E-ISSN 2656-8039
INTERNATIONAL JOURNAL OF
ENVIRONMENT, ENGINEERING & EDUCATION
VOL. 5, NO. 2, 2023

www.ijeedu.com

Research Article

Analyzing and Predicting Land Use and Land Cover Changes with an Integrated CA-Markov Model: A Spatiotemporal Perspective in Case of Chuko Town and Surroundings, Sidama Region, Ethiopia

Gashaw Kibret Goshem[1], Wendwesen Taddesse Sahile[1], Seid Ali Shifaw[1], Muh. Rais Abidin[2]

[1]Department of Land Administration and Surveying, Dilla University, Dilla 419, Ethiopia

[2]Department of Geography, Universitas Negeri Makassar, Makassar 90224, South Sulawesi, Indonesia

Received: *May 12, 2023;* ***Accepted:*** *August 12, 2023;* ***Published:*** *August 15, 2023*

Abstract: Land use and land cover changes fundamentally shape global environmental and societal dynamics. The study uses an integrated CA-Markov Model to analyze and predict the land use and cover changes from 2003 to 2023 in Chuko Town and its surroundings. LULC maps were extracted from Landsat 5, Landsat 7, and Landsat 8 data and the CA-Markov model simulated the LULC for 2043. The findings reveal a significant expansion of the built-up area, increasing from 243.18 hectares in 2003 to 356.60 hectares in 2013 and further to 982.33 hectares by 2023. In contrast, the bare land decreased from 426.74 hectares in 2003 to 388.86 hectares in 2013 and 280.26 hectares in 2023. However, the vegetation category remained relatively stable, with areas of 2241.81 hectares, 2221.58 hectares, and 2085.53 hectares in 2003, 2013, and 2023, respectively. The validation model for 2023 showed an overall KIA value of 0.8, indicating reasonable prediction accuracy. Looking ahead to 2023-2043, the built-up area is projected to increase by 721.81 hectares, while the areas of bare land, agriculture, and vegetation are predicted to decrease by 182.03 hectares, 386.29 hectares, and 153.49 hectares, respectively. This projection suggests reducing vegetation, agriculture, and bare land areas by 2043. Thus, understanding historical and simulated LULC changes is invaluable for decision-makers and urban planners to formulate effective policies and strategies to address urban growth, make informed decisions, and promote sustainable city development.

Keywords: Cellular Automata; Global Information Systems (GIS); Land Use Change; Markov Chain; Predication

1. Introduction

Land use and land cover changes are pivotal in shaping global environmental and societal dynamics [1]. Among the prominent catalysts of such changes in developing countries are rapid urbanization and population growth, which significantly pressures natural and built environments [2]. Moreover, multiple factors contribute to the transformation of land use and land cover (LULC), including socioeconomic, environmental, institutional, deforestation, overgrazing, natural ecological environment, and the emergence of informal settlements [3]–[5]. Regrettably, these alterations in LULC frequently result in the loss of habitats for numerous species [6].

In many developing countries, particularly in Africa and Asia, most of the population resides in rural areas. This can be attributed to limited access to essential services such as electricity, clean water, healthcare, and employment opportunities. Consequently, many prefer to migrate to urban areas for better living conditions and more favorable prospects [7].

This article citation: G. K. Goshem, W. T. Sahile, S. A. Shifaw, M. R. Abidin, “Analyzing and Predicting Land Use and Land Cover Changes with an Integrated CA-Markov Model: A Spatiotemporal Perspective in Case of Chuko Town and Surroundings, Sidama Region, Ethiopia,” Int. J. Environ. Eng. Educ., vol. 5, no. 2, pp. 63-71, 2023.
Corresponding author: Gashaw Kibret Goshem (gashawk@du.edu.et); **DOI:** https://doi.org/10.55151/ijeedu.v5i2.114

Urban growth in third-world cities and towns has been marked by intertwined structures and tendencies, exacerbating several detrimental effects, including pollution, ecological degradation, the loss of agricultural land and green spaces, and impoverished settlements [8]–[10]. Human activities, such as deforestation, urbanization, and land degradation, are often critical factors in response sable for changes in land use and land cover (LULC) [11], [12]. However, it is essential to acknowledge that natural factors can also shape LULC alterations [13], [14].

The field of land use and land cover (LULC) change involves applying various modeling techniques to comprehend and forecast changes in the Earth's surface over time. Some frequently utilized models in this domain include Land Change Modeler (LCM), Earth Trend, Cellular Automata (CA), Markov Chain, CA-Markov, GeoMod, and STChoice [15]–[17]. It is imperative for researchers to conscientiously weigh these differences and approach model selection and comparison with caution to ensure the production of robust and dependable outcomes in LULC modeling [16].

Numerous studies have been conducted to evaluate the changes in land use and land cover (LULC) and to model and predict the future extent of LULC in different regions across the country [18]–[21]. However, a notable gap exists in conducting a comprehensive analysis of the LULC drivers, particularly in areas predominantly characterized by agroforestry practices. Therefore, it is essential to systematically examine the spatiotemporal dynamics of land use and land cover in Chuko Town and its surrounding areas.

2. Material and Method

2.1. Description of Study Area

Chuko is located in the Sidama Region of Ethiopia, approximately 338 kilometers from the capital city, Addis Ababa. The study area is well-known for its rich diversity of agricultural products, which include coffee, Inset, pineapple, and avocado.

