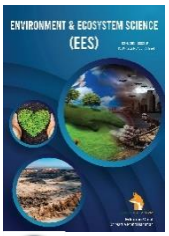
ZIBELINE INTERNATIONAL™ PUBLISHING

Environment & Ecosystem Science (EES)

DOI: http://doi.org/10.26480/ees.01.2023.21.29

ISSN: 2521-0882 (Print)
ISSN: 2521-0483 (Online)
CODEN: EESND2



RESEARCH ARTICLE

LAND USE LAND COVER CHANGE DETECTION USING GEOSPATIAL TECHNIQUES: THE CASE OF BURAYU TOWN

Birhanu Girma Abebe[a*], Agemasie Gebeyehu Amare[b], Bedane Shata Gemeda[c]

[a]Ethiopian Institute of Architecture, Building Construction and City Development, Addis Ababa University, Ethiopia
[b]Ethiopian Geospatial Information Institute, Addis Ababa, Ethiopia
[c]Addis Ababa City Land Development and Management Bureau
[*]Corresponding Author Email: birhanu.girma@eiabc.edu.et

ARTICLE DETAILS

Article History:

Received 27 March 2023
Revised 29 April 2023
Accepted 02 June 2023
Available online 16 June 2023

ABSTRACT

The rapid rate of urbanization in third world countries leads to rapid land-use land cover change. Thus, managing the land-use land cover change of the town is important for the proper urbanization process. To analyze the land-use land cover (LULC) change, multi-temporal and high-resolution aerial, geospatial techniques of GIS, remote sensing and satellite imagery methods were used. Results of this study revealed that the LULC coverage of forest, grasslands, and agricultural areas of the town rapidly decreased and converted to built-up areas. To control the rapid LULC change of the town, greenbelt principles have to be promoted. Hence, accordingly, findings of this research conclude that the town administration has to plan to acquire aerial photography of the town every three years to sustain the sustainable development.

KEYWORDS

Built-up area, Sustainability, Urbanization, Remote Sensing, Burayu town

1. INTRODUCTION

Urbanization is the process of a large number of people becomes continually dwelling in specific areas and forming cities (Britannica, 2019). Even though it is a worldwide phenomenon, the rate of urbanization is very speedy in third-world countries. So, the high rate of urbanization exposed land-use change (Ibrahim et al., 2015). According to the UN estimation in 2017, 4.1 billion people (55% of the world population) were living in urban areas. It occurs mainly because people move from rural areas to urban areas and it results in growth in the size of the urban population and leads to land-use change (Hannah et al., 2015).

Most of the users wrongly used and described the terms "land use" and "land cover" interchangeably. Nevertheless, each term has a very specific meaning. "Land use is commonly defined as a series of operations on land, carried out by humans, intending to obtain products and/or benefits through using land resources" (Coffey and Ryan, 2015). Whereas "land cover" defines the specific land cover on the ground, it could be vegetation, built-up infrastructure, water, grassland, or others. For that matter, the use of land may be different for lands with the same cover type. Hence; land-use change is the conversion of a piece of land used by people, from one purpose to another. This means the land can be converted from farmland to grassland or from vacant areas to urban development (FCRN, 2018). Therefore, land-use changes result in two major processes. The first process is due to the expansion of human activities changing the land cover and the second practice is a change of management type on existing land cover, this land-use change, can occur without shifting the land covers (Kyle et al., 2019).

Subsequently, detecting land use land cover is one of the most essential and common uses of remote sensing image analysis. Change detections can execute by visual interpretation of two images by a qualified interpreter or with GIS software and tools (Karen et al., 2018). To understand change over time, a high spatial and temporal resolution for several different years is required. The temporal resolution increases the detect-ability and assessment of land-use change in the past, present, and future. It can be possible to analyze the change using either satellite or aerial images (Source medium.com). Change detection techniques are useful to identify different land-use land cover changes over time. It is also common in Ethiopia to use low and medium-spatial resolution satellite and aerial imagery for detecting land-use changes (Terfa et al., 2020; Burayu, 2018; Alemu et al., 2008; Congedo, et al., 2012,).

