrid models, multi-agent models, statistical models, and evolutionary models, are developed [19]. In specific, the Markov model is a structure for anticipating the course of events of Markov stochastic process systems [20]. In the 1960s and 1970s, this model was widely employed to simulate the changing patterns of large-scale land use in the discipline of urban analysis. Using Land Use Land Cover (LULC) maps, the Markov model provides a transition probability matrix that enables the evaluation of the probability of LULCC to another category or continuation throughout the same classification [21].

CA, on the other hand, represents a discontinuous dynamic system commonly used for simulating global as well as local computation changes [22]. In part because of its ability to support sophisticated spatial patterns, this model has acquired a growing continuation in urban growth evaluation [23]. The Markov-Markovian Transition Estimator employs historical land use data and probabilities of transition to predict impending land use patterns (Wang & Osaragi, 2024). This approach implies that the probability of land use change depends entirely on the current state of land use, ignoring various variables that might impact land use changes [24]. CA-Markov Chain MCA, on the other hand, incorporates multiple criteria, including proximity to roads, population density, and land suitability…etc. to estimate the probability of land use conversion (Mondal, Sharma, Kappas, & Garg, 2019). This method provides a more comprehensive comprehension of the complicated nature of urban development by incorporating multiple factors. In the context of the district of Kurunegala, which is experiencing enhanced urbanization and rising concerns about urban encroachment, it is necessary to assess and compare the efficacy of the aforementioned modeling techniques. The purpose of this study is to evaluate the applicability and effectiveness of the CA-Markov model, a variant of CA/Markov Chain MCA, for forecasting modifications in land use resulting from urban expansion in the district.

This study will analyze and synthesize prior research on urban development modeling, concentrating on the implications of the Markov-Markovian Transition Estimator and CA-Markov Chain MCA. This research will contribute to a better comprehension of the abilities of the approach and applicability in forecasting urban development patterns by evaluating the advantages and disadvantages. This research will produce concrete knowledge into the LULCC and urban growth structure in the Kurunegala district through the use of secondary data, including Landsat images from 2007 and 2022, as well as methods such as supervised classification, Markovian transition estimation, and CA-Markov chain analysis. Through the outputs of the Markov-Markovian Transition Estimator and CA/Markov Chain MCA, this study seeks to identify critical differences and evaluate the precision and dependability of the approach in documenting urban growth patterns. This study will contribute to the existing corpus of knowledge on urban growth modeling, offering urban planners, policymakers, and researchers interested in sustainable urban development valuable insights. By comprehending the advantages and disadvantages of various simulation methods, stakeholders can make well-informed decisions and begin implementing successful strategies for handling and directing urban development in the Kurunegala district. Accordingly, section 01 discusses the introduction, and Section 02 discusses the literature review. Subsequently, the third section will discuss the methodology, and section 04 will illustrate the results and discussion. Finally, section 05 will include the conclusion of the research.

1.1. Study Area

Figure 01: Study area selected for the analysis Source: Author, 2023

Figure 01 shows the study area within Kurunegala that opted for the demonstration of the analysis, Kurunegala is one of the most thriving urban centers in the Northwestern province, of Sri Lanka. Thus, it is apparently, a significant urban center where it allows analyzing the urban growth patterns as well as the distribution of the clustering of urban densities. The study was conducted using the secondary data obtained from the USGS Earth Explorer and the data for the variable customization were analyzed and selected from the different organizations such as UDA (Urban Development Authority). This analysis of urban growth modeling was done using 32 variables (Maximum number of variables for IDRISI 17.0).

2. Literature Review

Urbanization is an inevitable process which is normally taking place due to economic development as well as the increased population growth in a region [25]. Urban growth is considered a significant worldwide phenomenon that addresses the percentage of the urban population along with the physical expansion of the existing urbanized areas. Accurate as well as updated LULCC information is required to comprehend and analyze the environmental consequences of such processes [26]. Urbanization is considered one of the major phenomena in the contemporary world that is influencing the outward spreading of cities with fewer city planning endeavors [27]. The built-up area is generally considered a fundamental parameter for quantifying the urban sprawl scenarios [28].

Unplanned urbanization which is taking place within cities can affect pollution levels, traffic congestion in the cities, congestion in places, and deforestation levels [29]. Uncontrollable urban population growth as well as migration patterns have created major issues like urban sprawl and population growth as well as urban sprawl has direct relationships [9]. Also, rapid and uncontrolled urban growth has become a fundamental challenge faced by urban planners and policy-makers and this condition has affected the urban sustainability as well as the livelihood conditions of the urban communities [30]. Modeling the spatial dynamics mostly depends on the LULCC [38]. Consequently, it is crucial to address the relationship between urban sprawl and LULCC through the process of simulation since LULC dynamics are vital to a sustainable urban environment [31,32]. This helps urban planners, policy-makers as well as resource managers to obtain the most up-to-date data on this rapidly changing urban environment [33].