Geographically, Chuko is positioned between 6°31' and 6°38' North latitude and 38°17' and 38°25' East longitude. The town's elevation varies between 1215 and 2029 meters above sea level, contributing to its varied terrain and ecological characteristics.

The study area experiences a mean annual rainfall ranging from 1240 to 1400 mm, further influencing its agricultural productivity and environmental conditions. The combination of favorable geographical features and climate conditions makes Chuko an essential area for studying land use and land cover changes and their implications on the region's agricultural landscape.

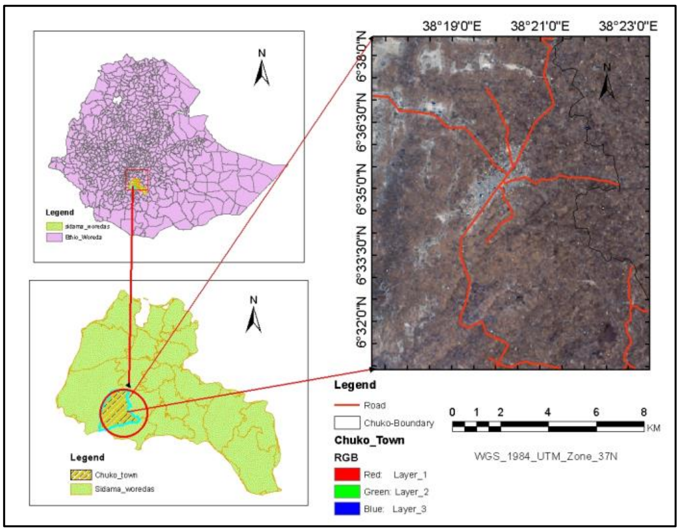


Figure 1. Locational Map of the Study Area

2.2. Software

Table 1 presents a list of software packages used in this research to support data analysis and processing in the context of map preparation and modeling of Land Use, and Land Cover (LULC) changes in the study area. These software tools play a crucial role in the analysis phase and are invaluable tools for researchers in processing image data, performing image classification, conducting change analysis, and performing atmospheric correction before the mapping process.

Table 1. Software Packages

No.	Software	Purpose
1	Arc GIS 10.8	For data analysis and map preparation
2	ERDAS Imagine 2015	For pre-processing and post-processing, such as image classification.
3	IDRISI Selva 17	For change analysis and modeling future LULC of the study area
4	QGIS	For pre-processing, such as Atmospheric correction

Utilizing these software packages is paramount in this research, as they play a crucial role in effectively processing data and providing comprehensive insights into the complexities of land use and changes in the study area. The accuracy and precision offered by these software tools are anticipated to enhance decision-making processes related to resource management and environmental protection within the researched region.

2.3. Data Sources

For the classification of land use and land cover (LULC), three sets of Landsat images from 2003, 2013, and 2023 were obtained from the USGS Earth Explorer websites. Specifically, Landsat 5, Landsat 7, and Landsat 8 images were utilized in this study.

To assess the accuracy of the LULC classification, historical images from Google Earth were incorporated, providing additional reference information. Moreover, ground reference points were collected using a Handheld GPS device, which served as ground truth data for the classification process. For a detailed overview of the data used in this study and their respective sources (Table 2).

Table 2. Data Sources

No.	Data Type	Acquisition Date	Sensor	Spatial Resolution	Sources	Cloud Cover	Path/Row
1	Landsat 8	15/02/2023	OLI-TIRS	30 meters	USGS Earth Explorer	0.02	168/55
2	Landsat 7	12/02/2013	ETM+	30 meters	" "	0.03	168/55
3	Landsat 5	17/02/2003	TM	30 meters	" "	0.01	168/55
4	Chuko Town Boundary	-	-	-	Chuko Town Municipality	-	-
5	Ground Truth data	-	-	-	Fieldwork and Google Earth	-	-

2.4. Image Pre-Processing

To ensure consistency and compatibility in the analysis, all Landsat data were subjected to image pre-processing. The data were adjusted and projected to the WGS 84 datum and UTM Zone 37 North coordinate systems. Additionally, the dark Object Subtraction (DOS) method was employed to effectively remove atmospheric noise from the images, enhancing the quality and accuracy of the subsequent analyses.

2.5. Land Use Land Cover Classification

In preparation for conducting supervised classification on the Landsat images of 2003, 2013, and 2023 using ERDAS IMAGINE, two preliminary steps were carried out to improve the accuracy of land-cover identification. First, the Normalized Difference Vegetation Index (NDVI) was applied to enhance the distinction between different land cover types. Next, unsupervised classification techniques were utilized to refine the identification process further.

After completing these pre-processing steps, the Landsat images underwent supervised classification using the maximum likelihood method. This approach identified and categorized the land-cover classes into four distinct groups: Built-up, bare land, agriculture, and vegetation.

2.6. Rate of Change of LULC in the Study Area

For each LULC, the rate of change was computed using the formula proposed [22].

$$R(\%) = \frac{(A2 - A1)}{(T2 - T1)} \times 100 \quad (1)$$

Where: Rate of change, A1 and A2 area of each time sequence, t1 and t2 corresponding time area.