According to a study higher spatial resolution imagery enhanced the accuracy of land-use land cover (LULC) classification and better analysis (Haregeweyn et al., 2012). In addition, the higher resolution images would provide more detailed information than the lower resolution images. Thus, the more pixels an image has allows remarkably identifying the small features, narrow streets on the ground. However, even though the medium-resolution images lack differencing features with the shadow, they argue the high-resolution images are a recent phenomenon. Consequently, the use of low and medium-resolution is mandatory to address the trends of the early years.

Therefore, to manage the rapid LULC change and associated consequences; analyzing LULC change over time is vital for the urban planner and decision-makers of the town Administration. Thus, this study attempts to address and analyze the major land-use land cover (LULC) changes of Burayu town from 1986 to 2020 using geospatial techniques and high-resolution aerial and satellite imagery. Besides, the study forecasts the LULC change trends of the town by 2030 and suggests potential points for the decision-makers and researchers.

2. STUDY AREA, DATA AND METHODS

2.1 Study Area

Before the development of early settlements, the area of Burayu town was

Quick Response Code	Access this article online	
	Website: www.environecosystem.com	**DOI:** 10.26480/ees.01.2023.21.29

Cite the Article: Birhanu Girma Abebe, Agemasie Gebeyehu Amare, Bedane Shata Gemeda (2023). Land Use Land Cover Change Detection Using Geospatial Techniques: The Case of Burayu Town. *Environment & Ecosystem Science, 7(1): 21-29.*

covered with dense forest. The town is found in Oromia National Regional State, under the Oromia special zone administration (Figure-1) and spatially connected with the city of Addis Ababa (Burayu Town Administration, 2018).As the census report of the Central statistics agency, the total population of Burayu town in 1984 was 4,138, and in 1994, and 2007 was 10,027 and 63,873 respectively. According to the 2007 census, the population projection in 2020 estimated 111,222 (CSA, 2013).

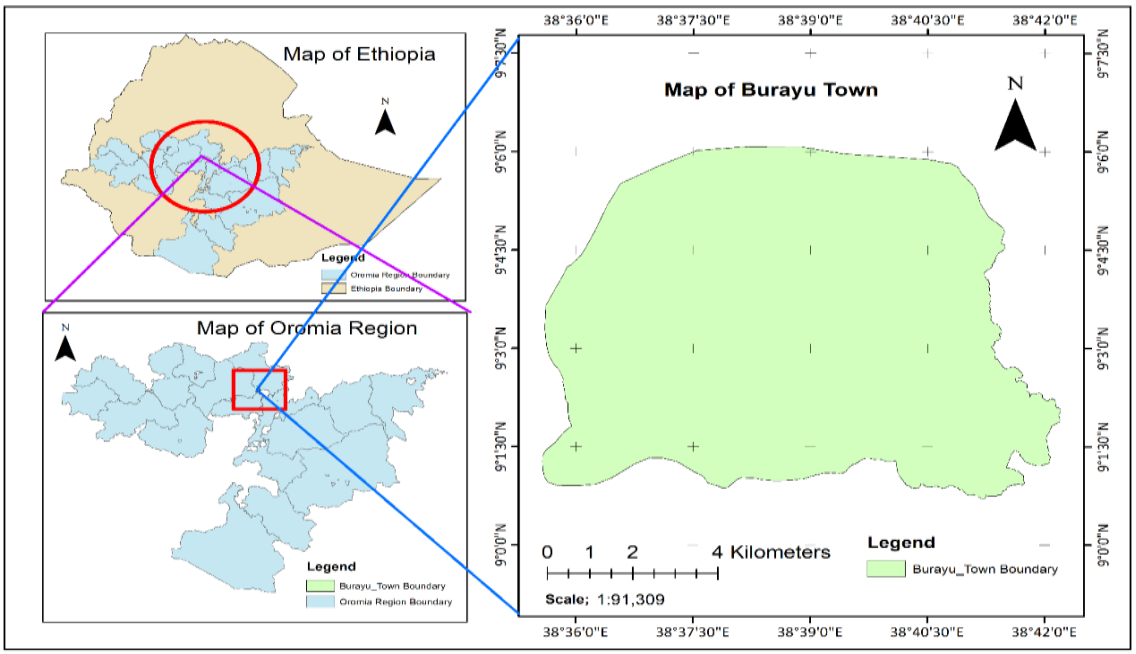


Figure 1: Map of the study area
Source: Computed using the town administration boundary shape file overlay with Ethio-GIS data, 2020

