Monitoring and Predicting Urban Growth Trends by Using Geo-Informatics Approaches, A Case Study of Hossana City, Southern Ethiopia

Yigezu Lenda Liyuneh

***Abstract:** In recent decades, urban sprawl has been a prominent element of urban expansion, particularly in developing nations like Ethiopia. To deal with this problem, it's necessary to forecast auto-spreading orientation toward rural areas through time to avoid haphazard urban growth. Although there were many Models applied to investigate urban growth trends all over the world, just a few studies have used these methods to look at Hossana City's urban expansion. The study used the Cellular Automata (CA) model in concert with MOLUSCE to monitor and evaluate spatial changes in the city over the last two decades. For this, Landsat data (TM, ETM+, and OLI) from the years 2000, 2010, and 2021 were used. A 30m DEM was used to extract several thematic layers such as distance to stream, topography, slope, and aspect. Distance to build up land and road networks were derived from classified LULC maps and OSM respectively. For comparison and assessment of the city's urbanization extent, Google Earth images were used. For accuracy testing, topo sheets were employed. ENVI software was used to preprocess satellite data and related auxiliary data. Land use and land cover maps were created using the maximum likelihood algorithm of supervised image classification. ArcGIS 10.8 was used to classify land use and land cover, as well as to evaluate accuracy. Overall accuracy and kappa coefficient results were higher than the minimum acceptable levels. The cumulative rate of urban growth in Hossana city has resulted in significant change during the last two decades (2000 to 2021). This reveals that there have been significant changes in several LULC categories, including bare land, agricultural land, water bodies, and green areas, which have declined by (-6.73 percent), (-18.69 percent), (-0.67), and (2.51) percent, respectively. Built-up areas and vegetation, on the other hand, increased by 22.88 percent and 5.73 percent, respectively. Projection of the future urban growth pattern processed through QGIS by using the CA model. As a result of the findings, significant changes in various LULCs are likely to occur between the present study period (2021) and the prediction year (2031). Thus agricultural land will reduce by 1.55 %, while bare land will shrink by 0.5%, but built-up areas and green areas will grow by 3.09 % and 0.91 %, respectively. Vegetation coverage would be reduced by 3.0%, while water bodies would be reduced by 0.17 %. Thus more change was made towards agricultural land and vegetation. Therefore Hossana city's urbanization rate is greatly expanding on agricultural land. The project output indicated that the increase in built-up of the town brings about high pressure on agricultural land. In general, Geoinformatics techniques enable us for sustainable management of urban sprawl and monitoring of urban expansion and future development.*

Manuscript received on 01 July 2024 | Revised Manuscript received on 13 July 2024 | Manuscript Accepted on 15 July 2024 | Manuscript published on 30 July 2024.
**Correspondence Author(s)*
Yigezu Lenda Liyuneh*, Lecturer, Arba Minch University, Ethiopia E-mail: yigezulan95@gmail.com, ORCID ID: 0000-0001-6652-6468
Dr. M. Kartic Kumar, Assistant Professor, Geomatics Engineering, Wachemo University, Ethiopia. E-mail: karthickumar.msm@gmail.com

***Keywords: -** Urban growth, Geoinformatics, Cellular Automata, LULC, Hossana City*

I. INTRODUCTION

Urbanization is a complex socioeconomic process that shifts the distribution of a population from dispersed rural settlements to dense urban settlements (United, 2021) [21]. Analyzing the land cover changes and understanding the subsequent trends of change contribute to the present complex dynamics of land cover is important for policy-making, planning, and implementation of natural resource management (Ioannis & M., 2011) [14] (Selçuk, 2008.) [18].

Ethiopia is one of the world's least urbanized countries. The level of urbanization is low even by African standards (Bekalo, 2009) [6] (Berhane, 2017) [7] (Fekadu, 2015) [10]. Despite the low level of urbanization and the fact that the country is primarily rural, the rate of urbanization is rapidly increasing. Hossana city is known for its rapid informal growth and squatting (Ashenafi, 2015) [2]. A Rapid increase in population growth, the high expense of urban living standards, illegal land grabs by urban speculators, and weak land leasing policies are all factors that contribute to squatting in Hossana City (Solomon, 1999) [20]. Although there were many Models applied to investigate urban growth trends all over the world, just a few studies have used these methods to look at Hossana City. Consequently, several steps still need to be made to prepare the city for its future dynamics of growth (Herold, et al., 2003) (Hakim A, et al., 2019)[11][12]. Thus, to prevent the spread of informal settlements and squatting activities in the city this study investigated the causes of these activities and provided potential remedies to concerned government agencies and other stakeholders of the city.

Using Geo-informatics techniques has become a crucial way to plan land use land cover development of concurrent cities (Aspeq Karsidi, 2004)[3] (Bauer, et al., 2003)[5] (Campbell, et al., 2005)[8]. Both remote sensing and GIS tools are applied in a wide variety of application areas including detecting and monitoring environmental changes, location and extent of urban growth, and environmental impact assessment (Bahiru, 2008) [4] [27].

According to Herold, et al., (2002) [13], remote sensing technology has great potential for the acquisition of detailed and accurate land use/cover information for the management and planning of urban regions.

*Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)*

Because of their cost effectiveness, temporal frequency, and extensibility, remote sensing approaches are widely used for change detection analysis (Jensen, 2007) [15].