2.7. Markov Chain Model

The Markov chain model is a predictive tool that determines the probability of transitioning from one state to another based on the principles of Markov stochastic process systems [23]. This model facilitates the analysis of how areas transition between different conditions over a specific period by evaluating and summarizing the changes in land use using various probabilities [24], [25].

The initial transition probability matrix (P) is obtained to transform distinct land use types. Mathematically, the elements of this matrix (Pij) can be expressed using equations (2) and (3). This mathematical representation allows for a systematic analysis of land use changes and provides valuable insights into the study area's future land cover dynamics.

$$S(t+1) = pij \times s(t) \quad (2)$$

$$Pij = \begin{pmatrix} p_{11} & p_{12} & p_{1n} \\ p_{21} & p_{22} & p_{2n} \\ p_{31} & p_{32} & p_{3n} \end{pmatrix} and$$
$$\left(0 \leq Pij < and \sum_{j=1}^{N} Pij = 1, (i,j = 2, \ldots n)\right) \quad (3)$$

Where: S (t) is the state of the system at time t, S (t +1) is the state of the system at a time (t +1); Pij is the matrix of transition probability in a form.

2.8. Cellular Automata (CA)

Cellular Automata (CA) is a widely used model for exploring spatial dynamics and understanding land use changes over time [26]. It is a renowned simulation model that operates on a discrete space and time, where interactions are localized [27]. In the CA model, the landscape is represented as a network of cells, and each cell is updated at each time stage (T+1) according to a transition law based on the states of its neighboring cells and following specified transition rules [24]. This local and iterative updating process allows the CA model to simulate the evolution of land use patterns over time, capturing the complex interactions and feedback mechanisms that drive land use changes.

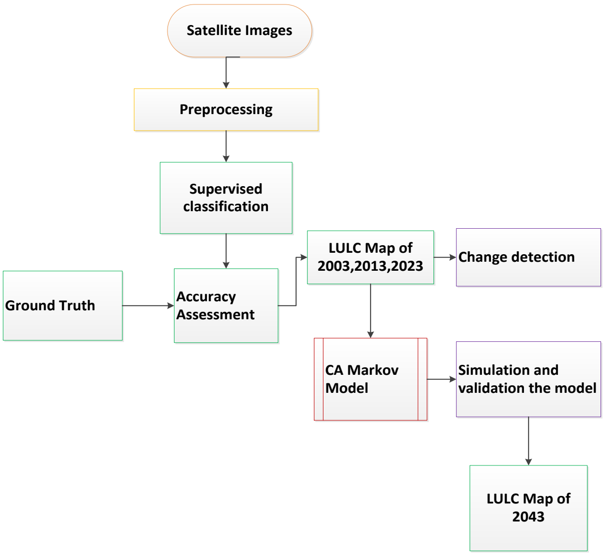
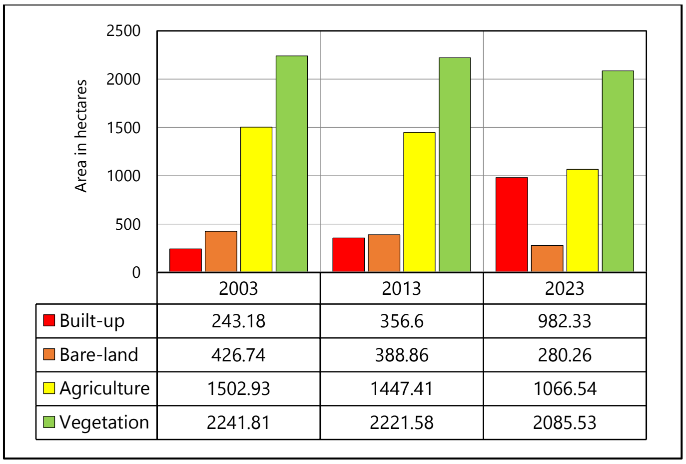


Figure 2. Methodology Flow chart

3. Result and Discussion

3.1. LULC Changes (2003-2023)

The analysis of land use and land cover (LULC) changes from 2003 to 2023 reveals significant transformations in the landscape. During this period, the built-up area experienced remarkable expansion, increasing from 243.18 hectares in 2003 to 356.60 hectares in 2013 and further expanding to 982.33 hectares by 2023. In contrast, the bare land category declined, shrinking from 426.74 hectares in 2003 to 388.86 hectares in 2013 and further decreasing to 280.26 hectares in 2023. Similarly, agricultural land decreased from 1502.93 hectares in 2003 to 1447.41 hectares in 2013 and 1066.54 hectares in 2023. Despite these changes, the vegetation category remained relatively stable, with 2241.81 hectares, 2221.58 hectares, and 2085.53 hectares in 2003, 2013, and 2023, respectively. These LULC dynamics reflect the complex interaction between urbanization and agricultural practices in the study area.



	2003	2013	2023
Built-up	243.18	356.6	982.33
Bare-land	426.74	388.86	280.26
Agriculture	1502.93	1447.41	1066.54
Vegetation	2241.81	2221.58	2085.53

Figure 3. Area Coverage of Land Use and Land Cover

The expansion of built-up areas and the decline of farming lands indicate the ongoing urban development and land use changes driven by population growth and economic activities. The relative stability of vegetation areas emphasizes preserving natural ecosystems amidst rapid urbanization.