2.2 Data Sources

Both primary and secondary data sources are used. Primary data was collected through a field and personal observation, and interviews. As this study-applied geospatial techniques to assess the land-use land cover change (LULC) detection, comprehensively secondary data from aerial and satellite images were used. Thus, 15cm (2014) and 25cm (2017) resolution aerial image, 5m (2006) resolution SPOT-5 images, and additionally 30m Landsat-5 (1986 & 1996) and Landsat-8 (2020) spatial and temporal resolution historical images were used to show the trends expressively. Additionally, books, journals, websites, and reports are used to associate and verify the findings (NOAA, 2018; NOAA, 2019).

2.2.1 Methods of Data Extraction and Analysis

Mainly the GIS and remote sensing software of Arc Map, ERDAS Imagine, and Microsoft office (Word, Excel, etc.), and other software programs used to extract, organize and analyze information's from the aerial and satellite imagery as well as field survey data. Furthermore, the quantitative data is presented through statistical tools (chart, table, figure, and map) and qualitative data were examined in the content analysis approach.

2.2.2 Data Processing

For LULC studies, multi-temporal images require to adjust to a similar coordinate system, spatial resolution, and spectral resolution (Lingli et al., 2008). As multi-temporal and spatial resolution aerial and satellite images are used, spatial, radiometric, and spectral enhancements are applied. Hence, to maintain the data consistency; the image coordinate system transformed to a local datum, the spatial resolutions of the image re-sampled to 5m resolution, and used similar spectral bands (red, green, and blue).

2.3 Methods

2.3.1 The Role of Geospatial Techniques

Remote sensing and GIS are the most fundamental and commonly used geospatial techniques to identify the LULC changes of the cities. It helps to detect the changes by visually interpreting the two different images and using trained GIS software. For the analysis of the urban pattern and process, remote sensing data are commonly used, but it is not enough to analyze the causes or consequences of the expansion (Bhatta, 2010).

According to recent study, the spatial resolution of images is classified into three categories; low resolution - over 60m, medium resolution- 10 to 30m, and high to very high resolution - 30cm to 5m (Earth Observing System, 2019). To map, the horizontal expansion of cities widely used remote sensing data and techniques. Lands at images are capable of detecting horizontal and vertical urban growth.

2.3.2 Land Use Land Covers Change Detection

In the context of remote sensing, change detection refers to the process of recognizing changes in land features by observing them at different times. This process can be executed both manually and/or automatically by interpreting the satellite images or aerial photos for a given area of interest and comparing them between images from two dates (Jason et al., 2019). Moreover, change detection can be computed by using multi-temporal images of the area and is commonly used for the study of water resources and forest coverage studies (Jain et al., 2003).

2.3.3 Land Use Land Cover Classification Technique

Image classification technique is the process of organizing pixels into a predetermined number of individual categories of data, based on their values. This means, when the pixel achieves a certain set of parameters, then the pixel is assigned to the class according to the defined parameters. Regarding this, unsupervised and supervised classifications techniques are the two most common image classification techniques in remote sensing (Humboldt State University, 2014).

Unsupervised classification is a form of pixel-based classification and is fully computer automated classification. The role of the user is limited. Almost the mainstream of the classification process of the spectral classes was created exclusively based on the pixel values of the bands of the images by the computer. Further ERDAS imagine software used the iterative self-organizing data-analysis technique algorithm (ISODATA) to perform an unsupervised classification. It is iterative in that it repeatedly performs an entire classification and recalculates statistics. The ISODATA method repeats the clustering of the image until either a maximum number of iterations are performed, or a maximum percentage of unchanged pixels reached between two iterations (ERDAS, 2016).

This type of classification is relatively fast, simple to run, and does not require extensive prior knowledge of the area. However, in unclassified classification technique has a drawback; the mismatching of spectral classes with the corresponding class information, and the limited interaction of the user to interpret the classification (Humboldt State University, 2014). Furthermore, according to Naif et al. unsupervised classification faced a problem associated with very high-resolution images. Because of the clustering classes categorized without training data and the complexity of the spectral attributes within each land cover class and between different classes (Naif et al., 2011).