CA models are dynamic models that are separate in the composition of time, space, and context [34]. Also, CA are rule-based approaches which are working on the micro-level contexts which have the flexibility towards simplifying the spatial simulations based on the transition rules [35]. CA models are commonly utilized in all urban growth models which are found to be performing well in the process of predicting urban growth more closely to the realistic nature rather than the mathematical models [36]. Hybrid models of CA are specifically dominating the existing geospatial domain such as the CA-Markov chain models, CA Logistic regression models [37]. CA uses site-specific rules in representing the land use transitions also, it uses the raster-based mechanisms for simulating the urban expansion for separate time steps [38]. CA models are predominantly used in geometrically simulating the spatial phenomenon [28]. There are some inadequacies in CA models such as some of these models fail to integrate with certain causal factors that drive the urban sprawl for instance; population growth, accessibility to available land plots, and proximity to centers of the nearest cities. To address these concerns, certain Machine Learning (ML) techniques are being introduced such as Neural Networks [28].

For analyzing the urban growth various geospatial and statistical models are utilized that can be attributed to the regression models, CA, Markov models, CA-Markov models, and CA-logistic regression models [39]. Among most of these established models, CA models are the most popular and used for the urban growth simulation processes [40]. For simulating the urban land use change, and analyzing the urban expansion, different variants of CA models are developed such as SLEUTH, DUEM (Dynamic Urban Evolution Model), MCE-CA (Multi-Criteria-Evaluation), MAS (Multi-Agent-System) CA, Markov CA Model, and Voronoi-CA model [41].

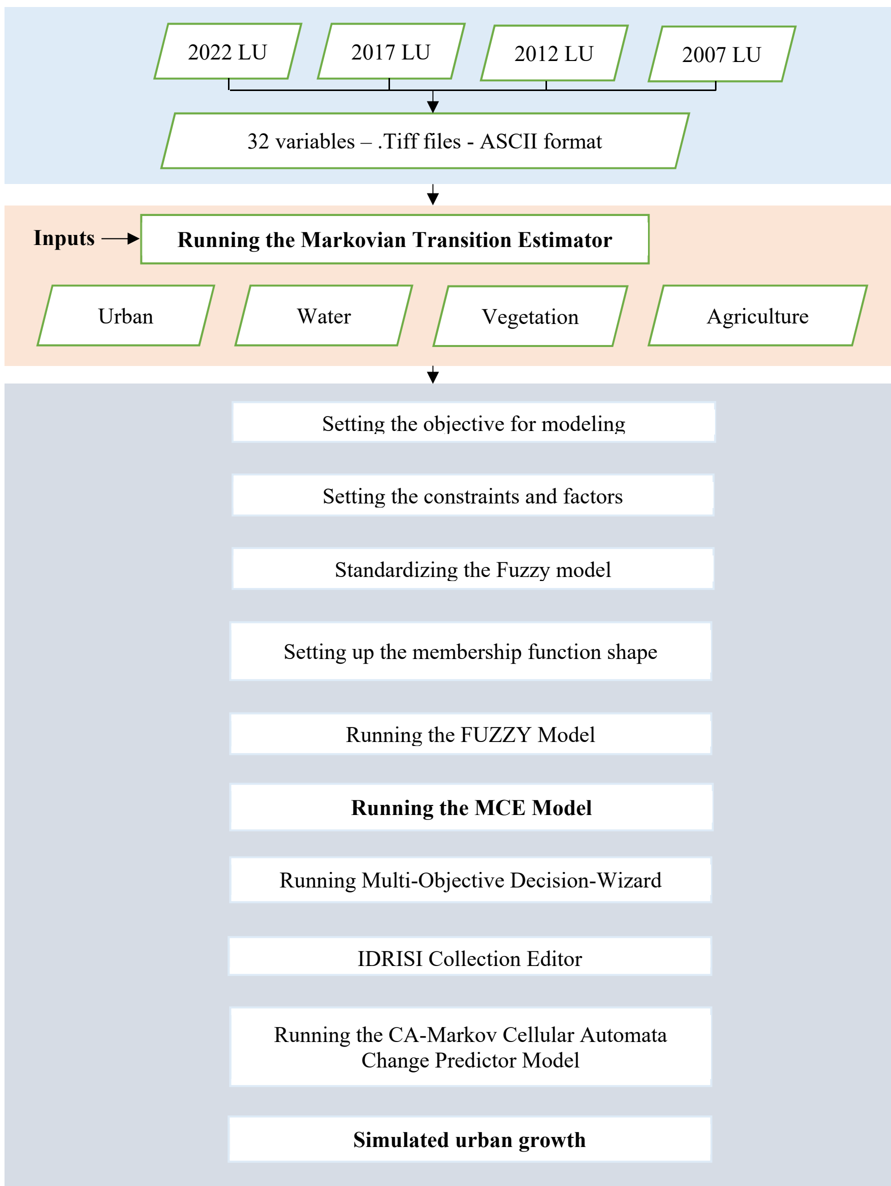
Modeling urban growth utilizing satellite-based images has become increasingly popular depending on the scope of the integrated statistical algorithms that use remote sensing data, also, the availability of high-resolution satellite imageries, which is affected by enhanced computational power [42]. GIS, remote sensing, and database management systems have become crucial technologies in analyzing, evaluating, and simulating urban sprawl scenarios [28]. The growth of advanced technologies such as GIS and Remote Sensing utilize high-resolution images which are to measure and evaluate the LULCC. Predominantly, these technologies are focused on the integration of spatial models that allow the users to analyze the transformation of land use while simulating. Apart from the historical land use data for the models, different types of agents triggering urban growth are also considered in urban modeling. Agents such as roads, slopes, development exclusion areas…etc. are used in exploring the urban growth [39].