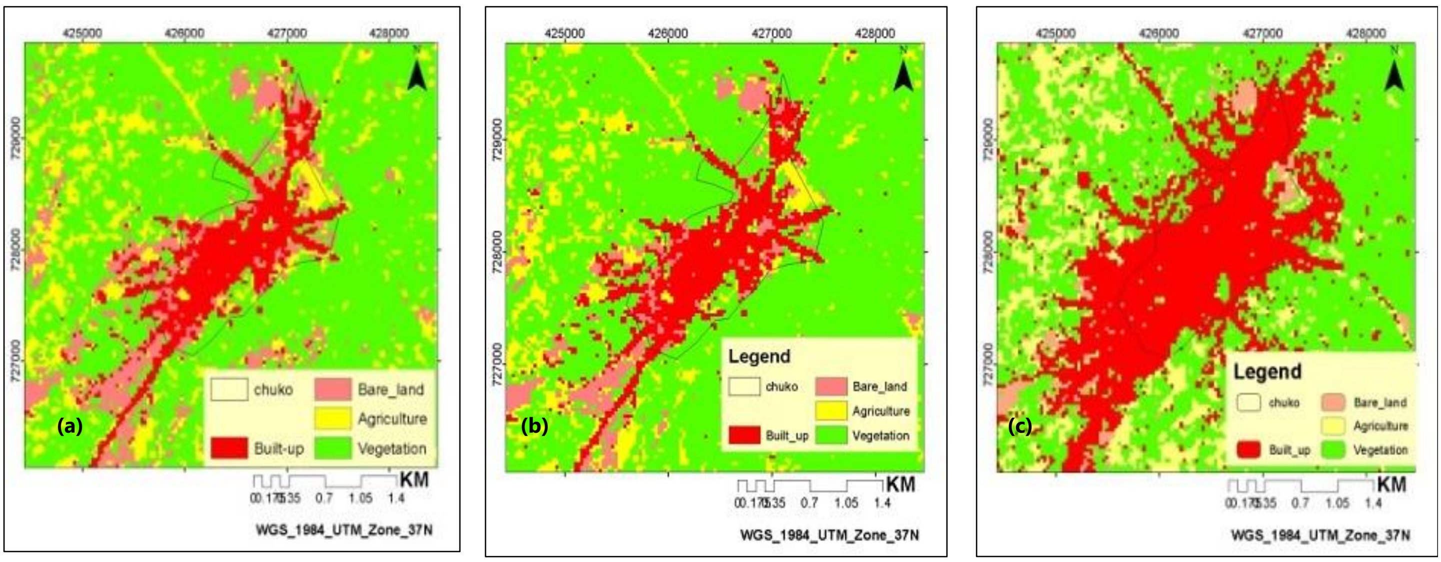


Figure 4. Land Use Maps in Different Years, (a) 2003; (b) 2013; (c) 2023.

3.2 Land Use Land Cover Change Detection (2003-2023)

The change detection analysis is crucial to examine the expansion and development of land and urban areas over time, calculated with equation (1).

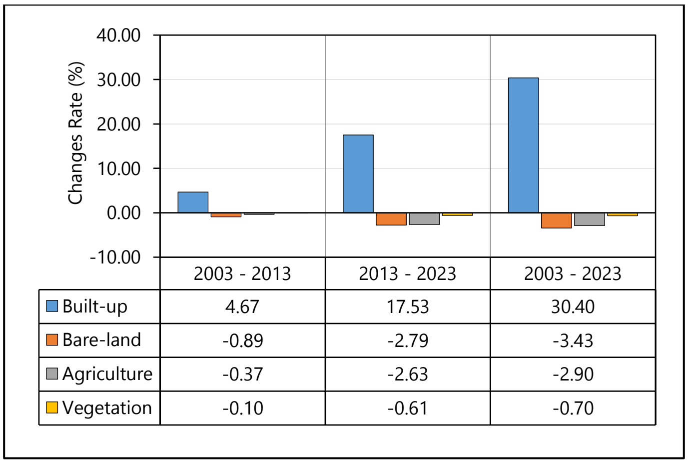


Figure 5. Land Use Land Cover Change Detection (2003-2023)

The above (Figure 5) represents the net change in each land category from 2003 to 2023. The built-up area increased by 739.15 hectares, showing a 30.40% year-to-year growth. However, there were decreases in the bare land category by 146.48 hectares, agriculture by 436.39 hectares, and vegetation by 156.28 hectares. Positive values generally indicate an increase in area, while negative values indicate a decrease.

3.3 Classification Accuracy Assessment

Google Earth and handheld GPS both provide complementary methods for evaluating accuracy. While Google Earth offers a visual platform for more extensive analyses, GPS devices provide ground-truth data with accurate location information. The kappa value ranges from 0.41 to 0.6, showing moderate agreements; 0.61 to 0.80, having strong agreements; and 0.81 to 1, indicating nearly perfect contracts [28]. For 2003, 2013, and 2023, Chuko Town's and surrounding overall categorization accuracy of kappa value is 83%, 85%, and 87.3%, respectively.

3.4 Markov Chain Transition Probabilities

The Markov transition probability matrix in Table 3 was calculated using equations (2) and (3). The LULC for 2023 was estimated using the 2003–2013 probability matrices, and the CA-MC Model is predicted using the 2013–2023 probability matrices.