In supervised classification, the user trains the machine using various pixels values or spectral signatures for each identified class. This process executes by selecting illustrative sample sites of known LULC areas. Then the computer algorithm uses the spectral signatures of the training areas to classify the entire image of the study area. When compare with unsupervised classification, it is more accurate and demands great effort, requires more time and money. However, it is highly dependent on the specified training data (Kassa et al., 2014; Wihbey et al., 2017).

2.3.4 Land Use Land Cover Classification Systems

Generally, there are three common landuse land cover classification systems, those are USGS (Anderson) classification, Coordination of Information on the Environment (CORINE) classification, and FAO classification (Christiane et al., 2011). The USGS classification classifies basically into nine categories; urban or built-up land, agricultural land, rangeland, forest land, water, wetland, barren land, tundra, and perennial snow or ice (James et al., 1976). Whereas, the CORINE classification which is developed by the European Environment Agency, classifies into five major categories; artificial surface, agricultural areas, forest and sim-natural areas, wetlands, and water bodies (European Environment Agency, 1985).

On the other hand, the FAO classification system categorizes the LULC classification in different ways primarily vegetated area and primarily non-vegetated area and further they classify into four different categories. However, there is no defined and internationally accepted landuse land cover classification system. Rather the researcher and institutions define the LULC classification system according to the objectives of their studies and goals.

2.3.5 Accuracy Assessment

Accuracy assessment is a significant tool and a critical step for assessing the quality of the image classification derived from aerial and satellite images. The accuracy assessment process is used to evaluate the accuracy of the classification with the ground fact (Jambally et al., 2013). It is used to compute the reliability of a classified image and to construct an error matrix. The classified LULC images represent in rows and columns in a square matrix. The error matrix calculates according to the number of rows and columns. It is determined using a higher resolution usually called "reference data" to verify the checkpoints sample area and the "ground truth". The checkpoint sample areas are used to fill the error matrix (Andarge et al., 2017).

The accuracy of the LULC classification was assessed using the accuracy matrix tools computed the overall accuracy(Eq-1), errors of commission(Eq-2), errors of omission(Eq-3), user's accuracy(Eq-4), producer's accuracy(Eq-5), and kappa coefficient(Eq-6).

$$\text{Overall Accuracy} = \frac{\text{Number of correctly classified points}}{\text{Total number of sample reference points}} \quad (1)$$

$$\text{Errors of Commission} = \frac{\text{Incorrectly classified reference points (included)}}{\text{Total number of sample reference points}} \quad (2)$$

$$\text{Errors of Omission} = \frac{\text{Incorrectly classified reference points (omitted)}}{\text{Total number of sample reference points}} \quad (3)$$

$$\text{User's Accuracy} = 100\% - \text{Commission Error} \quad (4)$$

$$\text{Producer's accuracy} = 100\% - \text{Omission Error} \quad (5)$$

$$\text{Kappa coefficient } (K^{\wedge}) = \frac{(n * \text{Sum } X_{ii}) - \text{Sum } (X_{i+} * X_{+i})}{n^2 - \text{Sum } (X_{i+} * X_{+i})} \quad (6)$$

Where, SUM = sum across all rows in matrix, Xii = diagonal, Xi+ = marginal row total (row i), X+i = marginal column total (column i) and n = # of observations.

2.3.6 Land Use Land Covers Classification Categories and Techniques

Forthis study, the USGS (Anderson) classification method was adopted, and the LULC of Burayu town was categorized into five major classes. The details are described below;

Table 1: Landuse Land Cover (LULC) Classification Catagories

LULC Class	Description
Agricultural Areas	Includes cultivated lands, areas along the Gefersa dam, and rivers that are used for irrigation and agricultural purposes.
Built-up Areas	Includes features with all types of artificial surfaces and development activities, including houses, roads, ongoing constructions, industrial areas, infrastructures, transportation.
Forest Areas	Includes areas with dense vegetation cover, such as those covered with shrubs forming closed canopies and trees. It also included scattered trees and forests.
Grass Lands	Includes grazing areas and community open spaces.
Water Bodies	Includes dames, streams, and waterways.