Wanhui, (2011) [22], study endorses that during the past decades, land use land cover change (LUCC) has taken place around most Chinese cities at unprecedented rates. Numerous rural areas, like wetlands and woodlands, have been converted into human settlements during this period. Several techniques have been used to deliver an assessment of urban growth. One of the interesting techniques is MOLUSCE (Modules for Land Use Change Evaluation). It is designed to analyze, model, and simulate urban land use/cover changes. The choice of MOLUSCE for this study is due to the reason of its availability as a plugin under QGIS software.

Nugroho, et al., (2018) [17] [23] [24] [25] [26] applied the MOLUSCE model to predict land cover changes and the direction of spatial distribution in Malang City, Indonesia. Hakim A, et al., (2019) used MOLUSCE to identify the spatial dynamics and predict LULC changes in Makassar city, Indonesia. According to Aspeq Karsidi, (2004) studies detection of land use/ land cover change, a post-classification comparison strategy was applied, and Cellular Automata Markov (CA MARKOV) was used to forecast expected future land use/ land cover patterns in the studied area. Addis Getnet Yesserie., (2009) [1], used in his study parallelepiped-maximum likelihood classification methods for change detection and applied Cellular Automata (CA) for urban growth prediction. Marwa WA, (2015) [16] used the CA-Markov integrated approach to monitor and predict future urban dynamics. Fabiyi, (2004) [9], analyzed land use change in Ibadan city from 1975 to 2004 using a combination of Landsat, MSS, Landsat TM, and Nigerian SAT 1. He computed the spatial growth at each data interval and projected the land use change in Ibadan city to the year 2015 using Geo-informatics investigation techniques.

To summarize, expansionism on agricultural lands and natural resources is the most visible difficulty associated with urban growth in Hossana City, as in other developing countries. To develop sufficient infrastructure to enable urban growth assessment, Spatio-temporal analysis of urban growth patterns is required. This paper focuses on monitoring and forecasting the urban growth pattern of Hossana city through Geo informatics techniques. This is critical in assisting urban planners in their decision-making process. To end, it is stated that integrated geoinformatics techniques are an important tool for tracking and projecting urban growth trends.

II. MATERIAL AND METHODS

A. Descriptions of Study Area

Hossana is a town in southern Ethiopia that serves as the administrative capital of the Hadiya Zone. It had an ancient name of Wachamo. Hossana is a city in Ethiopia's southwest region, around 232 kilometers from Addis Ababa through the Alemgena Butajira road. The city is located in the Southern Nations, Nationalities, and Peoples' Region (SNNPR), with coordinates of 7°33′N 37°51′E. It is surrounded by Lemo woreda, which it was once a part of.

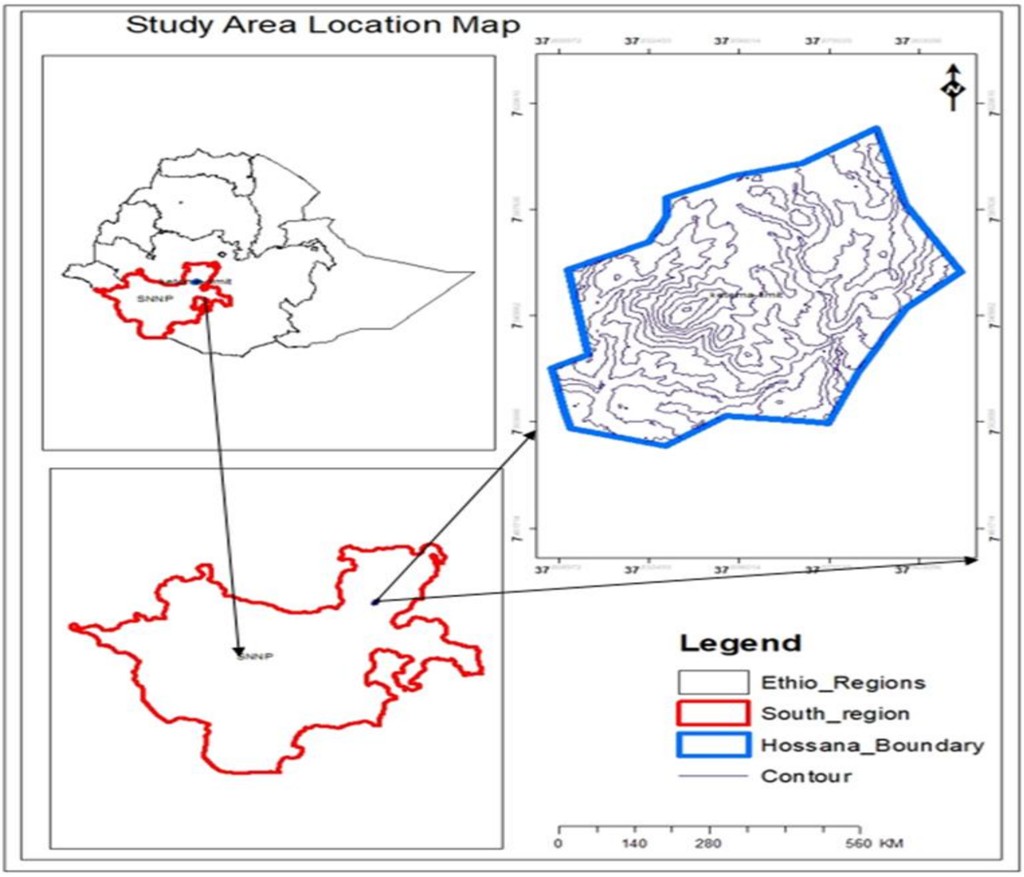

Figure 2.1 Study Area Locational Map

B. Data Sets Used for the Study

Different types of input data were employed to achieve the study's objectives. Satellite images were obtained from the USGS (https://glovis.usgs.gov/) online resource for this research. The study area's Google Earth imagery was also employed. Landsat imageries (TM, ETM+, and OLI) with a spatial resolution of 30 m were employed. The study's Digital Elevation Model was derived from the USGS's Shuttle Radar Topography Mission (SRTM). Elshalay Smart-GIS software was used to download the Google Earth imagery from the Google Earth database. The other datasets were obtained from various sources such as Topographic maps, internet sources, and other government-published data. Six driving variables were essentially taken into account as a factor for urban growth. Distance to the road, distance to the built-up area, distance to drainage, slope, aspect, and topography are the factors to consider. Table 2.1 shows more information about data sets.

