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Article

Spatiotemporal Analysis of Urban Expansion in Debark Town: Leveraging Machine Learning and Google Earth Engine with Multi-Temporal Satellite Imagery

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Abstract

Urban expansion is a pervasive global phenomenon with profound environmental, social, and economic implications, particularly in rapidly developing regions. This paper presents a spatiotemporal analysis of urban expansion in Debark Town, Ethiopia. In this study, machine learning algorithms, such as the random forest algorithm and support vector machine, were investigated for satellite image classification to observe spatiotemporal urban land cover changes. The Google Earth Engine has been utilized to pre-process the Landsat 7, 8, and Sentinel-2 Landsat imagery. Classification accuracy was assessed using an 80:20 training-to-testing split. RF demonstrated higher classification performance with overall accuracies of 95.86% (2000), 95.9% (2015), and 97.29% (2025), outperforming SVM's 95%, 93.06%, and 93.74% respectively. The research revealed that feature changes occurred during such transition periods. The results revealed agricultural land decreased markedly from 12,384.65 hectares (71.45%) to 7,951.21 hectares (45.88%), and urban land increased built-up areas from 780 hectares (4.50%) in the year 2000 to 2,741.52 hectares (15.82%) in the year 2025, an increase of approximately 1,961.55 hectares, or 11.32%. Furthermore, urban land rose rapidly due to declining vegetative cover, and the built-up areas increased at a rate of 78.46 ha per year. Overall, this research offers useful information regarding the urban land cover change that can assist decision makers, natural resource managers, and policymakers in making the right decisions. This concluded that urban expansion in the research area occurred, and subsequently, urbanization occurred at a high rate within the past years, leading to a decline in agricultural lands.

Keywords: classification; Google Earth Engine; machine learning; urban expansion; satellite image; spatiotemporal analysis

1. Introduction

Globally, urban expansion refers to the development of cities (Schneider & Woodcock, 2008). In addition, urbanization is defined as the process that involves transforming rural civilization into an urban one, followed by changes to the landscape (Gharaibeh et al., 2023). Urbanization is a primary driver of land use and land cover transformation in urban areas (Moisa et al., 2022). Today, urban expansion is a complex geographical and demographic process in which cities and urban settlements are viewed as centers of population focus owing to their distinctive economic and social traits, which represent an important component in the evolution of human civilizations (Dadras et al., 2015). The United Nations reported that just 13% of the world's population resided in cities in 1990. However, during the last two decades, the number of urban people has significantly outpaced their counterparts in the periphery. The concept of urban expansion is a rapidly changing and complicated

phenomenon; it frequently involves detrimental changes in land use and land cover (Gondwe et al., 2021).

Africa is considered the least urbanized region, with just 43% of its inhabitants living in cities compared to Asia and Europe. Although its urban development and people are not well recorded (Hamud et al., 2021). Rapid urbanization is frequently responsible for the worsening of urban eco-environmental quality, which includes ecological, environmental, and anthropogenic components (Pramanik *et al.*, 2022). Additionally, Ranagalage *et al.*, (2020) presented that rapid urbanization in a country's largest cities creates challenges for long-term development. The process of fast urbanization is poorly understood, particularly in Africa, and most studies focus on single cities.

Similarly, in the theoretical literature, it is stated by (Bedada et al., 2024) that Ethiopia has experienced significant LULC change in recent years, particularly due to growth in population, agricultural development, urban development, and overgrazing. The previous study presents a detailed comparative examination of the growth and spatial patterns of urban development in Ethiopia's three largest cities (Addis Ababa, Adama, and Hawassa) from 1987 to 2017 (Terfa et al., 2019). In comparison to urban expansion in the Valley, the rate of population growth has accelerated (Sofi, 2005). Understanding urban expansion spatiotemporally is vital for landscape and urban development planning utilizing remote sensing data and GIS technologies (Subasinghe et al., 2016).

Numerous studies have provided novel insights into understanding urban land dynamics, and their causes are crucial to managing and forecasting both urban growth and its associated environmental aspects (Shifaw et al., 2020). Referring to the 2025 report by Hassen et al., (2025) on the rapid urban expansion and impact on agricultural land reduction in central Ethiopian metropolitan districts (Addis Abeba and Sheger City), it emphasized these concerns while also providing opportunities for sustainable development. In contrast, Ethiopia has a low degree of urbanization, even by African standards, with just 18% of the population residing in urban areas, 23% of whom live in metropolitan Addis Ababa (Deribew, 2020). According to Regassa et al., (2020), Unexpected urban growth is currently a significant problem, particularly in developing nations where reliable and consistent data, including spatial data, is difficult to obtain.

Some studies in Ethiopian towns have some research to examined urban growth and how it reacts to the environment. For instance, Barow *et al.*, (2019) examined Jigjiga town's spatiotemporal changes throughout the previous thirty years. The quantification of the LULC dynamic in Hawassa city over thirty years using remote sensing and group action geographic information systems (Tessema & Abebe, 2023).

This study addresses the gap of previous studies related to the limited availability of high-quality, cloud-free satellite imagery; model performance; unbalanced training sample selection; preprocessing techniques; diverse feature extraction methods; spatial differences; and temporal changes. This study overcomes such challenges by using machine learning algorithms to improve the accuracy, efficiency, and scope of urban growth assessments. By utilizing the capabilities of strong machine learning algorithms, this study seeks to deliver more precise classification of features, such as bare land, built-up areas, agriculture, and vegetation, to enable better-informed and more sustainable urban planning processes.

The objective of this paper are: (i) to evaluate the effectiveness of machine learning (ML) models in accurately classifying these LULC categories, such as random forest, and support vector machine, (ii) to simulate urban expansion using remote sensing data and machine learning techniques, and (iii) analyzed the trend, and rate of urban expansion by utilizing multi-temporal satellite imagery, enabling a comprehensive understanding of how the urban environment has evolved.

Google Earth Engine is a popular tool that has recently gained a lot of popularity as a massive cloud-based system for global geospatial analysis. It leverages Google's enormous computing power to enable clients to easily view and consider satellite imagery. Tesfaye et al., (2024) had conducted Google Earth Engine (GEE), with its multiple machine learning algorithms, which have become the most powerful open-source worldwide platform for speedy and accurate LULC categorization. Generally, this study bridges the knowledge gap by utilizing machine learning algorithms to map

built-up areas in analyzing urban expansion in Debark Town. Machine learning algorithms were renowned due to their effectiveness in managing remote sensing data and their proven ability in classifying and mapping land cover accurately. In the context of Google Earth Engine (GEE), they produce precise and reliable land cover classification results by effectively handling complex spatial relationships and processing large-scale geospatial data.

The (Coq-Huelva & Asián-Chaves, 2019) established sprawl as a form of undesirable urban growth, which is defined as fast-paced and unplanned development that often leads to the deterioration of agricultural land and the challenges facing infrastructure planning. Globally, urban processes have been transformed immensely in the last two decades, converting previously stable geographies into highly expanding urban centers. Urban planners and resource managers, hence, require reliable tools to efficiently monitor the impact of urban expansion. For instance, the Urban sprawl was evaluated, according to (Bedada et al., 2024), to significantly influence land use and land cover (LULC) pattern changes, which primarily have negative environmental and socio-economic consequences. Furthermore, prior research has shown notable changes in land use and land cover (LULC), with an increase in built-up regions, lake bodies, and bare land and a decrease in mangroves, bushes, agriculture, and salt areas. Over the past 33 years, Djibouti's predominant land cover, bush land has been significantly transformed into urban centers, lake bodies, and bare ground. Additionally, the researchers assessed the Random Forest (RF) algorithm's performance in classifying land uses and analyzing temporal changes (Pandit et al., 2024). Hassen et al., (2025) used supervised random forest classification based on the Google Earth Engine (GEE) to generate LULC maps for 1990, 2000, 2010, and 2023. Their study implemented an all-encompassing analytical strategy, which comprised intensity analysis at interval, categorical, and transitional scales to quantify urban expansion patterns, as well as gradient direction and distance analyses to assess spatial extent patterns. Similarly, Mutale *et al.*, (2024) used Random Forest and Support Vector Machine classifiers within GEE to analyze atmospherically corrected, cloud-free surface reflectance imagery for selected years. These papers together show the effectiveness of merging cloud-hosted geospatial platforms and machine learning algorithms for monitoring and analysis of temporal urban growth patterns.