Source; Adapted from USGS (Anderson) classification method, 2020

Image classification technique is the process of organizing pixels into a predetermined number of individual categories of data, based on their values. This means, when the pixel achieves a certain set of parameters, then the pixel is assigned to the defined parameters. Regarding this, unsupervised and supervised classifications techniques are the two most common image classification techniques in remote sensing (Fisher et al., 2017). However, according to previous research, unsupervised classification faced a problem associated with very high-resolution (VHR) images and cannot accurately classify high-resolution images. On the other hand, the supervised classification is a more accurate technique and demands great efforts, requiring more time and money (Setyawan et al., 2019). Therefore, to attain the required objectives of the study, a supervised classification technique is applied. As accuracy assessment is the last step in the analysis of remote sensing data, it helps to confirm how accurate the classification results are (Anupam et al., 2017). Hence, 100 user-defined and evenly distributed quality checkpoints were used for checking the accuracy and the quality of the image classification.

Regarding the LULC change (Eq-7) and annual change rates (Eq-8); it has computed for each successive years; 1986 & 1996, 1996 & 2006, 2006 & 2014, 2014 & 2017, 2017 & 2020 and LULC categories

$$\text{LULC change} = \text{Area of year 2 - Area of year 1} \quad (7)$$

$$\text{LULC Annual Change Rate} = \left(\frac{\text{LULC change}}{\text{Total Area}}\right) * 100 \quad (8)$$

Moreover, the exponential growth (Eq-9) and decay function (Eq-10) function are used to project the LULC changes of the year 2030. In equation 9 and 10 (y), (a) represents the initial LULC class coverage area, (r) denotes growth rate or decay rate, and (t) is the time intervals between the initial and projected year (Donna et al., 2012).

$$y = a*(1+ r)^{t} \quad (9)$$

$$y = a*(1- r)^{t} \quad (10)$$

3. RESULTS

3.1 Land Use Land Cover Changes

Results indicate that the land use land cover of Burayu town is categorized into five categories; agricultural areas, built-up areas, forest areas, grasslands, and water bodies. The LULC classification was done for six different periods of 1986, 1996, 2006, 2014, 2017, and 2020 using high and medium-resolution aerial and satellite images (Mark et al., 2014). Therefore, the results of each year's land use land cover are described in Figure 2 and table 3 as follow.

As table-2 andfigure-2 described, the coverage of forest areas from 1986 to 2020, was decreased by 29% (2,728.76 ha) which assures more than half of the forest area coverage's are changed. In addition, the agricultural

areas increased from 1996 and 2006 but, later on gradually decreased. Similarly, the grasslands have a relatively similar trend with agricultural areas; there was higher grassland coverage (28%) in 1996 but gradually decreased to 12 % in 2020. This implies that the grasslands coverage of the town changed by 16% (1,474.73 ha) from 1996 to 2020 (UN, 2019; Yao et al., 2018; Dinsa et al., 2016).