Table 2. 1 Datasets used in the study

Datasets	Spatial Resolution & [Path and Row]	Source	Format
Landsat-image Series Land Sat 5-TM (2000) Land Sat 7 -ETM+(2010) Land Sat 8-OLI (2021)	 30 m [169,055] 30 m [169,055] 30 m [169,055]	U.S. Geological Survey	Geotif
Digital Elevation Model (DEM)	30m	U.S. Geological Survey, SRTM	Geotif
Road layers Built up areas Drainage, Slope, Aspect	-- -- --	OSM Municipality, Master plan Derived from DEM	Vector Raster
Hossana-city, boundary	---	Hossana-city Administration	Shapefile
Google Earth Images	High-quality	Google Earth online	KMz

C. Methodology

a. *Pre-Processing Remote Sensing Data*

Due to the inability to adequately identify each feature in the image, raw satellite images cannot be used for feature identification or other related applications. As a result, pre-processing will be carried out before the major data analysis and information extraction. As a result, the following pre-processing was carried out in the study as sub-setting, gap filling for ETM+ imageries, and applying the geometric correction.

b. *Image Classification*

The maximum-likelihood approach is a supervised method that employs training sites to determine the class center and the variability in raster values in each band for each class. This aids in determining the likelihood of a cell belonging to a specific class indicated by the training sites. The maximum likelihood classifier calculates class probabilities and categorizes the cells with the highest probability (Smith, 2011) [19].

c. *Accuracy Assessment*

It's done by comparing a map created with a remote sensing image to a set of reference data (ground truth).

D. Urban Growth Simulation Model

a. *Molusce*

Modeling and simulation tasks are made simpler for users by the user-friendly and intuitive plugin provided by MOLUSECE. The initial (period 1) and final (period 2) land use/ land cover maps as well as spatial variables are loaded in the initial stage. The person's correlation method is used to check the correlation among the spatial variables. Artificial Neural Network (ANN) algorithm applied for figuring transitional potential map as well as calibrating and modeling land use cover change. Urban growth simulations were trained by using Cellular Automata and finally, model validation was processed by computing kappa statistics.

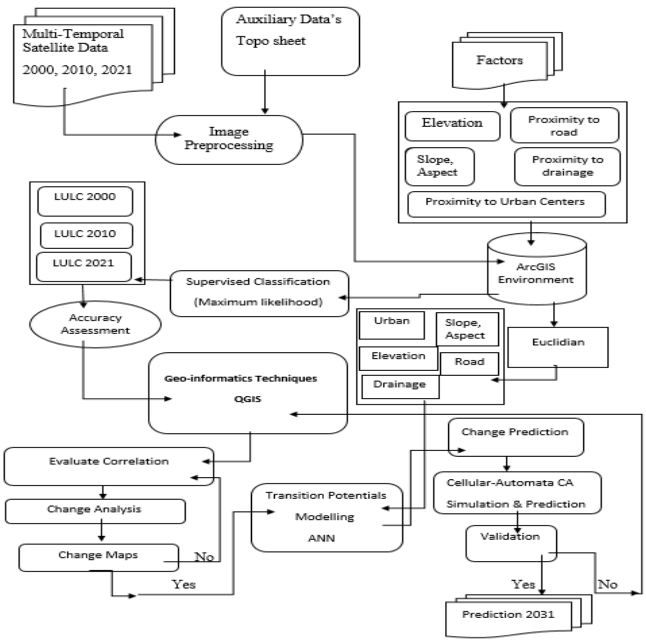

Figure 2. 2 Overall Work Flow Chart

Retrieval Number: 100.1/ijisme.F37720811622
DOI: 10.35940/ijisme.F3772.12070724
Journal Website: www.ijisme.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

III. RESULTS AND DISCUSSIONS

A. Changes in Land Use/Cover Structure

In the study, urban growth pattern was examined over a two-decade period subdivided into three intervals: first from 2000 to 2010, second from 2010 to 2021, and third from 2000 to 2021. These dates were chosen based on the availability of satellite images and other relevant data for the city. The analysis came up with the following results: Agricultural land reduced by 868.534 ha, bare land decreased by 745.563 ha, built-up increased by 236.34 ha, green spaces increased by 454.31 ha, vegetation area increased by 929.126 ha and water bodies decreased by 1.02ha over the first study period (2000 to 2010). For the second study period (2010-2021), there was a decline in agricultural land by 1001.053ha, bare land increased by 72.153ha, the built-up area increased by 2057.699ha, green spaces reduced by 705.473ha, vegetation area reduced by 355.994ha, and water bodies declined by 66.538ha. For the final study periods (2000-2021), agricultural land decreased by 1869.584ha, bare land decreased by 1033.410ha, built-up expanded by 2288.039ha, green spaces decreased by 251.163ha, vegetation area increased by 573.132ha, and water bodies decreased by 67.558ha over the final study period. In general agricultural land, green spaces, bare land, and vegetation have been more affected. Table 3.1 shows the temporal land use areas in Hossana City over the last two decades.