Durowoju *et al.* (2025) proved that the use of Google Earth Engine and machine learning algorithms can be used to study the dynamics of urban change. Their results showed that there are significant environmental changes in the study area, such as a 26.17% decline in bare surfaces and a whopping 95.79% reduction in water bodies over three decades. In the same way, Ouma et al. (2023) applied and tested the performance of various machine learning classifiers, and multi-temporal and multisensory Landsat imagery was employed in their study. Machine learning is a common tool for urban cover change evaluation.

This study enhanced the accuracy of urban land cover mapping and expansion forecasting in Debark town by applying machine learning algorithms, specifically random forest and support vector machine, to detect spatial patterns and trends beyond human capability. The findings provide reliable insights for informed decision-making, supporting sustainable urban planning, infrastructure development, and effective land use management.

2. Materials and Methods

This study adopted a comprehensive methodology tailored for cloud-based geospatial analysis, integrating multi-temporal satellite imagery with Machine Learning techniques on the Google Earth Engine platform.

2.1. Study Area

The study area is located in Debark town (see Figure 1), encompassing approximately 17,330 hectares within the Amhara National Regional State (ANRS) in northwestern Ethiopia. Located about 843 kilometers northwest of Addis Ababa, Debark was selected due to its strategic role as a gateway for travelers visiting the Simien Mountains National Park a UNESCO World Heritage Site (Desta & Gugssa, 2022). It functions as the center of the North Gondar zone. However, such growth brings

pressure on existing infrastructure, the establishment of Debarq University, and population growth. Administratively, Debarq Town is divided into eight kebeles: Zebena, Debir, Mikara, Kino, Kirar Wegamba, and Debarq Town Kebeles 01, 02, and 03. Geographically, it lies between longitudes 37°24'50"E and 37°56'56"E, and latitudes 13°02'28"N and 13°12'20"N. The elevation ranges from 1,993 to 3,207 meters above mean sea level (AMSL), with the northern region of the study area featuring some of the highest altitudes in Ethiopia.

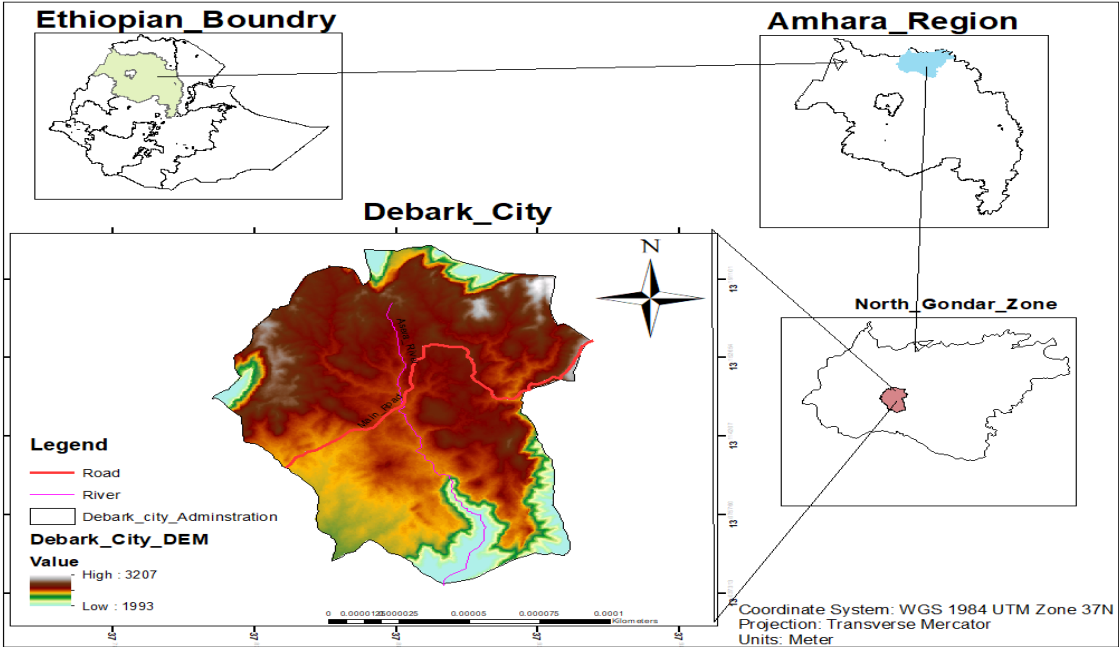


Figure 1. The geographic location of the study area.

2.2. Dataset

The United States Geological Survey (USGS) provides access to Landsat and Sentinel data in GEE (Loukika et al., 2021). This paper used multi-temporal Landsat satellite imagery gathered from the USGS over three different years: 2000, 2015, and 2025. These data were the backbone of our analysis (see Table 1). The ETM+ sensor provides high-resolution, multispectral imagery of Earth's surface. It generates eight spectral bands in blue, green, red, NIR, and mid-infrared (MIR). Bands 1-5 and 7 have a 30-meter resolution; it had a 185 km swath, 8-bit radiometric resolution, and 16-day revisited temporal resolution (Sigopi et al., 2024).

In historical studies, Landsat imagery is composed of data from multiple spectral bands; it has a 185 km swath, 12-bit radiometric resolution, and 16-day revisited temporal resolution, each capturing different parts of the electromagnetic spectrum (Dharani & Sreenivasulu, 2021). Sentinel-2 was a high-resolution multispectral imaging mission that enabled Copernicus Land Monitoring studies, which included the observation of vegetation, water cover, inland water bodies, and coastal areas. It had a 290 km swath, 12-bit radiometric resolution, and 5-day temporal resolution (equator-dependent) (Park et al., 2021).

Table 1. Description of satellites Landsat 8 OLI/TIRS, Sentinel-2, and Landsat 7.

Landsat7 (ETM+)			Landsat8 (LOI)			Sentinel-2		
Band no	Wavelength	Pixel	Band no	Wave length	Pixel	Band no	Wave length	Pixel
	(μm)	size(m)		(μm)	size(m)		(μm)	size(m)
B1	0.45-0.52	30	B1	0.433-0.45	30	B1	0.443	60

B2	0.52 - 0.60	30	B2	0.45- 0.515	30	B2	0.490	10
B3	0.63 - 0.69	30	B3	0.525- 0.60	30	B3	0.560	10
B4	0.76 - 0.90	30	B4	0.630- 0.68	30	B4	0.665	10
B5	1.55 - 1.75	30	B5	0.845-0.88	30	B5	0.705	20
B6	10.4 -12.3	60	B6	1.56 -1.66	30	B6	0.740	20
B7	2.08 - 2.35	30	B7	2.10 - 2.30	60	B7	0.783	20
B8	0.52 -0.90	15	B8	0.50 - 0.68	15	B8	0.842	10
			B9	1.36 - 1.39	30	B8A	0.865	20
			B10	10.3- 11.3	100	B9	0.945	60
			B11	11.5 -12.5	100	B10	1.375	60
						B11	1.610	20
						B12	2.190	20

In this study, a systematic procedure was followed to select the most appropriate Landsat spectral bands for accurate land cover classification. A wide range of spectral bands was utilized, including the blue, green, red, near-infrared (NIR), shortwave infrared 1 (SWIR1), and shortwave infrared 2 (SWIR2) bands (Roy et al., 2014).

Modern platforms like Google Earth Engine (GEE), ArcGIS 10.3, and QGIS significantly enhanced the precision and efficiency of LULC classification and spatial analysis. GEE and Python were also employed for applying machine learning algorithms, generating random sample points, and improving data visualization.

2.3. Methods

2.3.1. Data Preprocessing

The preprocessing refers to changing the raw data into a computer-readable format that the computer and machine learning algorithms could understand and analyze. This study involved several image preprocessing steps to ensure data quality and accuracy. These steps included masking clouds, applying geometric correction to the UTM Zone 37s projection, performing radiometric correction, stacking the image layers, applying pan-sharpening techniques, and creating appropriate band combinations for analysis. The scholars (Deep. et al., 2017) have discussed four stages in remote sensing image processing: preprocessing, enhancement, transformation, and classification. Preprocessing corrects any radiometric, atmospheric, or geometric distortions in the raw image data. Following this (see Figure 2), supervised classification was applied individually to the datasets from each year. All datasets were standardized to align with the study area's boundaries and projected using the UTM Zone 37 North in the WGS-84 coordinate system to ensure consistency and accuracy in spatial analysis.