Different types of LULC simulation approaches were developed for the evaluation of existing and future conditions of urban structures and though these approaches have evolved and these modeling techniques have a wide variety in their conceptual basis, the geo-simulation approaches have obtained considerable attention with reference to the development of GIS and remote sensing. As a result, to address these concerns, Markov chain CA models and multi-agent system models were introduced [43].

LULCC is important in many dimensions for the provision of various infrastructure-based services such as transportation, different utilities provisioning, medical facilities, schools… etc. Accordingly, this information can be obtained for planning future growth or to control future urban sprawl [44]. LULCC can be identified using various models such as Markov chain, CA, different hybrid models, evolutionary models, and statistical models as well as multi-agent models [45]. Markov models are fundamentally utilized for prediction that is formed out of Markov random process systems. Since the 1960s', these prediction models have been utilized for large-scale land-use simulations related to land use [46]. Tools for instance the city evolution trees, provide new approaches to investigating urban growth on a larger scale and provide an integrative vision of land use change also, how those changes affect the urban environment. Agent-based models (ABM) represent the linkage between individuals and land use change and this has become one of the latest techniques in urban growth modelling [39].

Markov model is a theoretical form that uses Markov random process systems in the evaluation of future statuses. Markov models are utilized to produce transition probabilities in two different periods of LULCC. By integrating the CA these models can be adapted to analyze the intricate spatial patterns. CA-Markov models are hybrid-based dynamic models that are fundamentally utilized for predicting urban land use change [47]. CA-Markov models are effective models that are effectively built utilizing CA and Markov models. As a result of this effective combination, these models can simulate long-term spatial variations [48]. Markov models are equipped with the facilitation of simple calibration abilities, are highly efficient also, the capability to simulate multiple changing patterns and scenarios [45].

3. Methodology



Source: Author, 2023

3.1. Data Source

This study was primarily conducted using the secondary data, which is the remote sensing data, and used the Landsat satellite images downloaded from the USGS Earth Explorer. Table 01 shows data which was obtained for the years 2007, 2012, 2017, and 2022.

Type of satellite	Image ID	Acquisition data	Resolution
Landsat 05 - 2007	LT05_L2SP_141055_20070323	2007 March 23	30m
Landsat 07 - 2012	LE07_L2SP_141055_20120328	2012 March 28	30m
Landsat 08 - 2017	LC08_L2SP_141055_20170113	2017 January 13	30m
Landsat 09 - 2022	LC09_L2SP_141055_20220204	2022 February 04	30m

Table 1 - Details about the satellite imageries, Source: USGS, 2023

Source: USGS Earth Explorer

3.2. Data Processing

After downloading the Landsat images, the composite band tool was used for the composition. Then utilizing the symbol options, the false color compositions were generated. All the satellite images were projected to the WGS 1984 coordinate system and for the image enhancement, sharpen, blur, and smoothing tools were utilized. After clipping to the study area, a supervised classification tool was used. After obtaining the training samples, a signature file was used for the maximum likelihood classification. The land use maps were categorized into four land use classes such as urban, vegetation, agriculture, and water bodies. A total of 145 ground truth points were generated at different locations for the Kappa accuracy assessment. All the land use classifications obtained an agreement between 0.6 and 0.8 which is nominated as good agreement. Classified images were then used for the land use simulation. Markov chain modeling was employed in monitoring, and simulating the future land use changes. The transition probability matrix for the land use change that took place was developed through the Markovian transition estimator.

4. Used Variables

32 variables have been utilized for the land use modeling and the opted variables and sources are mentioned below (Table 02).