Table 3. 1. Temporal Land use Areas in Hossana City for 2000 -2021

Class Name	2000		2010		2021	
	Land use (ha)	Land use (%)	Land use (ha)	Land use (%)	Land use (ha)	Land use (%)
Agricultural Land	3715.025	38	2846.491	29	1845.441	19.45
Bare Land	1485.784	15	740.221	8	812.374	8.00
Built-up	2395.353	25	2625.693	27	4683.392	48.00
Green Areas	644.298	6.4	1098.608	11	393.135	4.00
Vegetation	1381.011	14	2310.137	24	1954.143	20.00
Water Bodies	110.927	1.6	109.907	1	43.369	0.55

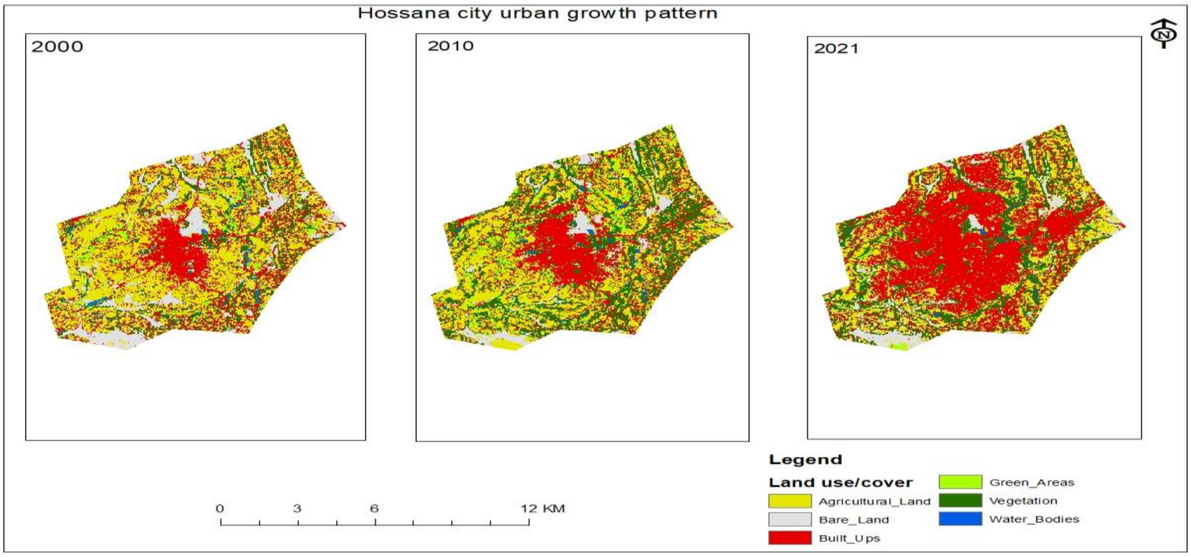

Fig. 3. 1. Time Series of Land Use Maps for 2000-2021

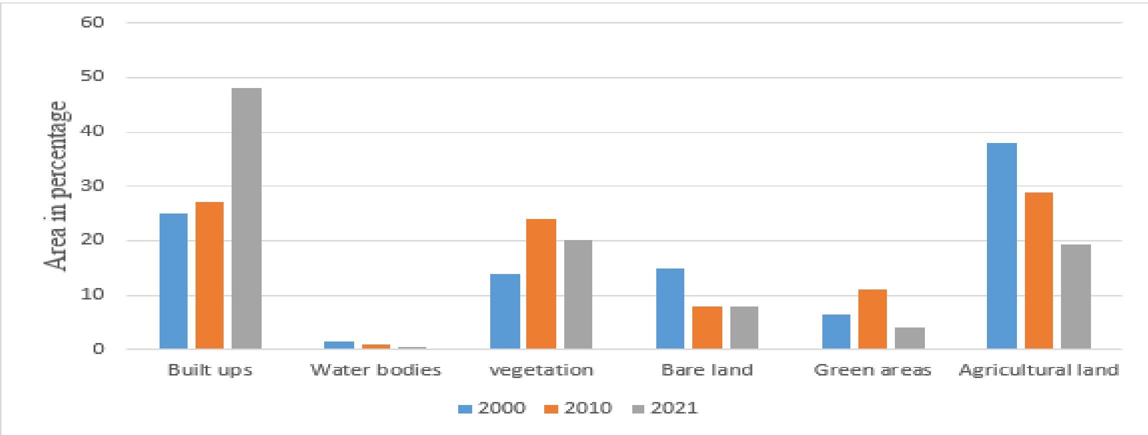

Fig. 3.2. Temporal Changes of Land Use Classes in 2000-2021

Retrieval Number: 100.1/ijisme.F37720811622
DOI: [10.35940/ijisme.F3772.12070724](https://doi.org/10.35940/ijisme.F3772.12070724)
Journal Website: www.ijisme.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

B. Accuracy Assessment

Accuracy was evaluated using error matrices within ArcGIS. For the study periods 2000, 2010, and 2021 the overall accuracy achieved from satellite image classification was 89.20 %, 87.90 %, and 83.4 %, respectively.