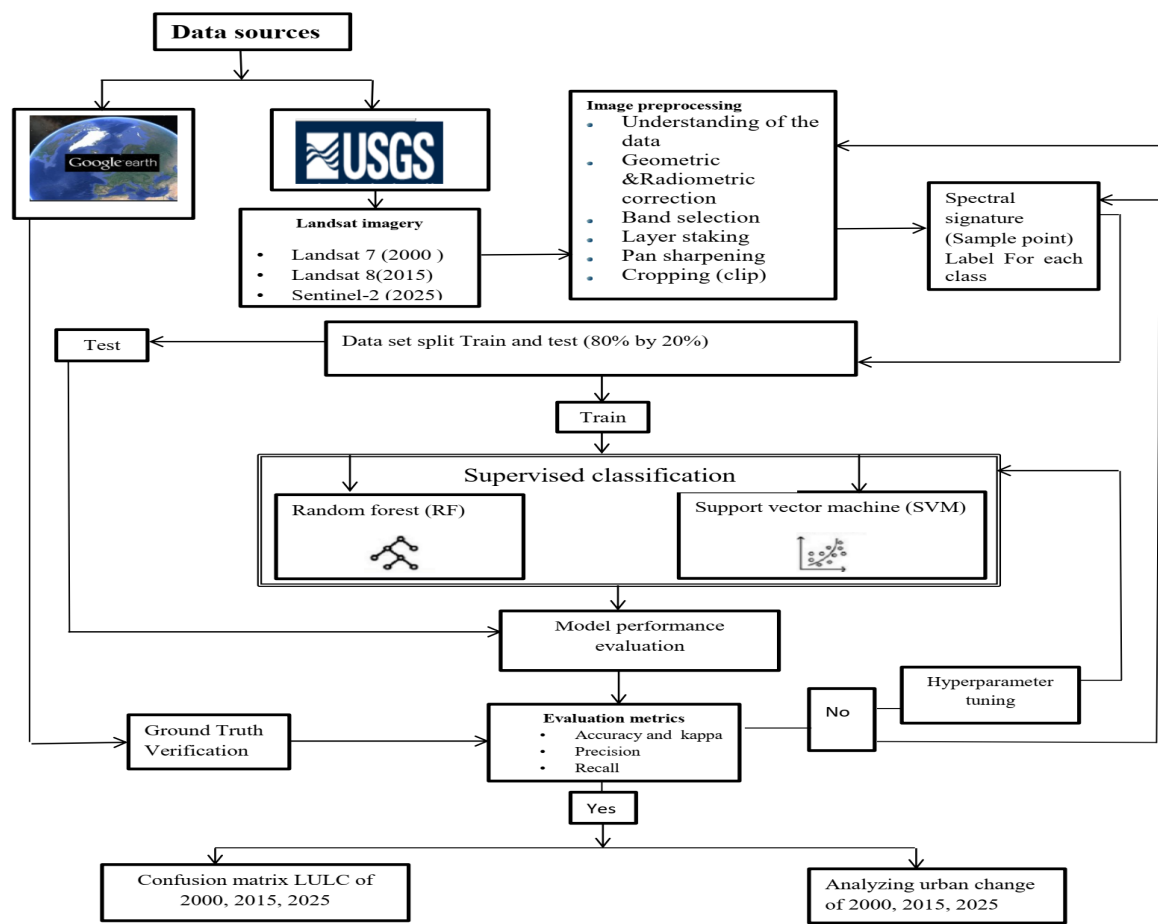


Figure 2. The methodological flow chart of the study.

2.3.2. Train and Testing Split

In developing a machine learning model for urban expansion analysis from satellite images, the dataset was labeled and divided into training and testing. The scholar Ouma et al., (2023) concluded that visual identification and interpretation of the Landsat imagery were used to obtain the training and testing data samples. In addition Sahak et al., (2024) conducted 80% of the data were employed for training purposes, while 20 % were kept for testing for each of the algorithms.

The training and testing sample distribution utilized for urban land use and land cover (LULC) classification in 2000, 2015, and 2025 Table 2 illustrates the training and testing sample distribution utilized for urban land use and land cover (LULC) classification in 2000, 2015, and 2025. In Google Earth Engine, points representing various land cover classes were manually digitized to prepare the training data. A total of 2055, 2450, and 2395 ground truth samples were collected, including 530, 621, and 603 samples each for bare land and agricultural land, 490, 593, and 586 samples for built-up areas, and 505, 615, and 603 samples for vegetation in each year’s respectively. These samples were split into training and testing datasets using by 80 to 20 ratios via a random sampling technique, resulting in 1644, 1960, and 1916 samples for training and 411, 490, and 479 samples for testing, respectively.

Table 2. Descriptions of land cover classes sample collection identified in the study area (2000-2025).

		Urban cover class			Data sets		
Years	Built up	Vegetation	Agriculture	Bare land	Training	Testing	Total
2000	490	505	530	530	1644	411	2055
2015	593	615	621	621	1960	490	2450
2025	586	603	603	603	1916	479	2395

2.3.3. Implementing the ML Algorithm

For urban land cover classification, we employed machine learning algorithms, such as support vector machines (SVM) and ensemble classifiers based on random forest (RF). Machine learning algorithms have been proven to be highly effective for image analysis operations, e.g., land-use classification, simulation, and predictive analysis (Mostafa et al., 2021).

Furthermore, urban growth patterns along with their driving factors have been geospatially and statistically modeled by researchers using ML algorithm classifiers (Kang, 2019). Existing technologies, particularly machine learning (ML) techniques, a subfield of artificial intelligence, are increasingly being employed for remote sensing (RS) data analysis and earth observation studies. These are essential tools to be employed by data scientists as well as by decision-makers when analyzing and making conclusions from large datasets. Vishwakarma (2024) describes ML as the study of algorithms that allow systems to learn from experience and improve over time. It is a strategy for teaching machines how to manage data more effectively. Machine learning algorithms create models based on existing data, which can then be used to predict future data. The (Puttinaovararat & Horkaew, 2017) was developed through a learning process that extracts useful patterns from previously observed data during the system's data generation process.

Random forest (RF)

Random Forest (RF) is among the most widely used machine learning algorithms available. Another more recent land cover classification technique is with ensemble methods, such as Random Forests (Gu et al., 2023). Strong in its operation, this algorithm relies on making multiple decision trees and then producing an output after taking their outputs to create the right output (Hamud et al., 2021). Researchers from different backgrounds are drawn to (Ouma et al., 2023), the RF is an ensemble of k random decision trees with at most a root node and trained on M bootstrap samples. In contrast to the traditional parametric multispectral image classification techniques, this study employed the non-parametric random forest classifier to classify the Landsat image.

Support Vector Machine (SVM)

The SVM algorithm is a supervised machine learning classifier. Mantero et al., (2004), demonstrated that SVMs are commonly applied in RS images because they can outperform traditional practices in terms of accuracy in classification, even when smaller training datasets are used. The SVM method uses support vectors to determine the best separating hyper plane by maximizing the class boundaries, a non-parametric statistical learning technique in which a hyper plane is formed to separate of different classes in such a way that the distance (margin) of the examples that are closest to it is maximized (Kuhn & Johnson, 2013) (Megahed et al., 2015) (Ouma et al., 2023).

Hyperparameter tuning

Grid Search was utilized as a systematic hyperparameter tuning technique in this research work to improve the performance of ensemble machine learning algorithms, support vector machines (SVM), and random forests (RF), for urban land cover classification (Chowdhury, 2024). Therefore, it helps to find the optimum set of parameters that leads to the most accurate model and overall model performance, ensuring good and stable classification results.

For the Random Forest model, achieving high accuracy in urban land cover classification involved fine-tuning Hyperparameters using a grid search approach. The chosen settings $n_estimators = 1000$, $max_features = 16$, $min_samples_leaf = 10$, $bootstrap = 0.8$, and $random_state = 42$ strike a balance between accuracy, generalization, and reproducibility, with 1000 trees enhancing stability and 16 features per split supporting robust decision-making within each tree.