Factors	Reference
Density of main governmental administrative functions	LUPPD
Density of schools	UDA
Developable land density	LUPPD
Distance from environment-sensitive areas	LUPPD
Distance from future sensitive areas	LUPPD
Distance from hazardous places	UDA
Distance from inappropriate garbage disposals	LUPPD
Distance from inappropriate landfills	LUPPD
Distance from industrial sites	LUPPD
Distance from industrial buildings	LUPPD
Distance from scenic beauty locations	UDA
Distance from the "B" type of roads	OSM
Distance from the disaster-prone areas - Protected areas	LUPPD
Distance from the expressways	OSM
Distance from the Major "A" type roads	OSM
Distance from the nearest sub-city centers	OSM
Distance from touristic attractive places	LUPPD
Distance from unauthorized activities	LUPPD
Distance to 2nd order type of Grocery shops - Marketplaces	OSM
Distance to bus stands	OSM
Distance to bus stops	UDA
Distance to health facilities - Hospitals	OSM
Distance to Main Town Center	LUPPD

Distance to railway stations	OSM
Distance to religious locations	OSM
Distance to water bodies	OSM
Land availability	UDA
Overall road density	OSM
Physical geographical characteristics - Slope	USGS
Population density	UDA
Population growth rate	UDA
Road infrastructure facility distribution	LUPPD

Table 2 - Factors used and references, Source – Author, 2023

(UDA – Urban Development Authority; LUPPD – Land Use Policy Planning Department; OSM – OpenStreetMap; USGS – United States Geological Survey).

The weights of the MCA have been obtained from literature reviews as well as expert opinions. For setting up the MCA Multi-Objective Decision-Wizard, for each variable, the membership function shape as well as the membership function type have to be set using the histogram shape.

Factors	**Membership function shape**	**Membership function type**
Density of main governmental administrative functions	Monotonically decreasing	J-Shaped
Density of schools	Monotonically decreasing	J-Shaped
Developable land density	Monotonically decreasing	Sigmoidal
Distance from environment-sensitive areas	Monotonically decreasing	J-Shaped
Distance from future sensitive areas	Monotonically decreasing	J-Shaped
Distance from hazardous places	Symmetric	Sigmoidal
Distance from inappropriate garbage disposals	Symmetric	Linear
Distance from inappropriate landfills	Symmetric	Sigmoidal
Distance from industrial sites	Monotonically decreasing	J-Shaped
Distance from industrial buildings	Monotonically decreasing	J-Shaped
Distance from scenic beauty locations	Symmetric	Sigmoidal
Distance from the "B" type of roads	Monotonically decreasing	J-Shaped
Distance from the disaster-prone areas - Protected areas	Monotonically decreasing	J-Shaped
Distance from the expressways	Monotonically decreasing	J-Shaped
Distance from the Major "A" type roads	Monotonically decreasing	J-Shaped
Distance from the nearest sub-city centers	Monotonically decreasing	J-Shaped
Distance from touristic attractive places	Monotonically decreasing	J-Shaped
Distance from unauthorized activities	Monotonically decreasing	Sigmoidal
Distance to 2nd order type of Grocery shops - Marketplaces	Symmetric	J-Shaped
Distance to bus stands	Symmetric	Sigmoidal
Distance to bus stops	Monotonically decreasing	Sigmoidal
Distance to health facilities - Hospitals	Symmetric	Linear
Distance to Main Town Center	Symmetric	Sigmoidal
Distance to railway stations	Monotonically decreasing	J-Shaped
Distance to religious locations	Monotonically decreasing	Sigmoidal
Distance to water bodies	Monotonically decreasing	J-Shaped
Land availability	Monotonically decreasing	J-Shaped

Overall road density	Monotonically decreasing	Sigmoidal
Physical geographical characteristics - Slope	Monotonically decreasing	Sigmoidal
Population density	Monotonically decreasing	J-Shaped
Population growth rate	Monotonically decreasing	J-Shaped
Road infrastructure facility distribution	Monotonically decreasing	J-Shaped

Table 3 - Membership function shape and type, Source – Author, 2023

Table 03 Describes the summary of membership function shape and type used in the MCA Multi-Objective Decision-Wizard.

5. Results and Discussion

5.1. LULCC analysis

Land use patterns were classified using the supervised classification technique to understand the urban growth simulation impacts in the Kurunegala district. Under the four land use categories, such as urban, vegetation, agriculture, and water the analysis was carried out for the years of 2007, 2012, 2017, and 2022. In the selected study area, the most prominent character can be identified as the vegetation cover. The next dominant land use type has been agricultural dissipation. The urban area dissipation from 2007 to 2022 has been identified as 52.78%, vegetation distribution has been lost by 8.13% from 2007 to 2022. Also, Agriculture has been reduced by 9.26% and finally, the water bodies in the study area have been increased by 29%.

LULC	2007	2012	2017	2022
Urban	58.4586	61.2548	75.075	89.311
Vegetation	796.255	798.459	755.259	731.489
Agriculture	478.562	448.326	439.022	434.259
Water	28.3254	33.5617	32.2458	36.5418