C. Model Validation

The kappa statistic is calculated during validation. The kappa statistic is commonly used to check the correctness of inputs. The simulated LULC and the classified LULC for the known years (2021) have a very high statistical consistency (Kappa coefficient) of 0.77 % and a very high spatial similarity constant of 0.78 %, according to an accuracy assessment. Using classified data and a simulated LULC map for the year 2021, the statistical accuracy check was performed. The computed confusion matrix shows that the classified map's overall accuracy is 83.4 %. The transition probability matrix was calculated using the temporal land use/land cover maps which depict the transformation of pixels belonging to each of the six feature classes through time (2000 to 2021). Figure 3.2. Shows that CA-based simulated urban growth for the years 2026 and 2031.

D. Urban Growth Simulation

Using earlier LULC maps and many contributing criteria such as proximity to major roads, built-ups and drainage lines, topography, slope, and aspect, urban growth modeling was undertaken to predict urban growth tendencies for the years 2026 and 2031. Under MOLUSCE CA-based, ANN was used to compute transitional potential modeling for predicting future changes. The simulated built-up for certain years matched the actual classified built-up.

Table 3.2. Projected Land use Changes in Hossana City by the Years 2021, 2026 and 2031

Class Name	Actual Land Use 2021 (%)	CA-Markov 2021 (%)	CA-Markov 2026 (%)	CA-Markov 2031 (%)
Agricultural Land	19.45	20.00	17.56	17.01
Bare Land	8.00	8.09	7.96	7.52
Built Ups	48.00	48.50	50.41	53.09
Green Areas	4.00	3.87	3.71	4.91
Vegetation	20.00	19.07	19.96	17.09
Water Bodies	0.55	0.47	0.39	0.38

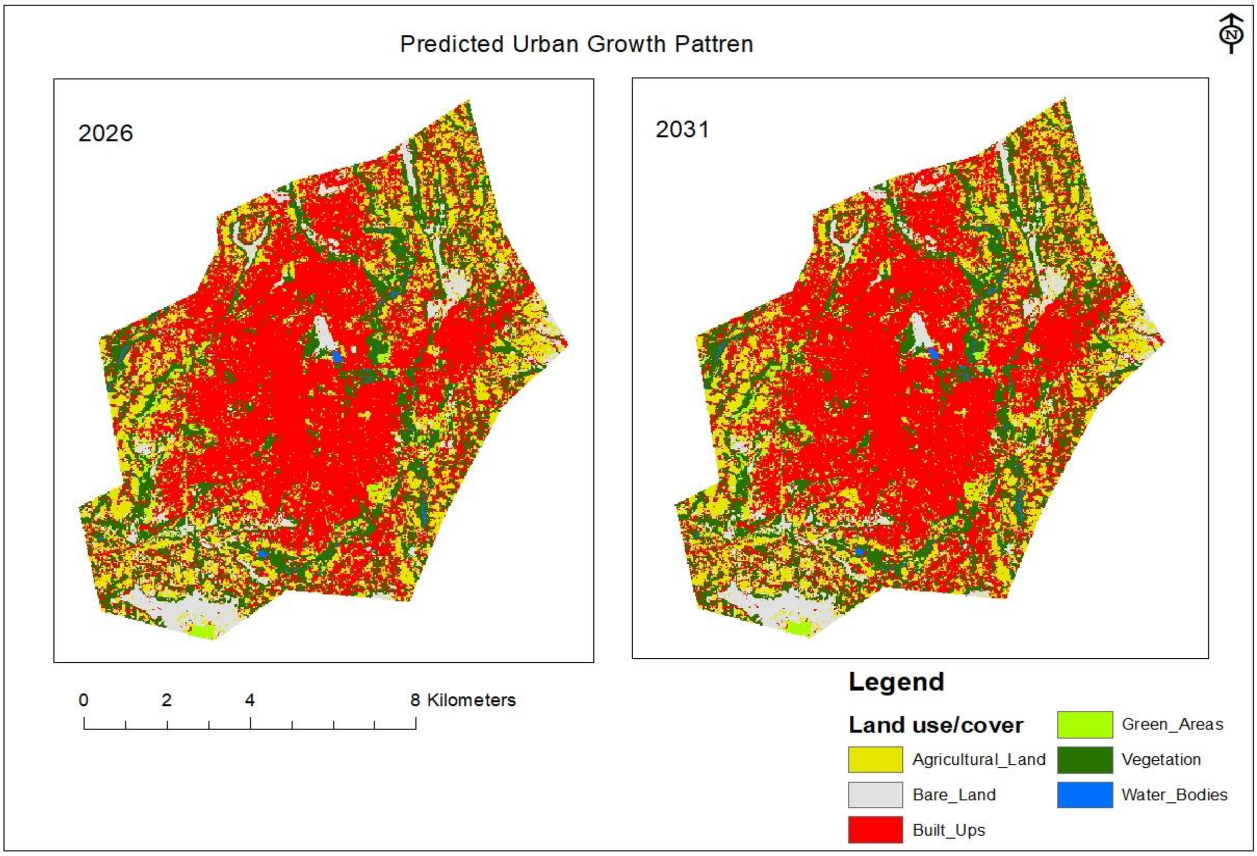

Figure 3.3. Markov Change Predicted Urban Areas

Table 3.3. shows that from the current study period of 2021 to the predicted year 2031, there was a significant change in several LULCs, as follows: agricultural land decreased by 1.55 %, bare land decreased by 0.5 %, but built-ups and green areas increased by 3.09 % and 0.91 %, respectively. The loss of vegetation coverage was 3.0%, and the loss of water bodies was 0.17 %. As a result, greater changes are being made to agricultural land and vegetation. The effect of distance from built-up areas on urban expansion was greatest in the core area. As a result, in the early years, people settled in the city's core areas.