Based on the matrix analysis (Table 3), the results indicate that the Built-up areas in 2003 tend to remain as Built-up until 2023 with a probability of 0.78. The likelihood of changing to Bare-land is 0.13, and to Agricultural regions is 0.09. The Bare-land areas in 2003 have a high probability (0.92) of remaining as Bare-land until 2023. The probability of changing into Built-up is 0.04, while changing into Agricultural or Vegetation areas each has a probability of 0.03 and 0.01, respectively. The Agricultural areas in 2003 also tend to maintain their status with a probability of 0.91. The probability of changing into Bare-land is 0.04, and changing into Built-up or Vegetation areas has a probability of 0.01 and 0.05, respectively. The vegetation areas in 2003 have a high probability (0.94) of remaining as vegetation until 2023. The probability of changing into Bare-land is 0.02, and changing into Built-up or Agricultural areas, each has a probability of 0.01 and 0.04, respectively.

Table 3. Markova Transition Probability Matrix

Period	Category	Built-up	Bare-land	Agriculture	Vegetation
2003-2013 For 2023	Built-up	0.78	0.13	0.09	0.00
	Bare-land	0.04	0.92	0.03	0.01
	Agriculture	0.01	0.04	0.91	0.05
	Vegetation	0.01	0.02	0.04	0.94
2013-2023 For 2043	Built-up	0.67	0.08	0.14	0.11
	Bare-land	0.33	0.16	0.16	0.36
	Agriculture	0.14	0.03	0.35	0.48
	Vegetation	0.11	0.01	0.20	0.68

The Built-up areas tend to maintain their status as Built-up with a probability of 0.67 until 2043. The probability of changing into Bare-land is 0.08, and changing into Agricultural or Vegetation areas has a probability of 0.14 and 0.11, respectively. The Bare-land areas in 2013 tend to remain Bare-land with a probability of 0.16 until 2043. The probability of changing into Built-up is 0.33 while changing into Agricultural or Vegetation areas each has a probability of 0.16 and 0.36, respectively. The Agricultural areas in 2013 have a probability of 0.48 to remain Agricultural until 2043. The probability of changing into Built-up is 0.14, and changing into Bare-land or Vegetation areas each has a probability of 0.03 and 0.35, respectively. The Vegetation areas in 2013 have a high probability (0.68) to remain vegetation until 2043. The probability of changing into Built-up is 0.11, and changing into Bare-land or Agricultural areas has a probability of 0.01 and 0.20, respectively.

3.5 Integrated CA–MC Model Implementation and Validation

Table 4 compares the area coverage for each Land Use and Land Cover (LULC) class between the classified and simulated maps for 2023. The area coverage for each LULC class in the classified and simulated maps is comparable, indicating a close agreement between the simulated and actual classified areas. For instance, the built-up area in the classified map covered 982.33 hectares, while the simulated map showed an area coverage of 1010.86 hectares for the year 2023. Table 4 compares the classified and simulated LULC areas (in hectares) for each LULC class in 2023.

Table 4. Comparison of Classified and Simulated LULC

No.	LULC (Ha)		Purposes
	LULC	2023 Classified	2023 Simulated
1	Built-Up	982.33	1010.86
2	Bare-Land	280.26	250.43
3	Agriculture	1066.54	976.65
4	Vegetation	2085.53	2176.72

Table 4 presents the validation results for each Land Use and Land Cover (LULC) class. The overall Kappa Index of Agreement (KIA) value of the validation model for 2023 was found to be 0.80. Among the LULC categories, the built-up area exhibited the highest similarity, with a KIA of 0.90, while the vegetation category showed a moderate level of similarity, with a KIA of 0.75 for the simulated and classified LULC maps of 2023. Both bare land and agriculture demonstrated high similarity, with a KIA of 0.80 between the simulated and classified maps for the same year.

Table 5. KIA of Each Land Use and Land Cover (LULC) Class

LULC Class	Built-up	Bare-land	Agriculture	Vegetation
KIA	0.90	0.80	0.81	0.75

Using the classified map of 2023 as a reference, the simulated map achieved an accuracy rate of 87.3% in matching the classified map. These results provide a robust foundation for predicting future Land Use and Land Cover (LULC) changes, including the LULC projection for the year 2043.

In Figure 6, the projected built-up expansion will occur in various directions, to varying degrees, replacing different land-use types. Specifically, it is anticipated that the built environment's LULC changes between 2023 and 2043 will primarily occur near the urban outskirts, particularly in the southwest and northeastern regions of the town. During this period, bare and agricultural land will be converted into built-up regions more than vegetation.

The built-up area will increase from 982.33 hectares in 2023 to 1704.14 hectares in 2043, representing significant growth. In contrast, the bare land will decrease from 280.26 hectares in 2023 to 98.23 hectares in 2043, and agriculture will also decrease from 1066.54 hectares in 2023 to 680.25 hectares in 2043. The vegetation will experience a slight decrease from 2085.53 hectares in 2023 to 1932.04 hectares in 2043.