Table 4 - LULCC from 2007 to 2022 in sq. km, Source – Author, 2023

6. LULC from 2007 to 2022

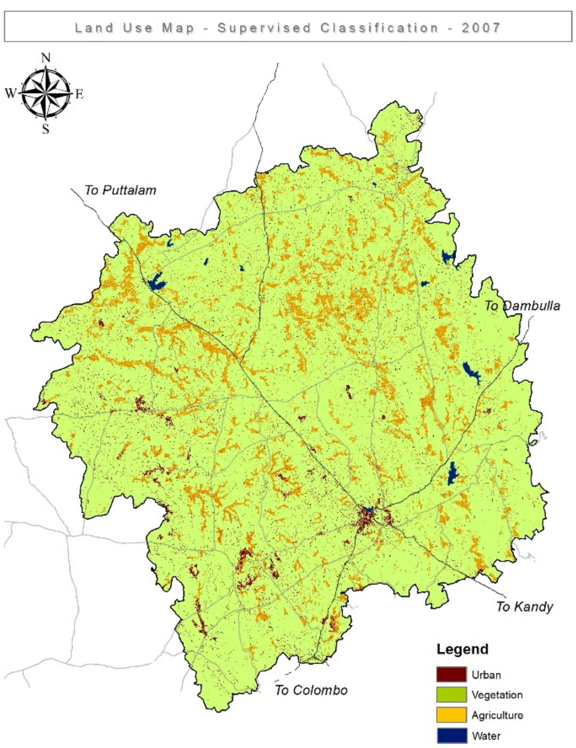


Figure 2 – LULC – 2007, Source: Author, 2023

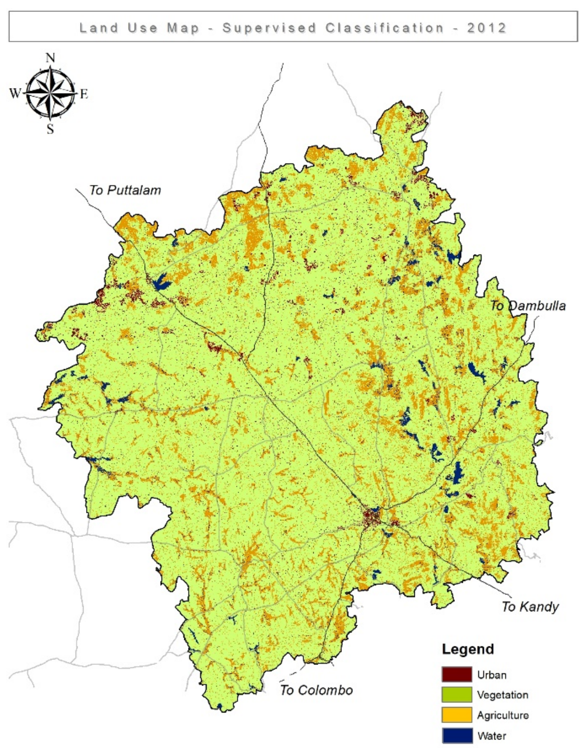


Figure 3 - LULC - 2012, Source: Author, 2023

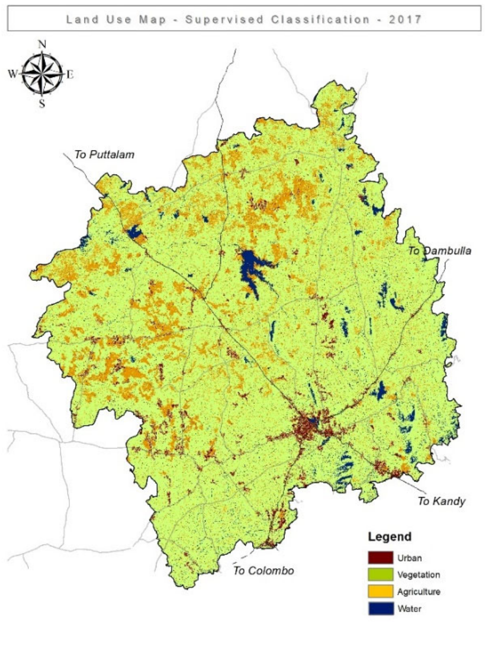


Figure 4 - LULC - 2017, Source: Author, 2023

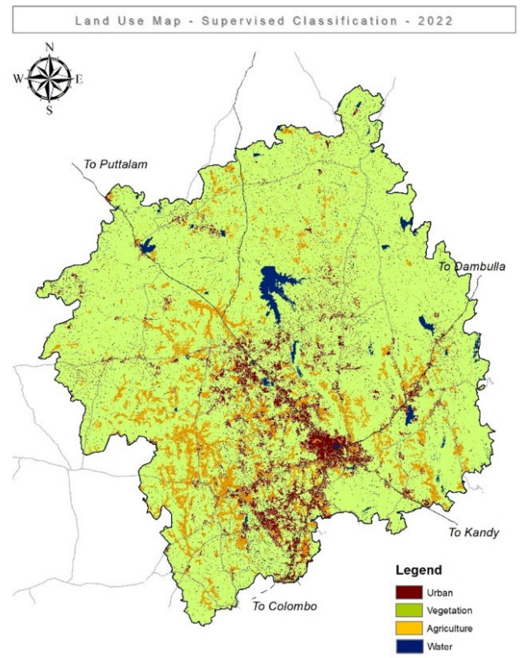


Figure 5 - LULC - 2022, Source: Author, 2023

Figures 2, 3, 4, and 5 show the LULC classification conducted for the years 2007, 2012, 2017, and 2022 respectively. Overall Kappa accuracy values have also been obtained in Table 05. The overall accuracy of each period has received over 70% accuracy and the Kappa Accuracy has received a good precision which ranges from 0.65 to 0.88.