Retrieval Number: 100.1/ijisme.F37720811622
DOI: 10.35940/ijisme.F3772.12070724
Journal Website: www.ijisme.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

People eventually preferred to dwell in established neighborhoods, resulting in the densification of the built-up region. The growth of infrastructure in newly developed areas such as Gonbora, Naramo, and others, on the other hand, influenced the decentralization of the urban population in later times.

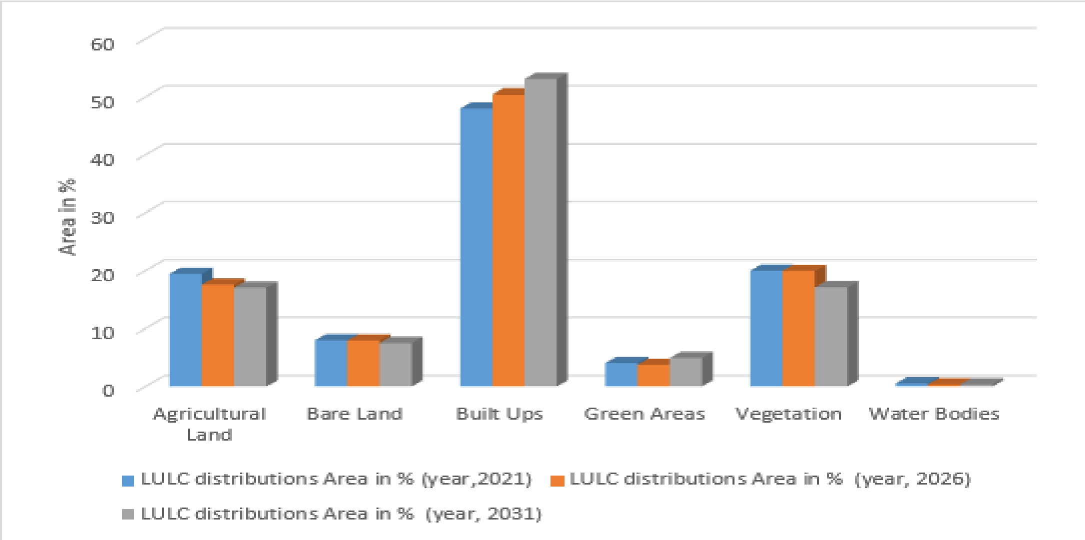

Fig. 3.4. Temporal Changes of Land Use Classes in 2021, 2026 and 2031

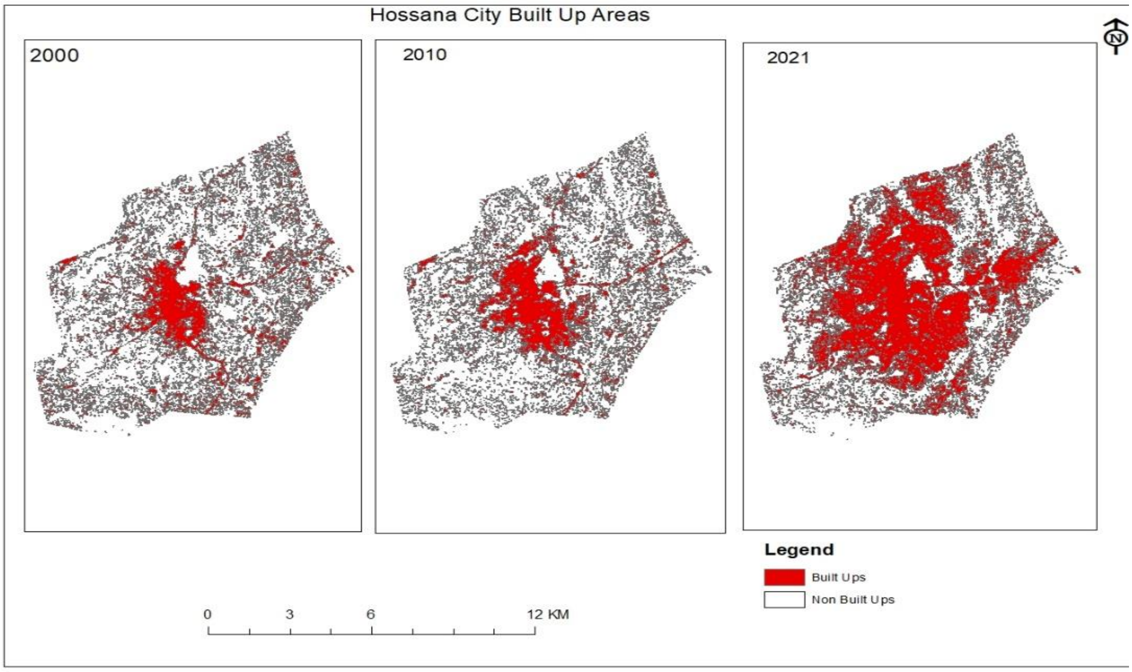

Figure 3.5. Change in Built-Up Areas for 2000 to 2021

IV. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

Because of the high pace of urbanization, urban growth has become a serious issue around the world. Especially developing countries have experienced and are experiencing unprecedented urban expansion, which has detrimental consequences for intensive land use and land cover if not effectively controlled systematically. Hossana city, like many other provinces in developing countries, is suffering the same challenge. Rapid and unsustainable urbanization has wreaked havoc on the natural landscape, destroying enormous areas of farmland, water bodies, and flora. It is crucial to anticipate the auto-spreading trend toward rural areas throughout time to reduce unplanned urban growth. Remote sensing data are critical for monitoring and predicting urban growth because they give spatial and temporal information. The post-classification comparisons method was employed in this study to detect changes in land use and land cover, which is vital for understanding historical and contemporary urban growth patterns. It's crucial to understand the complex interactions between changes and their drivers over time and space to forecast future urban growth. The findings of this research show that there has been a vital urban expansion taking place in the city. It indicates that more change has occurred on agricultural and barren land.