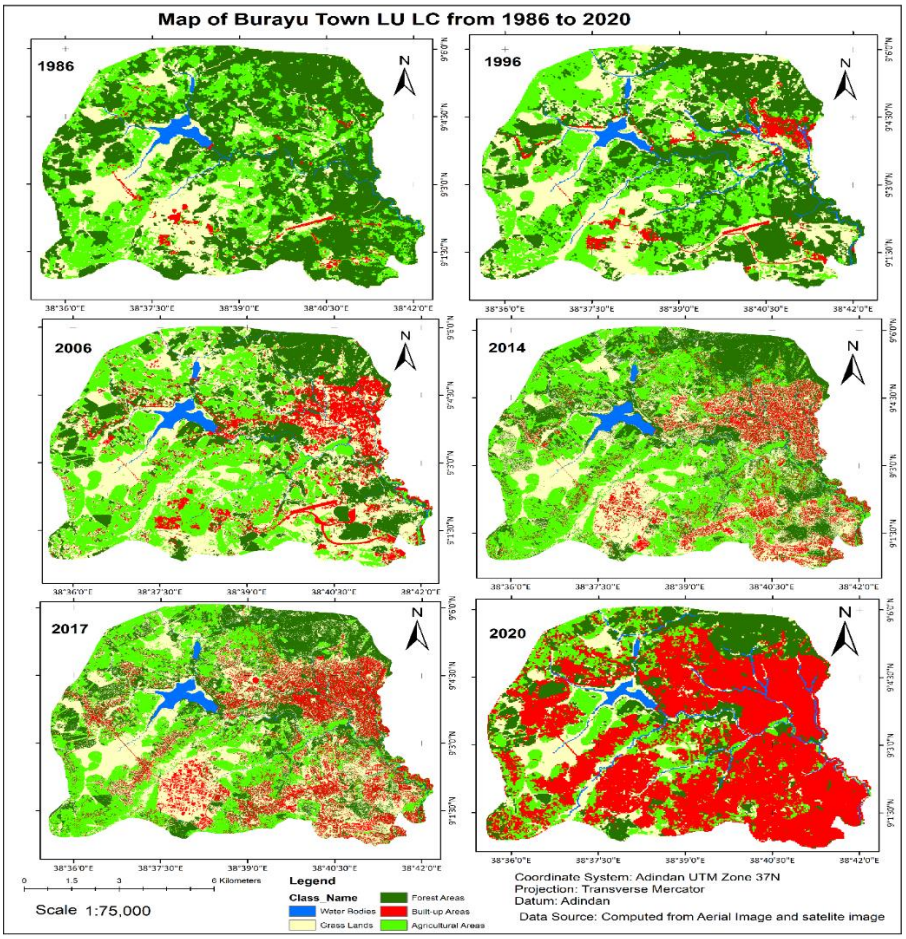
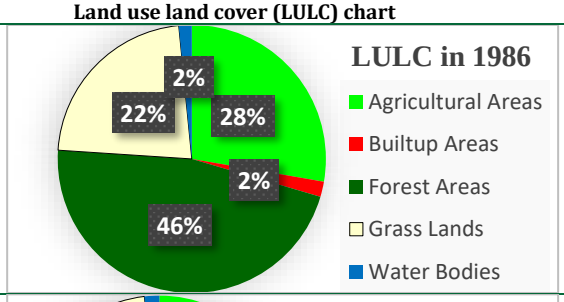
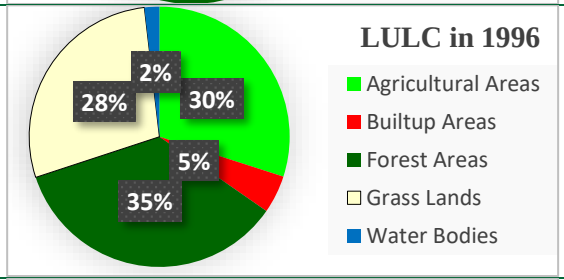
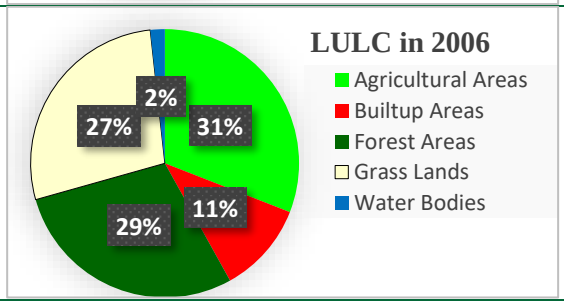
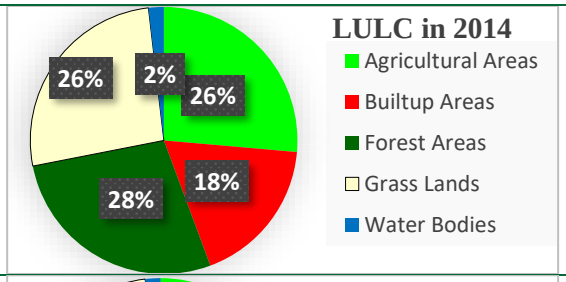


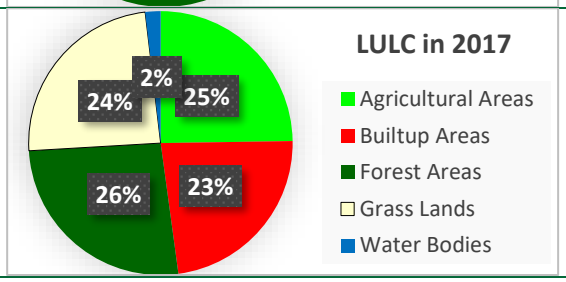
Figure 2: Landuse land cover (LULC) map from 1986 to 2020
Source: Computed from aerial and satellite image, 1986 to 2020