The SVM algorithm's performance in classifying urban land cover is highly influenced by key hyperparameter: kernel type, gamma (γ), and cost (C). In this study, using an RBF kernel with gamma = 0.1 and cost = 100 enabled the model to effectively capture complex, non-linear spatial patterns

while balancing flexibility and generalization making it well-suited for high-dimensional land cover classification tasks.

2.3.4. Image Classification

The process of classifying satellite images used two machine learning methods, random forest (RF) and support vector machine (SVM), to create maps showing how land was used in urban areas for the years 2000, 2015, and 2025. Applying both classifiers to multi-temporal satellite images, the study was able to capture spatial and temporal land cover changes effectively as urban expansion, vegetation patterns, agricultural practices, and land degradation. Detecting, recognizing, and classifying multiple objects according to their true classifications on the ground is made practical by image classification, a very efficient technique for analyzing satellite image data (Sapkota et al., 2024). According to (Tikuye et al., 2023)(Sahak et al., 2024), four broad LULC types were classified for the selected satellite images based on previous literature on LULC classification in study (Pushpalatha et al., 2024)(Khan & Sudheer, 2022). As shown in Figure 3, we obtained our preliminary urban land cover classification results by training and testing supervised classifiers on GEE Random Forest (RF) and Support Vector Machines (SVM) on the Sentinel-2 and Landsat image composites.

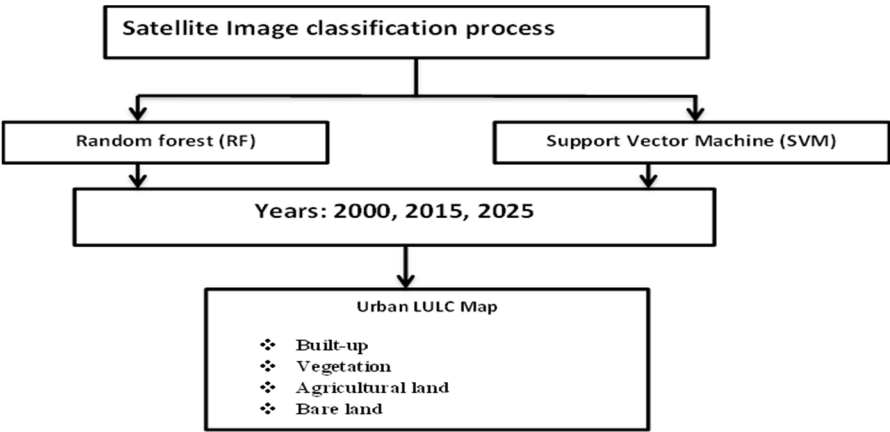


Figure 3. Process of satellite image classification.

The visualization of the Landsat images taken in the years 2000, 2015 and 2025 exhibits clear trends. Urban land use land cover (LULC) classes of the study area as differentiated by the maps into four prevalent classes conventional colors are built-up (red), vegetation cover (green), agricultural land (yellow), and bare land (brown). The study was divided into four distinct classes (built-up, vegetation, agriculture, and bare land) utilizing the machine learning supervised classification algorithm. A detailed explanation of each class is provided in Table 3 (Gawali, 2009).

Table 3. Description of urban LULC classifications features.

LULC class (features)	Description of the class (features)
Vegetation Area	Areas characterized by natural or partially natural vegetation, such as urban forests, areas dominated by shrubs, and grass land
Built Up Area	Areas decided on as residential, commercial, industrial, urban settlements, and transportation facilities
Bare Land	Areas with minimum plants in the main comprise uncovered earth substances which include stone, gravel, sand, silt, and clay. Examples include sandy areas, barely exposed rocks, degraded lands, and quarries.
Agricultural Area	Agricultural croplands, cultivated lands, and agricultural fallow lands and irrigated agriculture area, perennial crops

2.3.5. Accuracy Assessment

Land use and land cover (LULC) classification was accomplished by the Random Forest and Support Vector Machine algorithms within the Google Earth Engine (GEE) environment. An accuracy assessment of the generated classification was then carried out to ensure the validity and credibility of the study's findings. Accordingly, Gessesse et al., (2015) has significantly contributed to improving the sample generated by the stratified random sampling reference data collection technique, accuracy evaluation indices comprising the producer's accuracy (also known as "recall"), user's accuracy (also known as "precision"), and overall accuracy, as well as the Kappa coefficient of agreement, which were adjusted to the known areal fraction of map categories (Tassi et al., 2021). With greater sensitivity and specificity, the F-score is a composite metric that assesses algorithm reliability (Abdi, 2020) (Sokolova et al., 2006).

- ❖ **Overall Accuracy (OA):** is the number of pixel correctly classified by the total number of instances, indicating the extent to which the classification outcomes match the reference data (Al-Saady et al., 2015).

$$OA = \left(\frac{1}{N}\right) \sum_{i=1}^n n_{ii} \quad (1)$$

- ❖ **Recall:** The link between true positives and the sum of true positives and false positives is another way to define PA, or recall the omission error's complement is the PA.

$$PA_j = \frac{n_{jj}}{n_{j+}} \quad (2)$$

- ❖ **Precision:** the relationship between true positives and the overall number of true positives and false negatives is another definition of the UA, or precision (Yang et al., 2025). The commission error's complement is the UA.

$$UA_i = \frac{n_{ii}}{n_{i+}} \quad (3)$$

Where, in the confusion matrix, n_{ij} refers to the value (or count) the intersection of row i (actual class) and column j (predicted class), and OA refers to Over All Accuracy.

- ❖ **Kappa coefficient:** measures agreement between predicted and actual classifications while correcting for chance agreement. One of the most widely utilized accuracy indicators (Bedada et al., 2024), the accuracy of land use classification in this study, was tested using the Kappa coefficient.

$$Kappa = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^r (X_{i+} * X_{+i})} \quad (4)$$

Where, N represents the total number of observations (samples), r indicates the number of rows or columns in the matrix, X_{ii} represents the numbers at the intersection of row i and column i , X_{i+} represents the sum of values in row i , and X_{+i} is the sum of values in column i .

2.3.6. Change Detection

The maps were utilized to determine the urban LULC class regions and the urban LULC analysis and change rates to determine. Based on the previous studies (Bedada et al., 2024), highlighted that it was tested that the analysis of the urban LULC change was computed using equation (5).

$$\text{Urban cover change} = \frac{(A_f - A_i)}{A_i} * 100 \quad (5)$$

Where, A_f is the final produced urban LULC area in ha, and A_i is the previous area of urban LULC (e.g., urban LULC at an earlier time t) in ha.

- ❖ **Rate of change (RC)**

For every urban LULC type, the yearly rate of change was determined using Equation 6 (Molla et al., 2024) (Zhang et al., 2020) using the data derived from the remote sensing image analysis. The

urban expansion rate (UER) was adopted to evaluate the changes in urban coverage over a certain period of time and was the main indicator of changes in urban expansion.

$$UER=\frac{Af-Ai}{Ai*\Delta t} * 100$$

(6)

Where UER is the urban expansion rate of the annual rate of change, Ai and Af are the areas of a class in time one and time two classification maps, respectively, and Δt is the time interval between time one and time two classification maps.

3. Results

3.1. Image Classification and Accuracy Assessment

In urban land cover classification, remote sensing data play a crucial role. The accuracy of such maps depends on various factors, including the choice of classification algorithms, the quality of training and testing data, the complexity of the urban environment, and the specific satellite datasets employed. The study illustrated the classification result obtained from three different satellite missions of different years. Satellite imagery from Landsat 7, Landsat 8, and Sentinel-2 was utilized to classify land cover into distinct classes: built-up areas, vegetation, agriculture, and bare land. Feature extraction was guided by a combination of literature review and expert knowledge of the study area of band composition.

In this study, two supervised classification methods were evaluated on the 2000, 2015, and 2025 dataset. As shown in Figure 4 and illustrated in Table 4, and then we used a testing dataset that was distinct from the training datasets to evaluate the accuracy of each classifier. Generally, the study area was separated into four mutually exclusive classes: built-up, vegetation, agriculture, and bare land for each year under consideration, allowing appropriate insight into land cover dynamics over the years.

Table 4. Overall model performances comparison of the three experiments.