Retrieval Number: 100.1/ijisme.F37720811622
DOI: 10.35940/ijisme.F3772.12070724
Journal Website: www.ijisme.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

According to the study's findings, the city's increased built-up areas are due to a high increase in population growth. The transition from bare land to vegetation is the second most important change that occurred. Consequently, bare land, agricultural land, water bodies, and green areas have decreased by -6.73%, -18.69%, -0.67%, and -2.51% respectively from the initial to the final study period. While the rest classes namely built-ups increased by 22.88% and vegetation increased by 5.73%. Projection of the future urban growth pattern processed through MOLUSCE by applying the CA model. As a result of the findings, significant changes in various LULCs are likely to occur between the present study period (2021) and the prediction year (2031). Thus agricultural land, bare land, Vegetation, and water bodies are expected to reduce by 1.55 %, 0.5%, 3.0%, and 0.17 % respectively. But built-ups and green areas would increase by 3.09 % and 0.91 %, respectively. As a result, the urbanization in the city has resulted in a significant increase in built-up area and a decrease in agricultural land. In general, we can conclude that geoinformatics approaches enable us to regulate urban sprawl and sustainably monitor urban expansion and development.

B. Recommendations

This research provides some recommendations that will aid future planning and policymaking. It is also beneficial for government authorities and planners to notice such growth patterns in this wallet to better utilize land resources, as follows:

- Since the urban area has expanded and is distributed over the study area, planners should improve urban planning in the study area by offering both short and long-term plans. In addition, the lack of urban planning has allowed for unrestrained expansion.
- A new master plan for the city should be provided by the government, the present one has already passed its termination date. This is necessary due to a decrease in the proportion of agricultural land and rather than allowing it to be converted to built-up land, green space should be expanded.
- Using high-resolution satellite images, such as Geo Eye, IKONOS, and QUICK-bird, with a resolution of 5m or less, is more suited and significant for classifying LULC, and will result in a tiny scale of inaccuracy.
- Additional methods that incorporate other variables, such as suitability characteristics, are required to estimate a future pattern of urban growth. Because the suitability technique takes into account other variables such as water, road network, and slope, it is not only based on previous changes.

DECLARATION STATEMENT

Funding	No, I did not receive.
Conflicts of Interest	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	Not relevant.
Authors Contributions	All authors have equal participation in this article.

REFERENCES

1. Addis Getnet Yesserie., 2009. Spatio-temporal land use/land cover changes analysis and monitoring in the Valencia municipality, Spain. Universidad Jaume I.
2. Ashenafi, G. A., 2015. THE FACTORS CONTRIBUTING TO THE EXPANSION OF INFORMAL SETTLEMENTS IN HOSSANA TOWN, SOUTHERN ETHIOPIA. Selected Essays, Addis Ababa University Press, 2015.
3. Aspeq Karsidi, 2004. Spatial analysis of land use/ land cover change dynamic using remote sensing and geographic information system: A case study in downstream and surrounding of the Ci Tarum watershed, the University of Adelaide.
4. Bahiru, Z., 2008. The City Center: A Shifting Concept in the History of Addis Ababa, in Bahiru Zewde (ed. 2008), Society, State, and History:. Selected Essays, Addis Ababa University Press.
5. Bauer, M., Yuan, F. & Saway, K., 2003. Multi-Temporal Landsat Image Classification and Change Analysis of Land cover in the Twin Cities (Minnesota) Metropolitan Area. Workshop on the Analysis of multi-temporal remote sensing images, Italy. https://doi.org/10.1142/9789812702630_0041
6. Bekalo, M. T., 2009. Spatial metrics and Landsat data for urban land use change detection: Case of Addis Ababa, Ethiopia. Geo Spatial Technologies in Urban Environment, 2nd edit.
7. Berhane, K., 2017. Cellular Automat Model Based Urban Sprawl Mapping: A Case of Mekelle City, Ethiopia.
8. Campbell, D., DP, L. & TA, S., 2005. Multiple methods in the study of driving forces of land use and land cover change: a case study of SE Kajiado district Kenya. Human Ecology, Volume 33, pp. 763-794. https://doi.org/10.1007/s10745-005-8210-y
9. Fabiyi, O., 2004. Analysis of traditional urban land use change from remote sensing data; A case study of Ibadan city.
10. Fekadu, T., 2015. Urban Expansion and Its Effects on Peripheral Farming Communities (Harmaya University 2015): in hadiya hosaena.
11. Hakim A, S, B., D, R. & S, A., 2019. Spatial Dynamic Prediction of Landuse/Landcover Change (Case Study: TamalanreaSub-District, Makassar City). IOP Conference Series: Earth and Environmental Science, Volume 280, p. 1–9. https://doi.org/10.1088/1755-1315/280/1/012023
12. Herold, M., Goldstein, N. & Clarke, K., 2003. The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote sensing of Environment, Volume 86, pp. 286-302. https://doi.org/10.1016/S0034-4257(03)00075-0
13. Herold, M., Scepan, J. & Clarke, K., 2002. The Use of Remote Sensing and Landscape Metrics to describe Structures and Changes in Urban Land Use.
14. Ioannis, M. & M., M., 2011. Multi-temporal Landsat image classification and change analysis of land cover/use in the Prefecture of Thessaloiniki, Greece.. Proceedings of the International Academy of Ecology and Environmental Sciences,, 1(1), pp. 15-26.
15. Jensen, J. a. I. J., 2007. Remote sensing change detection in urban environments: Geo Spatial Technologies in Urban Environment, 2nd edit.. pp. 7-31. https://doi.org/10.1007/978-3-540-69417-5_2
16. Marwa WA, H., 2015. Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA, Alexandria University.
17. Nugroho, A B Hasyim, A W & Usman F, 2018. Urban Growth Modelling of Malang City using Artificial Neural Network Based on Multi-Temporal Remote Sensing. Civil and Environmental Science Journal, I(No. 2, 52). https://doi.org/10.21776/ub.civense.2018.00102.2
18. Selçuk, R., 2008.. Analyzing Land Use/Land Cover Changes Using Remote Sensing and GIS in Rize, North-East Turkey. Aksaray University, Faculty of Engineering, Department of Geodesy and Photogrammetry.
19. Smith, 2011. image processing and GIS for Remote Sensing.
20. Solomon, M., 1999. Public ownership of Urban land and low-income home ownership in Addis Ababa, Ethiopia.. Eastern Africa Social Science Research Review, OSSREA, Addis, 15(1).
21. United, N., 2021. World Population Prospects Highlights; Department of Economic and Social Affairs, Population Division: New York, NY, USA, 2019;. Available online: https://population.un.org/wpp/Publications/Files/WPP2019_10KeyFindings.pdf.