Accuracy type	LU 2007	LU 2012	LU 2017	LU 2022
Overall Accuracy	75.65%	74.12%	81.25%	88.96%
Kappa Index Accuracy	0.6932	0.66748	0.7958	0.8745

Table 5 - Accuracy Assessment, Source – Author, 2023

7. MCA Analysis

MCA analysis was done prior to the LULC simulation. MCA is a popular as well as a powerful tool for analyzing the most conflicting factors that influence land-use decisions. MCA can accommodate most complex decision-making that can also balance various factors such as environmental sustainability, economic aspects, infrastructure requirements, and economic development. Additionally, for the integration of diverse parties and the incorporation of varied perspectives, MCA can be used. Therefore, this approach enables the integration of diverse parties as well as the provisioning of quantitative and transparent decision support. Additionally, for scenario planning and identifying future simulations, MCA can be effectively utilized [49].

MCA was used by the land use types utilized (Refer to Table 04). The MCA-related illustrations were generated using IDRISI 17.0 software (Refer to figures 6, 7, 8, and 9).

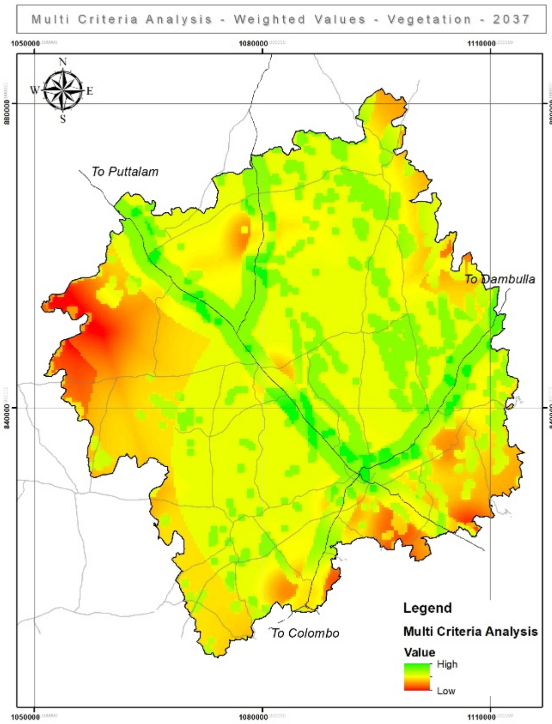


Figure 6 - MCA Vegetation, Source: Author, 2023

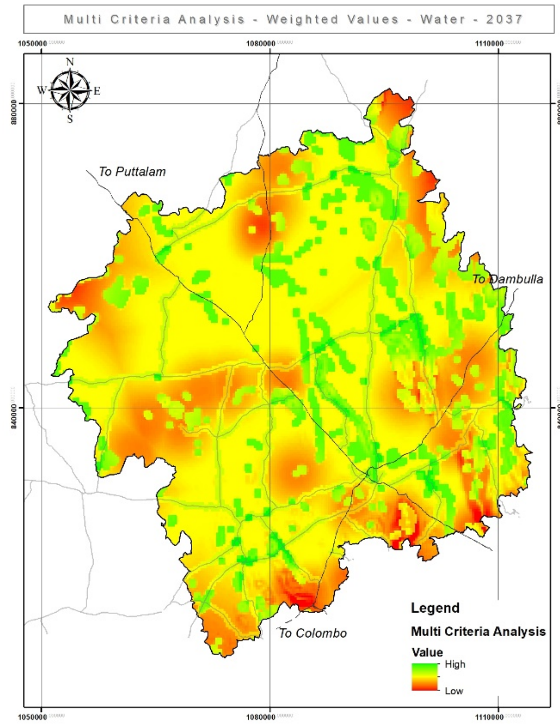


Figure 7 – MCA Water, Source: Author, 2023

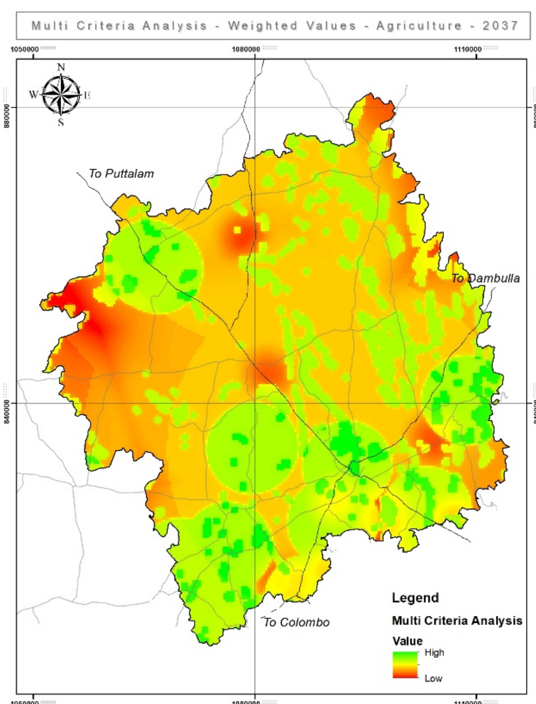


Figure 8 - MCA Agriculture, Source: Author, 2023

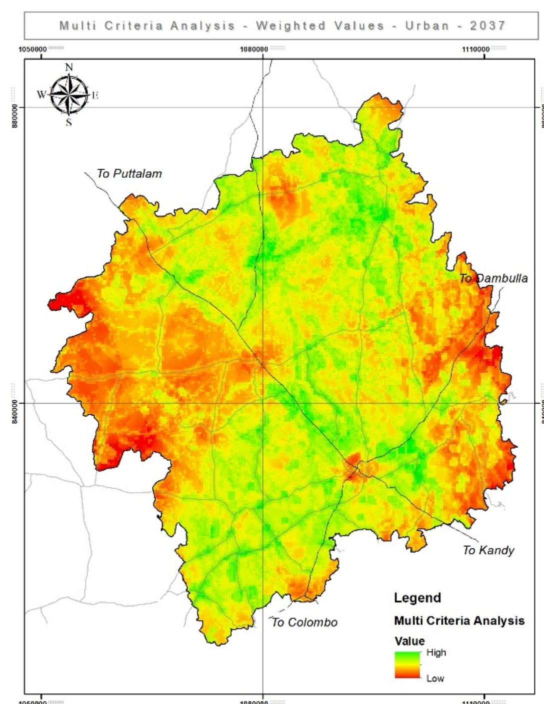


Figure 9 - MCA Urban, Source: Author, 2023

8. Simulated Land Use Change

The land use prediction was simulated using the CA-Markov chain model that generated significant land use changes in the overall configuration. Figures 10 and 11 illustrate the simulated LULC in 2027 and 2037. In the simulated LULC maps, the land use categories have been dropped to three and fundamentally three land use categories stand out such as Urban, water, and vegetation.