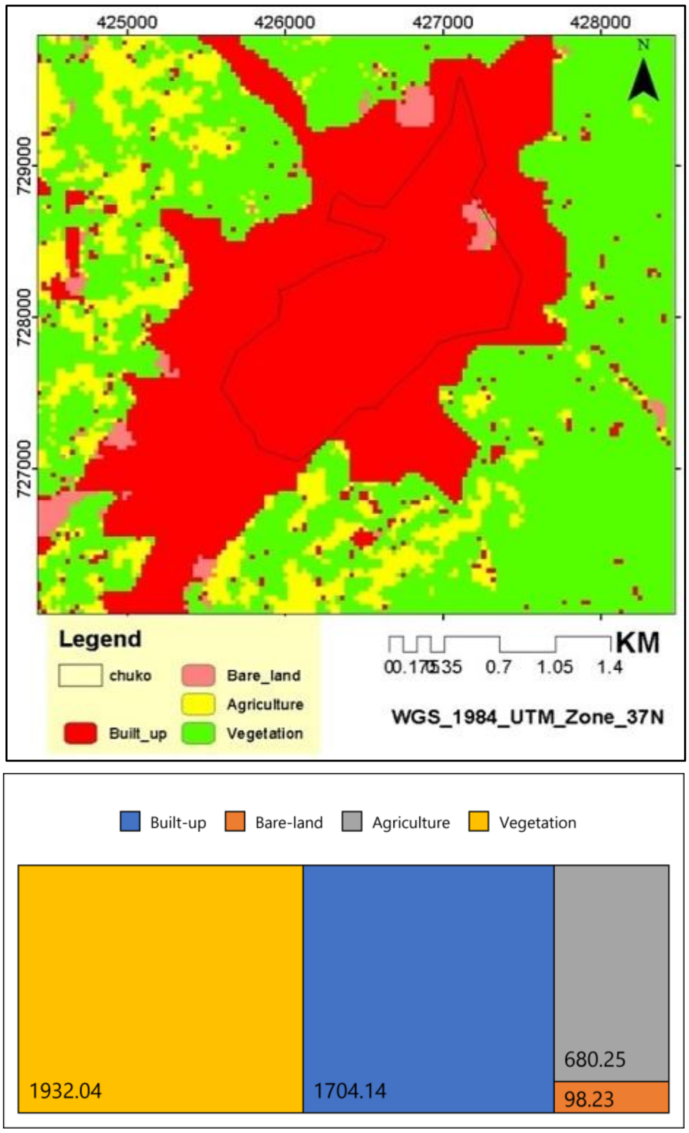


Figure 6. Predicted LULC of 2043 (Map and Graphic)

As a result, the predicted built-up area is expected to increase by 39% in the town's southern, southwestern, and northeastern parts. This expansion will notably impact the overall landscape and highlights the importance of managing urban development to balance growth and environmental preservation.

In the simulated LULC map of the study area for the year 2043, it was observed that the built-up area expanded by 1704.14 hectares. Conversely, bare land, agriculture, and vegetation experienced a decline over time, with reductions of 98.23, 680.25, and 1932.04 hectares from their respective total areas. These findings are consistent with numerous studies on predicting and simulating Land Use and Land Cover (LULC) changes. The present study's findings align with several previous studies that have addressed the issue of predicting and simulating LULC changes [29]–[33]. These collective findings provide additional support and validity to the conclusions drawn in this research, further reinforcing the importance of understanding and managing LULC dynamics for sustainable land use planning and environmental conservation. To assess the performance of the CA-Markov model, a comparison was made between the classified and simulated values for each LULC category. The results indicated that the model over-predicted built-up areas compared to the actual classification. Conversely, the model underestimated the extent of bare land, agriculture, and vegetation in the study area.

The Kappa Index of Agreement (KIA) was used to forecast the LULC map 2023 for model validation. An overall KIA value of 0.8 exceeded the minimum acceptable standard, demonstrating a solid agreement between the observed and predicted LULC classes in Chuko Town and its surroundings. Specifically, the built-up classes exhibited relatively higher deal, while the bare land, agriculture, and vegetation classes demonstrated moderate understanding. The effectiveness of the CA-Markov model in predicting future spatiotemporal LULC changes in Chuko Town and its surroundings has been supported by various researchers who reported acceptable KIA values when applying this model in different areas [34]–[37]. These findings reinforce the reliability and utility of the CA-Markov model in studying LULC dynamics and projecting future changes in diverse geographic regions.

4. Conclusion

This study employed advanced geospatial tools and models, including ERDAS Imagine 2015 and ArcGIS 10.8, to generate land use and land cover (LULC) maps for 2003, 2013, and 2023 in Chuko Town and its surrounding areas. The CA-Markov model was utilized to analyze LULC dynamics and simulate future LULC distribution. The findings revealed significant changes in the LULC of the study area between 2003 and 2023, with a notable expansion of built-up areas at the expense of bare land, vegetation, and agriculture. The CA-Markov model's validation results demonstrated a strong agreement between the classified LULC map and the modeled LULC map for the year 2023, confirming the reliability of the simulation. Based on the simulated LULC map for Chuko Town and its surroundings, it is evident that by the year 2043, built-up areas are projected to further expand by 1704.14 hectares, while the extent of bare land, agriculture, and vegetation is expected to decrease by 98.23, 680.25, and 1932.04 hectares, respectively. Knowing historical and simulated LULC changes is invaluable for decision-makers and urban planners. Armed with this information, they can develop effective policies and strategies to address rapid urbanization, make informed decisions, and foster the development of sustainable cities.