Model	Evaluation metrics		years		
			2000	2015	2025
RF	Accuracy		95.86%	95.9%	97.29%
	User’s accuracy (Precision)	Built up	93.75%	94.67%	97.58%
		Vegetation	96.15%	96.08%	95.83%
		Agriculture	97.48%	97.53%	97.79%
		Bare land	94.44%	94.78%	97.28%
	Produce’s Accuracy (Recall)	Built up	88.24%	93.55%	96.03%
		Vegetation	96.5%	96.09%	98.57%
		Agriculture	95.68%	96.93%	97.79%
		Bare land	99.17%	96.21%	97.28%
	Kappa coefficient		94.15%	94.5%	96.32%
	Accuracy		95%	93.06%	93.74

SVM	User's accuracy (Precision)	Built up	87%	91.40%	94.35%
		Vegetation	96%	92.16%	86.84%
		Agriculture	96%	94.48%	96.21%
		Bare land	97%	93.18%	94.56%
	Produce's Accuracy (Recall)	Built up	92%	91.40%	92.86%
		Vegetation	93%	92.16%	94.29%
		Agriculture	96 %	94.48%	93.38%
Bare land		97.50%	93.18%	94.56%	
Kappa coefficient		93.94%	90.63%	91.5%	

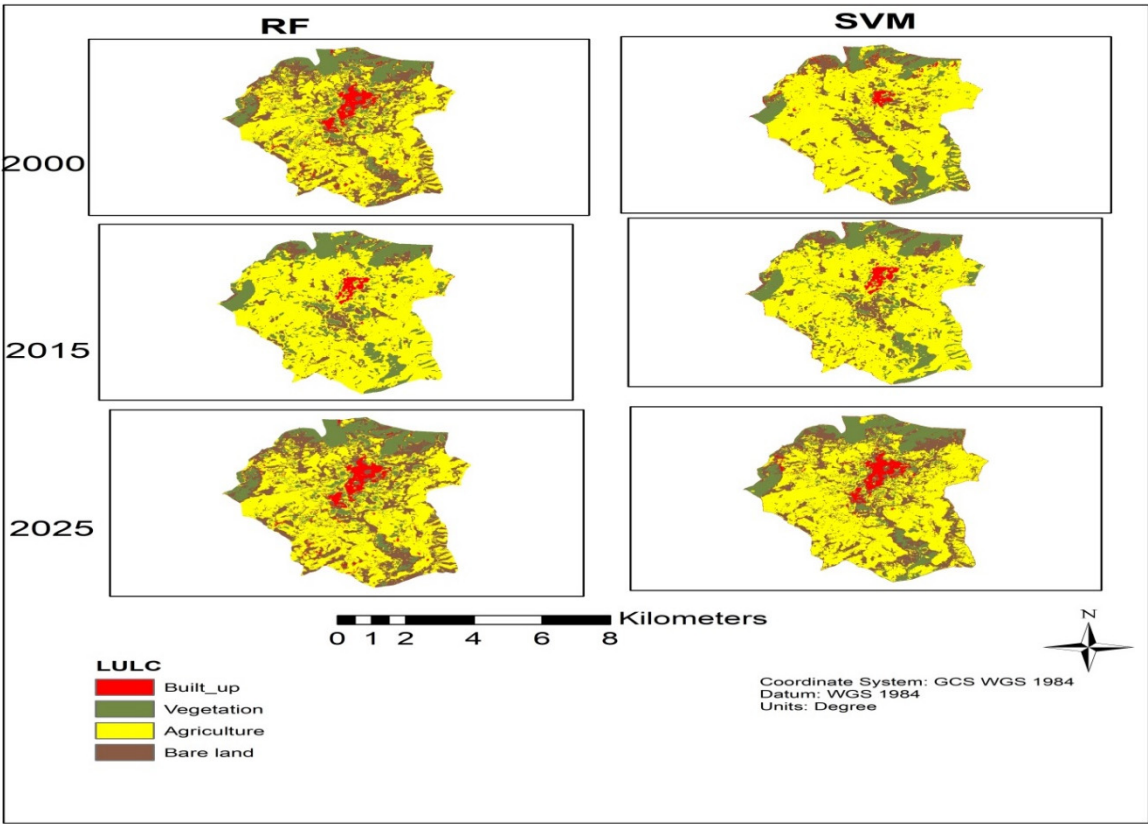


Figure 4. Classification results with SVM, and RF, in 2000, 2015 and 2025 years.

3.2. Accuracy Assessment and Comparison of Classification Models

The experiments were conducted to select the optimal classification model and develop suitable classification methods. Each experiment involved applying machine learning algorithms to satellite data with four varied features assigned by the researchers. To have a comprehensive evaluation, three different experiments were conducted using two popular machine learning algorithms: random forest and support vector machine. For all three experiments and both algorithms, the same list of objective-based measuring metrics was used. These included accuracy, precision (user accuracy), recall (producer accuracy), and the Kappa coefficient, allowing direct comparison of model performance. In these findings, the researchers conducted a total of three experiments, and four land cover classes were used in each experiment. The features that were identified were used as input in developing a classification model for analyzing urban cover change in Debark town.

According to Table 4, a comparison of the overall performance of the SVM and RF models in the years 2000, 2015, and 2025 reveals that the RF model has better performance than the SVM in nearly

all the metrics taken into consideration. RF has better overall accuracy in all three years: 95.86% (2000), 95.9% (2015), and 97.29% (2025), compared to SVM's 95%, 93.06%, and 93.74%, respectively. In addition, the Kappa coefficient, which measures reliability of classification, also favors RF, increasing from 94.15% in 2000 to 96.32% in 2025, indicating more consistent agreement between predicted and actual classes. Conversely, SVM has declining Kappa values with time (93.94% in 2000 to 91.5% in 2025), suggesting a relative decline in classification reliability.

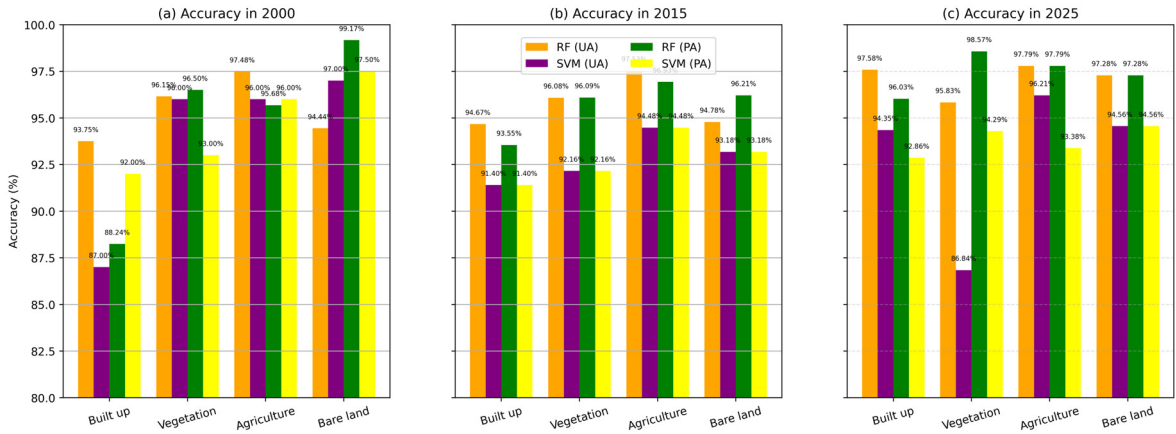


Figure 5. Comparison of user and producer accuracy of a) 2000 (RF, SVM), b) 2015(RF, SVM), and c) 2025(RF, SVM) models for urban LULC classes.

For example, in 2025, RF gets high user accuracy (precision) of 97.58% in built-up area and 97.28% in bare land, whereas SVM is just 94.35% and 94.56%, respectively. RF also obtains higher producer's accuracy (recall) for vegetation (98.57%) and built-up (96.03%) in the year 2025, indicating higher sensitivity in identifying these classes. SVM, however, exhibits more variability and an overall declining trend in the performances of the prominent classes; in other words, vegetation accuracy falls to 86.84% for 2025.

3.3. Urban Simulation

The urban land cover simulation of the study area as it existed in 2000-2025, as evident from Figure 6, shows four dominant land cover types: urban land, vegetation, agricultural land, and bare land. The dominant land cover component was agricultural land that occupied the majority of the land. This implies that the region was primarily used for agriculture and other related agricultural activities throughout the time. Conversely, built-up areas or development occupied the lowest percentage of land cover, with only slight urbanization and a relatively low level of infrastructure extension in 2000.