9. 2027 and 2037 LULC analysis

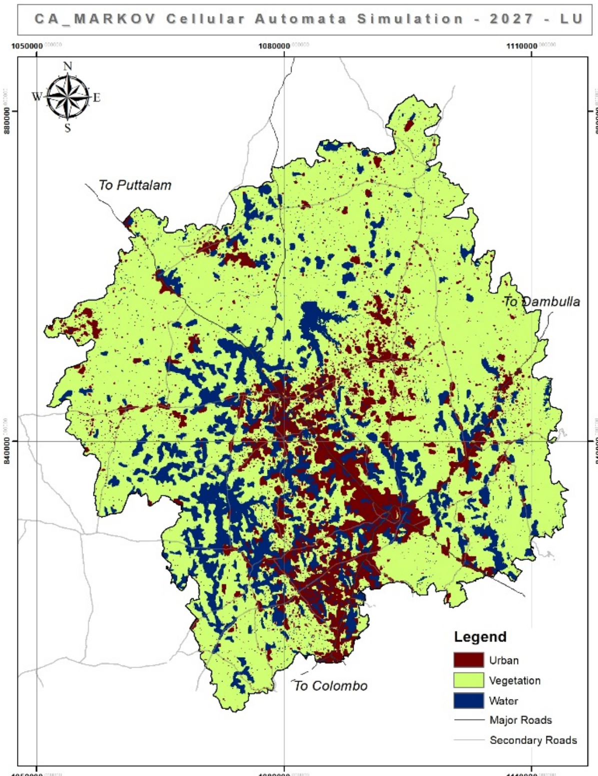


Figure 10 - Simulated 2027 Land Use, Source: Author, 2023

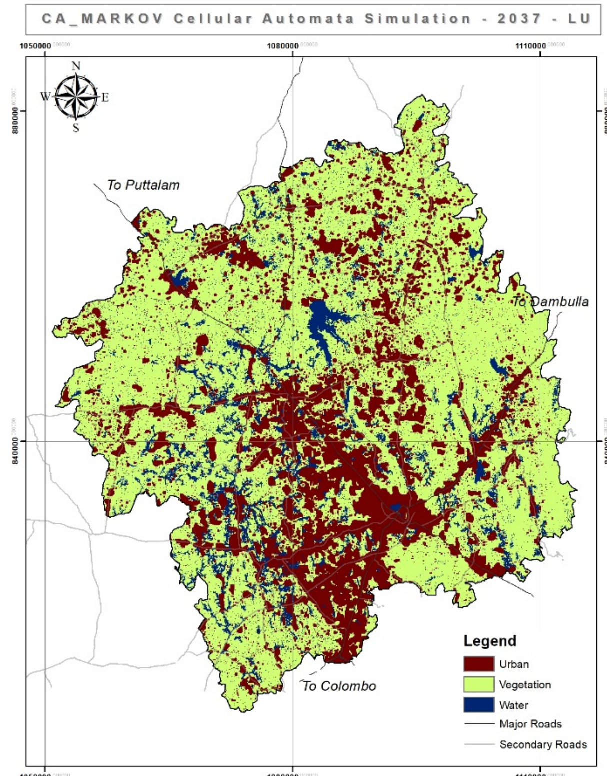


Figure 11 - Simulated 2037 Land Use, Source: Author, 2023

10. Validation

For the analysis conducted using the MCA using CA-Markov chain modeling, the new cutting threshold value, is normally used for classifying the observations into two groups based on the model's predicted probabilities. The main objective of the new cutting threshold value is to match the actual and predicted values. The simulation got the new cutting threshold value as 0.1071 which is a lower threshold value of 0.5 and this indicates that even in cases when the observations' expected probability is not very high, the model is identifying them as positive values. Additionally, the model has got True Positive Rate (TPR) of 98.88% which is a good value and this indicates model is able to successfully identify most of the actual positive cases in the simulation process. Also, this value suggests a good sensitivity. Moreover, the Markov model simulation obtained the Adjusted Odds Ratio (AOR) as 6.9755. This implies a strong relationship between the dependent and independent variables. Furthermore, the model has a False Positive Rate (FPR) of 3.13% and this suggests that the model has misclassified this amount of negative cases as positive and this value can be emphasized using the high TPR value too. Accordingly, the model seems to perform well based on the TPR and AOR. Finally, the Markov model obtained the (Receiver Operating Characteristic) ROC value as 0.7142 and this signifies a moderate performance in distinguishing between different classes in the model. (ROC = 1 indicates a perfect fit, and ROC = 0.5 indicates a random fit). Apart from the above statistical analysis obtained from the Markov model, the development suitability evaluation was conducted using the same model