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

Yigezu Lenda Liyuneh, M. Kartic Kumar

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 hazardous 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 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), (-9.67), 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, Geo-informatics techniques enable us for sustainable management of urban sprawl and monitoring of urban expansion and future development.

Keywords: - Urban growth, Geo-informatics, 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.
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.


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 Alemgna 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 wereda, which it was once a part of.

![Figure 2.1 Study Area Locational Map](image-url)
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 images (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

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

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.
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

<table>
<thead>
<tr>
<th>Class Name</th>
<th>2000</th>
<th>2010</th>
<th>2021</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Land use (ha)</td>
<td>Land use (%)</td>
<td>Land use (ha)</td>
</tr>
<tr>
<td>Agricultural Land</td>
<td>3715.025</td>
<td>38</td>
<td>2846.491</td>
</tr>
<tr>
<td>Bare Land</td>
<td>1485.784</td>
<td>15</td>
<td>740.221</td>
</tr>
<tr>
<td>Built-up</td>
<td>2395.353</td>
<td>25</td>
<td>2625.693</td>
</tr>
<tr>
<td>Green Areas</td>
<td>644.298</td>
<td>6.4</td>
<td>1098.608</td>
</tr>
<tr>
<td>Vegetation</td>
<td>1381.011</td>
<td>14</td>
<td>2310.137</td>
</tr>
<tr>
<td>Water Bodies</td>
<td>110.927</td>
<td>1.6</td>
<td>109.907</td>
</tr>
</tbody>
</table>

Fig. 3.1. Time Series of Land Use Maps for 2000-2021

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

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

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.
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

Fig. 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.
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 uncontrolled 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**

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

REFERENCES

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

22. Wanhui, Y., 2011. Analyzing and modeling land use land cover change (LUCC) in the Daqing City, China. The University of Wisconsin-Milwaukee,


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 institutional roles, I am a dedicated enthusiast in the field of Geoinformatics Engineering, constantly seeking news 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.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of the Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) journal and/or the editor(s). The Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

© Copyright: All rights reserved.