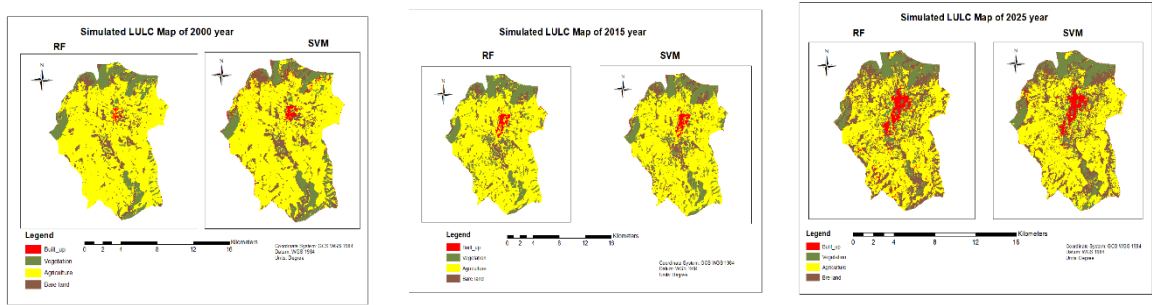


Figure 6. The simulated map in the 2000 between 2025.

3.4. Change Detection Between 2000 and 2025

This study applied two machine learning classification methods, random forest (RF) and support vector machine (SVM), on Landsat and Sentinel satellite imagery. This finding selected the optimum algorithm for each image from their performance as described in the above section. Urban growth was analyzed by measuring pixel-level change from 2000 to 2015 and 2000 to 2025.

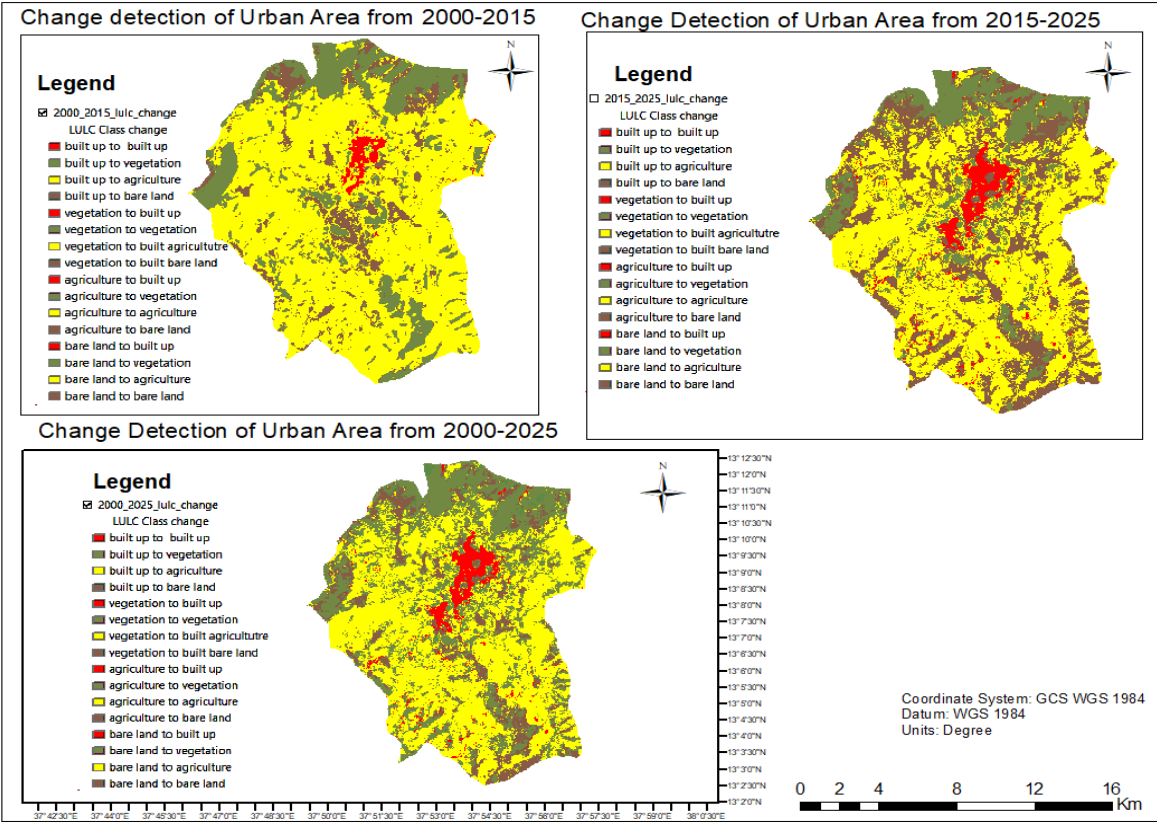


Figure 7. Land covers change detection in the years of 2000-2015, 2015-2025 and 2000-2015.

Between 2000 and 2015, as is clear from Table 5 bellow, urban land cover (LC) in the study area experienced significant change, indicating dynamic socio-economic as well as environmental changes. Figure 8 shows a visual comparison done through overlaying three satellite images captured in different years to assess the extent of built-up area expansion. The research confirms that for the 25 years of study, urbanized areas expanded noticeably in all directions except northeast and covered other categories of urban land use and land cover (LULC), such as vegetation, agricultural land, and bare land.

The expansion in space implies the process of ongoing urbanization and its effects on the landscape. The most obvious land cover alteration between 2000 and 2015 was the significant expansion of built-up areas, which grew from 779.97 ha (4.50%) in 2000 to 1,875.65 ha, (10.82%) in 2015. That represents 1,095.68 ha (6.32%) increase, revealing fast urbanization and infrastructural development caused by population growth and settlement expansion. As indicated in Table 5, the built-up area of Debark town expanded steadily over the study years. In the early 2000s, built-up areas were highly fragmented.

Table 5. Area of LC change between 2000 and 2015.

LULC Class	Area 2000 (ha)	2000 Area (%)	Area 2015 (ha)	2015 Area (%)	Change (ha)	Change Area (%)
Built up	779.969	4.50%	1875.646	10.82%	+1,095.68	+6.32%
Vegetation	2,275.16	13.13%	3,013.55	17.39%	+738.39	+4.26%
Agriculture	12,384.65	71.45%	10,696.33	61.69%	-1,688.32	-9.76%
Bare land	1,890.64	10.91%	1,744.90	10.07%	-145.74	-0.84%

The spatial trend and magnitude of these changes are represented graphically in Figure 8 presenting a concise graph of the evolving urban form. The figure is a critical element in understanding each trend and pattern shaping ULULC conversion within the study area.

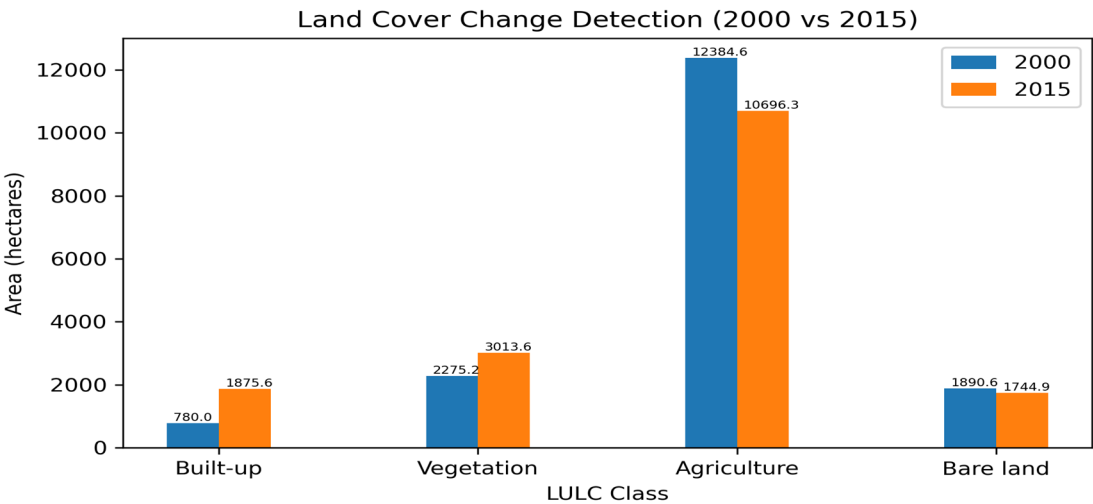


Figure 8. The Urban cover change in the 2000 and 2015.