Acknowledgments

I thank my co-authors for their invaluable assistance and thoughtful critiques of my articles. Their constructive criticism and valuable recommendations have significantly contributed to improving the quality and scope of my work. I am also profoundly thankful to the USGS for generously providing free access to their invaluable data, greatly enriching my research and analysis. Furthermore, I wish to express my sincere appreciation to the Chuko Town Administration for their collaborative efforts and unwavering support throughout my study. Their cooperation has been instrumental in obtaining relevant data and ensuring its accuracy, making this research possible. I am sincerely grateful to all the individuals and organizations mentioned above for their contributions, without which this study would not have been successful. Their support and assistance have been instrumental in the completion of this work.

References

[1] M. Yourek *et al.*, “Downscaling global land-use / cover change scenarios for regional analysis of food , energy , and water subsystems,” no. January, pp. 1–22, 2023, doi: 10.3389/fenvs.2023.1055771.

[2] N. Ann, “Spatiotemporal Monitoring of Urban Sprawl in a Coastal City Using GIS-Based Markov Chain and Artificial Neural,” pp. 1–24, 2023.

[3] J. Cui, M. Zhu, Y. Liang, G. Qin, J. Li, and Y. Liu, “Land Use / Land Cover Change and Their Driving Factors in the Yellow River Basin of Shandong Province Based on Google Earth Engine from 2000 to 2020,” 2022.

[4] C. Liu, W. Li, G. Zhu, H. Zhou, and H. Yan, “remote sensing Land Use / Land Cover Changes and Their Driving Factors in the Northeastern Tibetan Plateau Based on Geographical Detectors and Google Earth Engine : A Case Study in Gannan Prefecture.”

[5] P. Lukas, A. M. Melesse, and T. T. Kenea, “Prediction of Future Land Use / Land Cover Changes Using a Coupled CA-ANN Model in the Upper Omo – Gibe River,” 2023.

[6] K. Dimobe, A. Ouédraogo, and S. Soma, “Identification of driving factors of land degradation and deforestation in the Wildlife Reserve of Bontioli (Burkina Faso , West Africa),” *Glob. Ecol. Conserv.*, vol. 4, pp. 559–571, 2015, doi: 10.1016/j.gecco.2015.10.006.

[7] M. T. Urban, S. A. Stability, M. Hove, and E. T. Ngwerume, “The Urban Crisis in Sub-Saharan Africa : A Threat to Human Security and Sustainable Development,” vol. 2, no. 1, pp. 1–14, 2013.

[8] A. F. Koko, W. Yue, G. A. Abubakar, and R. Hamed, “Monitoring and Predicting Spatio-Temporal Land Use / Land Cover Changes in Zaria City , Nigeria , through an

Integrated Cellular Automata and Markov Chain Model (CA-Markov)," 2020.

[9] I. Barow, M. Megenta, and T. Megento, "Spatiotemporal analysis of urban expansion using GIS and remote sensing in Spatiotemporal analysis of urban expansion using GIS and remote sensing in Jigjiga town of Ethiopia," no. November, 2018, doi: 10.1007/s12518-018-0245-z.

[10] M. A. Ade and Y. D. Afolabi, "Monitoring urban sprawl in the Federal Capital Territory of Nigeria using Remote Sensing and GIS techniques," *Ethiop. J. Environ. Stud. Manag.*, vol. 6, no. 1, pp. 82–95, 2013.

[11] J.-L. Kouassi, A. Gyau, L. Diby, Y. Bene, and C. Kouamé, "Assessing land use and land cover change and farmers' perceptions of deforestation and land degradation in South-West Côte d'Ivoire, West Africa," *Land*, vol. 10, no. 4, p. 429, 2021.

[12] C. C. Sang, D. O. Olago, and Z. J. Ongeri, "Discover Sustainability The factors driving land cover transitions and land degradation and the potential impacts of the proposed developments in the Isiolo dam watershed , LAPSSET corridor , Kenya," *Discov. Sustain.*, 2023, doi: 10.1007/s43621-023-00126-w.

[13] L. Fang *et al.*, "Identifying the impacts of natural and human factors on ecosystem service in the Yangtze and Yellow River Basins," *J. Clean. Prod.*, vol. 314, no. January, p. 127995, 2021, doi: 10.1016/j.jclepro.2021.127995.

[14] A. Y. Yesuph and A. B. Dagnew, "Land use / cover spatiotemporal dynamics , driving forces and implications at the Beshillo catchment of the Blue Nile Basin , North Eastern Highlands of Ethiopia," *Environ. Syst. Res.*, 2019, doi: 10.1186/s40068-019-0148-y.

[15] C. S. Reddy, S. Singh, V. K. Dadhwal, and C. S. Jha, "Predictive modelling of the spatial pattern of past and future forest cover changes in India," vol. 2005, 2017, doi: 10.1007/s12040-016-0786-7.

[16] H. M. Olujide, N. B. Amoo, S. M. Oguntayo, S. K. Aroge, and A. O. Amoo, "Geospatial analysis of land use and land cover dynamics in Akure, Nigeria," *Dutse J. Pure Appl. Sci.*, vol. 4, no. 1, pp. 379–393, 2018.