Table 2: Land Use Land Cover (LULC) Ratio From 1986 to 2020

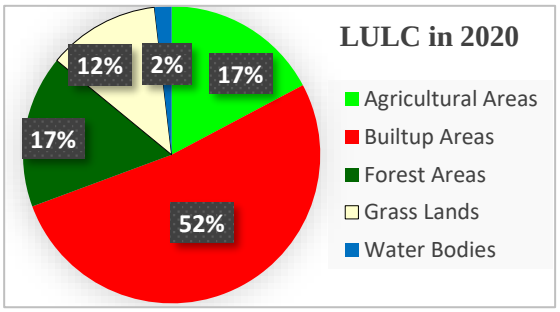
Land use land cover (LULC) chart	Description
	In 1986, 46% of the total area was covered by forest areas, whereas 28% and 22% of the total areas were covered with agricultural areas and grasslands respectively. Built-up area and water bodies cover the remaining 4% of the whole area.
	In 1996, 35% of the total area was covered by forest areas. Whereas, 30% and 28% of the total areas were covered with agricultural areas and grasslands respectively. In addition, the remaining built-up areas covered 5%, and water bodies covered 2% of the town.
	In2006, the highest coverage of the total area (31%) was covered with agricultural areas, and forest areas and grasslands covered 29% and 27% of the total areas respectively. While 11% of the town is covered by a built-up area, the remaining 2% of the town is covered with water bodies.



In 2014, 28% of the total area was covered with forest areas, agricultural areas, and grasslands covered 52% of the total areas equally. Whereas, the built-up areas and water bodies covered 18% and 2% of the town respectively.



In 2017, forest areas, agricultural areas, and grasslands covered 26%, 25%, and 24% of the total areas respectively. Whereas, the built-up area covered 23% of the town and the remaining 2% of the town was covered with water bodies.



In 2020, 52% of the total area covered with built-up areas. Whereas, the remaining 48% of the town is covered by agricultural areas (17%) and forest areas (17%), grasslands (12%), and water bodies (2%).

Source: Computed from aerial and satellite image, 1986 to 2020

Unlike, forest area, the coverage of built-up areas rapidly increased from 1986 to 2020. Moreover, when the built-up areas coverage of 2020 compared with 1986 and 2017, it was increased additionally by 50% (4,634.3 ha) and 29% (2,674.45 ha) respectively (see Table 3). This boldly expresses the LULC of Burayu town is rapidly and dramatically converted and changed to built-up areas. On the other hand, the coverage of water bodies had no significant change from 1986 to 2020 (Bekele et al., 2010; Yass et al., 2017).

Table 3: Burayu Town Land Use Land Cover (LULC) Area Coverage, 1986 to 2020

LULC type	1986	1996	2006	2014	2017	2020
	Area/ ha	Area/ ha	Area/ ha	Area/ ha	Area/ ha	Area/ ha
Agricultural	2,555.43	2,761.84	2,851.32	2,432.79	2,282.26	1,589.67
Built-up Areas	169.41	433.70	1,013.76	1,654.73	2,129.26	4,803.71
Forest Areas	4,258.94	3,253.25	2,646.70	2,543.19	2,418.30	1,530.18
Grass Lands	2065.23	2,599.95	2,536.98	2,418.33	2,218.80	1,125.22
Water Bodies	170.49	170.80	170.73	170.5	170.9	170.71
Total	**9,219.5**	**9,219.5**	**9,219.5**	**9,219.5**	**9,219.5**	**9,219.5**

Source: Computed from aerial and satellite images, 1986 to 2020

Table 4: Accuracy Assessement Report of Burayu Town

Accuracy Matrix	LULC classification					
	1986	1996	2006	2014	2017	2020
Overall Accuracy	94%	94%	98.00%	99%	98%	97%
Average User's Accuracy	96.36%	94.91%	98.38%	99.05%	97.98%	96.73%
Average Producer's accuracy	87.70%	93.29%	97.59%	98.75%	98.67%	95.87%
Average Errors of Commission	3.64%	5.09%	1.62%	0.95%	2.02%	3.27%
Average Errors of Omission	12.3%	6.71%	2.41%	1.25%	1.33%	4.13%
Kappa Coefficient	0.91	0.92	0.97%	0.99	0.97	0.96