The urban land cover (LC) data considered for 2015-2025 gives pivotal trends of land use for the area. Specifically, the urban area has recorded phenomenal growth, from 1,875.646 ha (10.82%) in 2015 to 2,741.515 ha (15.82%) in 2025. This increase of approximately 865.87 ha accounts for an impressive rise of 5%, reflecting enhanced urbanization and development. Conversely, the area of vegetative cover declined significantly from 3,013.55 ha (17.39%) to 2,033.85 ha (11.74%), translating into a loss of about 979.70 ha and signifying a decline of 5.65%.

Table 6. Area of LC change between 2015 and 2025.

LULC Class	Area 2015(ha)	Area 2015(%)	Area 2025 (ha)	2025 Area (%)	Change (ha)	Change Area (%)
Built up	1875.646	10.82%	2741.515	15.82%	+865.869	+5.0%
Vegetation	3,013.55	17.39%	2,033.85	11.74%	-979.700	-5.65%
Agriculture	10,696.33	61.69%	7,951.21	45.88%	-2,745.120	-15.81%
Bare land	1,744.90	10.07%	4,604.01	26.56%	+2,859.110	+16.49%

The urban LC statistics between 2000 and 2025 below Figure 9 indicated that drastic alterations in most of the land use categories suggested a dramatic overhaul of the landscape. Typically, the

built-up area increased from 779.969 hectares (4.50%) to 2,741.515 ha (15.82%), representing a rise of approximately 1,961.55 ha or 11.32%. This growth suggests a vigorous process of urbanization, most likely driven by an expansion of the population and consolidated infrastructure development.

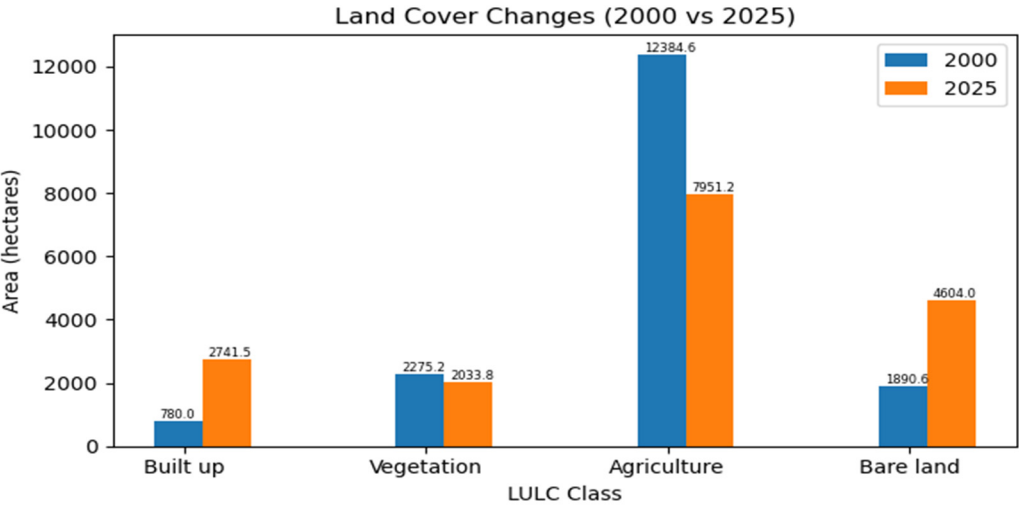


Figure 9. The Urban cover change in the 2000 - 2025.

The spatial arrangement and trends (see Figure 10) of geographic features was obtained by subjecting the classified images to spatial analysis; the information about changes in land cover proportion was derived. Subsequently, changes in the spatial composition of geographic features were obtained by comparing the classified images of 2000, 2015 and 2025 against each. In the present study, the analysis of urban land use increased by approximately 4.5% to 15.82% in 2000–2025 in the study areas, and the expansion of built-up areas mostly occurred over agricultural land. Built-up areas increased rapidly throughout the 25-year period, according to the spatial data obtained via the temporal analysis of land cover graphs

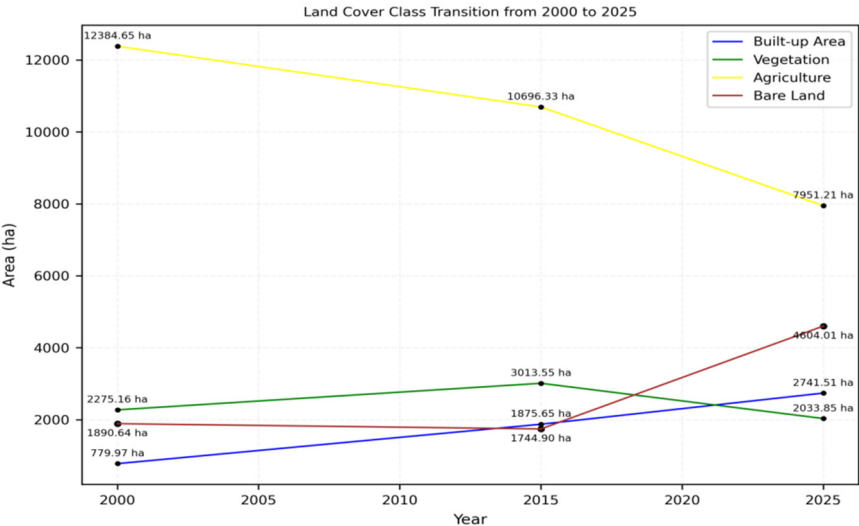


Figure 10. the spatial trends of the urban land cover change over the years.

Annual Rate of Urban Expansion

From 2000 to 2025, the area of investigation experienced significant land cover alteration, with urbanized land increasing very rapidly at an average annual rate of 78.46 ha, equivalent to a year-over-year percentage increase of 0.45%, showing accelerating urbanization. On the other hand, agricultural land decreased substantially by losing 177.34 ha each year or 1.02% annually, showing extensive conversion of agricultural land into urban and other uses. Bare land also registered a higher

increase of 108.53 ha/year (0.63% per year) due to land clearing or degradation that is attributed to development activities. Vegetation cover decreased slightly, by 9.65 ha or 0.06% per year is presented in (Figure 11). These trends reflect unbalanced land use planning and highlight the need for sustainable urban development policies to protect agricultural and natural land while managing urban growth responsibly.

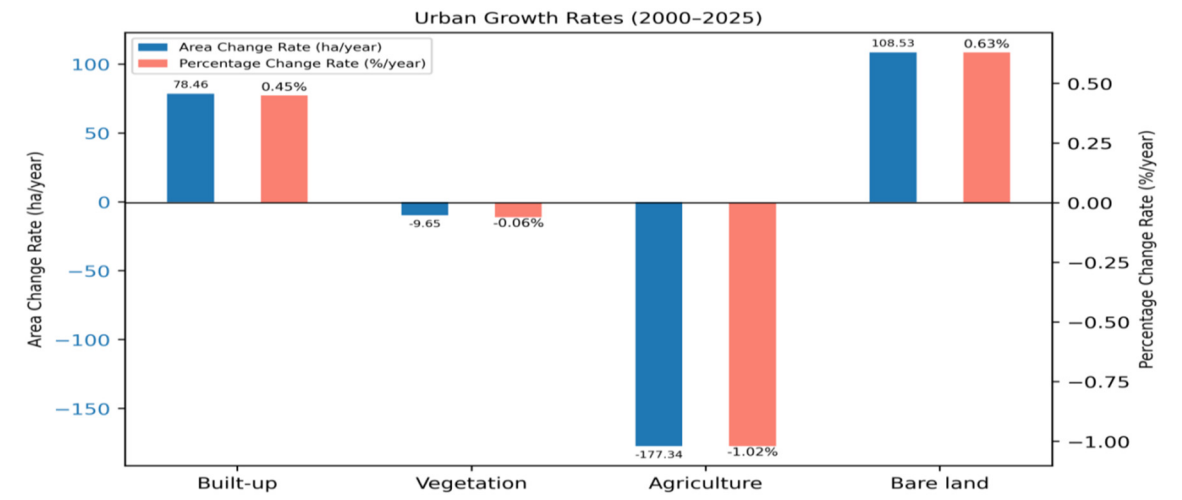


Figure 11. The annual urban expansion rate (%) from 2000 to 2025 with the given class.