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

22. Wanhui, Y., 2011. Analyzing and modeling land use land cover change (LUCC) in the Daqing City, China. The University of Wisconsin-Milwaukee,
23. Thangaperumal, S., Maneckam, N. M., & Nachiappan, G. (2020). Urban Growth Assessment of Chennai District by Remote Sensing and Gis Techniques. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 6, pp. 5119–5125). https://doi.org/10.35940/ijrte.f9059.038620
24. Singh, B., & Sarkar, C. (2020). Monitoring Urban Growth and Detection of Land Use/ Land Cover Change in Silchar City, Assam and Balurghat City, West Bengal. In International Journal of Innovative Technology and Exploring Engineering (Vol. 9, Issue 8, pp. 796–803). https://doi.org/10.35940/ijitee.h6656.069820
25. Barman, A., Roy, Dr. M., & Dasgupta, Dr. A. (2021). Climatic Envelope as an Urban Planning Tool to Configure Urban Fabric of Guwahati City to Support Daylight and Natural Ventilation. In International Journal of Engineering and Advanced Technology (Vol. 10, Issue 3, pp. 239–248). https://doi.org/10.35940/ijeat.c2208.0210321
26. Kapur, Dr. R. (2023). Understanding Characteristics of Religion within Urban, Rural and Tribal Societies. In Indian Journal of Social Science and Literature (Vol. 2, Issue 1, pp. 50–56). https://doi.org/10.54105/ijssl.b1097.092122
27. Gupta, S., Rana, A., & M., L., Dr. (2021). A Take on Geo-informatics Systems with Pin-Codes as Atomic Unit. In International Journal of Soft Computing and Engineering (Vol. 10, Issue 4, pp. 13–16). https://doi.org/10.35940/ijsce.d3484.0310421

AUTHORS PROFILE

Yigezu Lenda Liyuneh, a passionate individual with a Master of Science in Geoinformatics Engineering. As a Lecturer and Researcher at Arba Minch University, I actively engage within the Institute of Technology, Faculty of Civil Engineering, Department of Surveying Engineering. Throughout my tenure, I have been instrumental in spearheading diverse training programs that cover a wide spectrum of geospatial sciences, including Urban Planning, Cadastral Surveying and Mapping, Remote Sensing, Photogrammetry, and Digital GIS. My commitment to sharing knowledge and fostering learning has allowed me to contribute significantly to the academic and professional development of students and fellow researchers. In addition to my educational and instructional roles, I am a dedicated enthusiast in the field of Geoinformatics Engineering, constantly seeking new and innovative approaches to advance the industry. My energy and dedication have made me a valuable asset within the academic community, and I am eager to continue making meaningful contributions to the ever-evolving field of geospatial sciences. My holistic approach to education and research sets me apart, and I am constantly seeking opportunities to expand my knowledge and make a positive impact within the realm of Geoinformatics Engineering.

Dr. Karthic Kumar, As an Assistant Professor at Wachemo University in the Department of Geomatics Engineering, I, Dr. Karthic Kumar, am a dedicated and passionate academic with a wealth of experience and expertise in geospatial sciences. Throughout my career, I have been driven by a deep commitment to shaping the future of geomatics professionals through impactful mentorship, innovative research, and curriculum development initiatives. My comprehensive knowledge spans various areas, including Geographic Information Systems (GIS), Remote Sensing, and Surveying, and I have continually sought to integrate cutting-edge technologies and methodologies into both my teaching and research efforts. In my role, I strive to inspire and empower the next generation of geospatial experts by fostering an environment of academic and research excellence. I am actively engaged in developing and implementing forward-thinking teaching practices that integrate real-world applications, enabling students to gain practical insights into the field.