[17] S. V Kumar, C. D. Peters-lidard, Y. Tian, P. R. Houser, and J. Geiger, "Land information system: An interoperable framework for high resolution land surface modeling," vol. 21, pp. 1402–1415, 2006, doi: 10.1016/j.envsoft.2005.07.004.

[18] M. K. Leta and T. A. Demissie, "Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed , Upper Blue Nile Basin , Ethiopia," no. Lcm, 2021.

[19] M. Mathewos, S. M. Lencha, and M. Tsegaye, "Land use and land cover change assessment and future predictions in the Matenchose Watershed, Rift Valley Basin, using CA-Markov simulation," *Land*, vol. 11, no. 10, p. 1632, 2022.

[20] H. Yohannes, T. Soromessa, M. Argaw, and A. Dewan, "Heliyon Changes in landscape composition and con fi guration in the Beressa watershed , Blue Nile basin of Ethiopian Highlands: historical and future exploration," *Heliyon*, vol. 6, no. September, p. e04859, 2020, doi: 10.1016/j.heliyon.2020.e04859.

[21] A. A. Biratu *et al.*, "Ecosystem Service Valuation along Landscape Transformation in Central Ethiopia," 2022.

[22] H. Al-bilbisi, "Spatial Monitoring of Urban Expansion Using Satellite Remote Sensing Images: A Case Study of Amman City , Jordan," 2019.

[23] A. A. A. Al-sharif and B. Pradhan, "Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellula," no. September, 2013, doi: 10.1007/s12517-013-1119-7.

[24] W. Sun *et al.*, "ResearchArticle Geospatial Analysis of Urban Expansion Using Remote Sensing Methods and Data: A Case Study of Yangtze River Delta , China," vol. 2020, 2020.

[25] H. Mohammadian, J. Tavakoli, and H. Khani, "Monitoring land use change and measuring urban sprawl based on its spatial forms The case of Qom city," *Egypt. J. Remote Sens. Sp. Sci.*, vol. 20, no. 1, pp. 103–116, 2017, doi: 10.1016/j.ejrs.2016.08.002.

[26] S. Adhikari and J. Southworth, "Simulating Forest Cover Changes of Bannerghatta National Park Based on a CA-Markov Model: A Remote," pp. 3215–3243, 2012, doi: 10.3390/rs4103215.

[27] G. International and S. Mondal, "Modeling of spatio-temporal dynamics of land use and land cover in a part of Brahmaputra River basin using Geoinformatic techniques," no. September 2015, 2013, doi: 10.1080/10106049.2013.776641.

[28] T. K. Agyemang, J. Heblinski, K. Schmieder, H. Sajadyan, and L. Vardanyan, "Accuracy assessment of supervised classification of submersed macrophytes: the case of the Gavaraget region of Lake Sevan , Armenia," pp. 85–96, 2011, doi: 10.1007/s10750-010-0465-7.

[29] H. H. Entahabu and A. S. Minale, "Modeling and Predicting Land Use / Land Cover Change Using the Land Change Modeler in the Suluh River Basin , Northern Highlands of Ethiopia," pp. 21–25, 2023.

[30] G. Abebe, D. Getachew, and A. Ewunetu, "Analysing land use / land cover changes and its dynamics using remote sensing and GIS in Gubalafito district , Northeastern Ethiopia," *SN Appl. Sci.*, no. December, 2021, doi: 10.1007/s42452-021-04915-8.

[31] M. Alsharif, A. A. Alzandi, and R. Shrahily, "Land Use Land Cover Change Analysis for Urban Growth Prediction Using Landsat Satellite Data and Markov Chain Model for Al Baha Region Saudi Arabia," 2022.

[32] W. Zewdie and E. Csaplovies, "Remote Sensing based multi-temporal land cover classification and change detection in northwestern Ethiopia Remote Sensing based multi-temporal land cover classification and change detection in northwestern Ethiopia," vol. 7254, 2017, doi: 10.5721/EuJRS20154808.

[33] S. H. Gebresellase, Z. Wu, H. Xu, and W. I. Muhammad, "Scenario-Based LULC Dynamics Projection Using the CA – Markov Model on Upper Awash Basin (UAB), Ethiopia," 2023.

[34] M. A. Derebe, S. D. Hatiye, and L. A. Asres, "Dynamics and Prediction of Land Use and Land Cover Changes Using

Geospatial Techniques in Abelti Watershed , Omo Gibe River," vol. 2022, 2022.

[35] A. Cherinet and S. Worku, "Land Use Land Cover Change Dynamics of Jigjiga Town and Toga Watershed : Using GIS and Remote Sensing Technique," vol. 4, no. 3, pp. 17–25, 2020.

[36] M. Mariye, L. Jianhua, and M. Maryo, "Land use land cover change analysis and detection of its drivers using geospatial techniques : a case of," *All Earth*, vol. 34, no. 1, pp. 309–332, 2022, doi: 10.1080/27669645.2022.2139023.

[37] B. Matlhodi, P. K. Kenabatho, B. P. Parida, and J. G. Maphanyane, "Analysis of the Future Land Use Land Cover Changes in the Gaborone Dam Catchment Using CA-Markov Model : Implications on Water Resources," 2021.