The annual rate of urban expansion evaluates the gains and losses in the urban land cover class. It was found that from 2000 to 2025, 78.46 ha of built up area were increased annually. In contrast, from 2000 to 2025, the agricultural land was an annual loss of 177.34 ha/year. Finally, between 2000 and 2025, 108.53 ha of bare lands were gain to other LULC categories annually, and this represented the highest amount of lost agricultural lands.

4. Discussion

4.1. Result Comparison with Other LULC Datasets

Findings of this research align with other studies, to compare findings from other studies that have applied ML techniques to urban LC classification and change detection.

4.2. Machine Learning Model Performance Comparisons

As discussed in the recent (2024) study report by (Nigar et al., 2024), who analyzed the spatiotemporal variation in land use and land cover (LULC) in Sukkur, Pakistan, employing supervised classification techniques. Durowoju et al., (2025) compared some ML models and found that RF worked best with a total accuracy of 80% and kappa value 60%. Other models such as MARS, SVM, and KNN were less accurate. Although their accuracy for the free RF model was lower than the result, their study verifies that RF is generally more accurate for change detection in cities. Similarly, (Zhu & Ling, 2024) demonstrated the efficacy of RF classification using the Google Earth Engine (GEE) platform, with a reduction in open areas from 91.83% to 69.63% between 1980 and 2020. While slightly less accurate their study emphasizes the usability of RF to track land cover at large scales and long durations and confirms the findings of diminishing open and agricultural land for urbanization.

Amini et al. (2022) demonstrated the strong capability of the RF algorithm in 1985-2019 urban land use and land cover classification with 94.44% overall accuracy, 93% Kappa, and 93% F1-score, which far outweighed the Copernicus global land cover layers map. Their conclusions, with robust consensus over 90%, support the study, where RF achieved even higher accuracy (97.29%) and Kappa (96.32%), confirming RF as a highly accurate model for accurate urban LULC mapping and monitoring sudden land changes. As far as the performance of classification is concerned, the use of

the random forest (RF) algorithm that recorded a maximum accuracy of up to 97.29% outperformed the accuracies reported by (Ouma et al., 2023), who compared different machine learning techniques and different Landsat sensors and concluded that RF achieved a lowest average accuracy of 92.8% compared with other classifiers such as MLP-ANN (91.2%), SVM (90.9%), and GTB (87.8%). The implications emphasize the robustness of RF in urban LULC classification; this suggests that RF is better suited for handling complex, heterogeneous landscapes and multi-temporal data.

In the recent study conducted by Atef et al. (2023), evaluated the performance of various classification algorithms including MLH, RF, and SVM algorithms for monitoring spatiotemporal land use changes in El-Fayoum, Egypt, reporting the highest classification accuracy with SVM (kappa = 91.6%), followed by RF (90.9%) and MLH (87.8%). In contrast, our study found that RF outperformed SVM, achieving a higher overall accuracy of 97.29% is notably high and compares favorably with similar land cover classification studies in Africa and other developing regions, where overall accuracies typically range between 85% and 95%. The implications emphasize the robustness of RF in urban LULC classification; this suggests that RF is better suited for handling complex, heterogeneous landscapes and multi-temporal data.

4.3. Urban LULC Change Detection

Frimpong & Molkenhain (2025) quantified LULC dynamics in Kumasi and noted that urban land occupied 4,622.49 ha (23.78%) in 1986 but 14,004.60 ha (72.05%) in 2015. This is consistent with a discernible trend of urban growth overtaking agricultural and forested areas, as noted in the study, though on a lower absolute extent of urbanization. The (Dibaba, 2023) observed rapid urban expansion between 2001 to 2021 in Nekemte and Jimma Cities, with the built-up area growing by 929.25 ha (172.75%) and 2,285.64 ha (226.93%), respectively. These movements are of the same order as own observation of a 1,961.55 ha increase of built-up area, exhibiting the same trend of urban expansion in other areas. Salim *et al.* (2025) applied the RF algorithm on Landsat images of the Lucknow district. There was a net urban expansion of 48,459 ha accompanied by significant declines in forests (7,544 ha) and wetlands (67,452 ha). Similar to the observation of urban sprawl across natural and agricultural land is the study's accuracy of 97.29%, although higher than that of Salim.

Some of the previous studies recorded similar results to this study. Furthermore, the study follows along the same lines as that of Bisewur Eyaya (2014), Nyamekye et al. (2020), and Ouma et al. (2023) by highlighting the emerging trend of urbanization at the expense of agricultural land loss. We observed results indicate a significant reduction in agricultural area under cultivation by approximately 4,433.44 ha (25.57%) and an increase in urban area by approximately 1,961.55 ha (11.32%) between 2000 and 2025, consistent with the urban expansion rates documented by Bisewur Eyaya (Belay, 2014) of 113.32 ha in 13 years and 10,626 ha within 5 years. Similarly, (Nyamekye et al., 2020) considered a persistent rate of land use transition, dominated predominantly by urban built-up (21.24%) and agricultural land conversions (13.19%). Similarly, Fenta et al., (2017) also observed significant land use changes in Mekelle City, noting expansion of built-up areas at the expense of agricultural and vegetative lands. Likewise, Temesgen and Tesfaye (2020) reported spatiotemporal urban growth in Bure town, with forest and farmland declining due to increasing urban coverage. The rapid urban expansion in Debark town from 2000 to 2025, characterized by a massive increase in built-up land at the loss of agricultural land and vegetative cover, illustrates Figure 9 implications that call for sustainable urban development.

4.4. Annual Rate Change of Urban Expansion

In the present study, the analysis of urban land use annual rate change shows that the rate of the built-up area at a rate of 78.46 ha per year, equivalent to an annual percentage increase of 0.45%, increased by approximately 4.5% to 15.82% in 2000–2025 in the study areas, and the expansion of built-up areas mostly occurred over agricultural land. Built-up areas increased rapidly throughout the 25-year period, according to the spatial data obtained via the temporal analysis of land cover graphs (see Figure 11). This is similar to the previous studies Hassan & Southworth (Hassan &

Southworth, 2018), in contrast, the annual population growth rate was assessed in the earlier research. Similarly, according to Temesgen and Tesfaye (2020), due to the expansion of Bure town, from the year 1989 to 2019, the farmland lost 5.13km² (513ha) within with rate changes 0.17km² (17ha/year) in 30 years. In addition, the study result of Debark town is directly agreed with the findings of (Molla et al., 2024), which is conducted in Hawassa City expansion from 1984 – 2021 using Landsat images in ten year intervals, the result portrayed that the built-up area increased by 85.10 ha per year.

The results were confirmed the extent and rate of urban expansion in Debark Town. The analyses were showing how the town has grown both spatially and in terms of density over the past two decades. We anticipate a substantial increase in built-up area, likely at accelerated rates in the more recent period (2015-2025) compared to the earlier one (2000-2015), aligning with Ethiopia's general urbanization trends. The detailed LULC change matrix were reveal the primary land covers being consumed for urban development, critically highlighting the conversion of agricultural land and natural vegetation.

5. Conclusion

This study successfully conducted a spatiotemporal analysis of urban expansion in Debark Town, Ethiopia, utilizing multi-temporal Landsat satellite imagery, Machine Learning techniques, and the Google Earth Engine cloud computing platform. The research quantified and mapped the significant increase in built-up area over the past two decades, revealing rapid urban growth rates and distinct spatial patterns of expansion. The employed Random Forest classifier within GEE demonstrated high accuracy in delineating LULC classes, affirming the robustness and efficiency of the methodological framework.

The findings underscore the immense pressure on surrounding agricultural lands and natural environments due to uncontrolled urban sprawl. This research provides critical, spatially explicit data that has been historically lacking for Debark Town, offering invaluable insights for local authorities and urban planners. By understanding the historical trajectories and patterns of growth, future urban development can be guided towards more sustainable and resilient pathways, mitigating negative environmental impacts and ensuring equitable resource allocation for the growing population of Debark.

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Availability of data and materials: The data supporting the findings of this study were presented in the tables and figures within the article.

Declarations

Ethics approval and consent to participate: This study is primarily ecological in nature and did not involve any animal and plant species experiments. Therefore, the sections pertaining to ethics approval and participant consent do not apply to this investigation.

Consent for publication: Not applicable.

Competing interests: The authors declare that they have no competing interests.

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