to reevaluate the development pattern. The above image (Figure 12) shows the development suitability that has been derived using the CA-Markov model. The urban growth distribution and dissipation for the years 2027 and 2037 have obtained favorable results that correspond to the development suitability that was obtained above. Accordingly, this outcome can also be taken for the validation of the derived results as per the areas that are appropriate for further development.

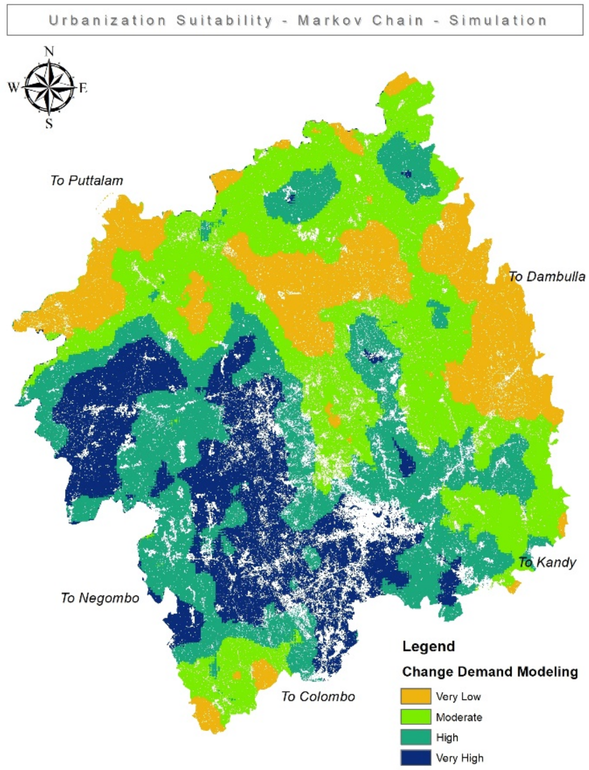


Figure 12 - Markov Chain simulation - Suitability, Source: Author, 2023

11. Conclusion

Urban sprawl is a phenomenon that can be analyzed using the built-up area dissipation which is taking place due to the various socioeconomic developments [31]. Due to this phenomenon, the structure of the land can be changed drastically. The land use patterns are mostly affected by various anthropogenic activities such as housing developments, infrastructure development projects, and commercialization impacts. Thus, this research approach attempted to simulate the LULCC using the CA-Markov model through the IDRISI 17.0 software. This projection provides a higher accurate prediction of the land use change that was done using MCA with 32 spatial variables which was identified as a fresh attempt to utilize this number of spatial factors in any of the urban growth models. Based on the results generated from this attempt, the LULC map for 2037 would be a prospect for the land use prediction. However, the development techniques can impact the built-up area change in this area and the simulated map can be used for the development of suitability modeling maps for Kurunegala, which has been predominantly growing from 2007 to 2022. Consequently, effective and necessary planning initiatives will be demanded in the future to control this urban sprawling effect in Kurunegala [50,51].

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