Source: Computed from the classified LULC aerial and satellite images, 1986 to 2020

As Table 4 indicates, the best overall accuracy assess in 2014 (99%) and the lowers overall accuracy was assessed in 1986 and 1996 (94%). Further, the best user and producer accuracy was assessed in 2014(99.05% and 98.75% respectively). Whereas relatively the worst user accuracy was assessed in 1996 (94.91%), and producer accuracy was assessed in 1986 (87.7%). On the other hand, the greater average error of omission was computed in 1986 (12.3%) and the lower average omission error in 2014 (1.25%). Also, the higher and lower average commission error is 5.09% (1996) and 5.09% (2014). Similarly, the average error of omission and commission was also lower in 2014, 2017, and 2006 as compared with others (Mark et al., 2016; Gemechu et al., 2018). The kappa coefficient values of classification shows also close to positive ones, which means the classification is done with higher quality.

As indicated in Table-5 and figure-3 the negative values of the change indicate that the specific LULC coverage decreased between the specified years. But the positive value shows the increments of the LULC. Thus, the forest area was decreased rapidly and the greater forest area change was detected from 1986 to 1996 (-1,005.7 ha), 2017 to 2020 (-888.1 ha), and 1996 to 2006 (-606.6 ha). Even though the agricultural areas increased from 1986 to 1996 (206.4 ha), and 1996 to 2006 (89.5 ha), it gradually decreased. Moreover, a larger agricultural area change was detected from 2017 to 2020 (-418.5 ha), 2006 to 2014 (-150.5 ha), and 2014 to 2017 (-92.6 ha). Similarly, the grassland areas coverage increased from 1986 to 1996 (534.7 ha), but like agricultural areas, its coverage decreased progressively and the larger grassland change detected from 2017 to 2020 (-1,093.6), and from 2014 to 2017 (-199.5 ha), 2006 to 2014 (-118.7 ha),

and 1996 to 2006 (-62.97 ha) grasslands are changed to other LULC (Pengfei et al., 2016; World Bank Group, 2015).

Unlike the forest areas, the coverage of built-up areas continuously increased from 1986 to 2020. The largest land use change was detected from 2017 to 2020 (2,674.5 ha), and from 2006 to 2014 (641 ha), 1996 to 2006 (580.1 ha), 2014 to 2017 (474.5ha), 1986 to 1996 (264.3 ha). However, the change of water bodies is not significant, which changes from -0.07 ha (1996 to 2006) to 0.4 ha (2014 to 2017).

Besides, as figure-4 shows, the highest and lowest annual LULC change rate of built-up areas are 9.7% (2017 to 2020) and 0.3% (1996 to 1986) respectively. This implies that due to the rapid growth of the population of the town, the built-up areas raised accordingly. Moreover, the population growth exposed trigger unmanageable housing demand and an informal settlement (Nijhoff et al., 1986; Ancot et al., 1983). On the contrary, the annual change rate of forest areas was 3.2% (2017 to2020) and 0.14% (2006 to 2014). This means there was higher deforestation in the study area from 2017 to 2020.

Table 5: Burayu Town LULC change/ha and Annual Change Rate From 1986 to 2020

LULC type	1996-1986		2006-1996		2014-2006		2017-2014		2020-2017	
	*/ha	**/%	*/ha	**/%	*/ha	**/%	*/ha	**/%	*/ha	**/%
Agricultural A.	206.41	0.22	89.48	0.10	-418.53	-0.57	-150.5	-0.54	-692.59	-2.50
Built-up Areas	264.29	0.29	580.06	0.63	640.97	0.87	474.5	1.72	2,674.45	9.67
Forest Areas	-1,005.69	-1.09	-606.55	-0.66	-103.51	-0.14	-124.9	-0.45	-888.12	-3.21
Grass Lands	534.72	0.58	-62.97	-0.07	-118.65	-0.16	-199.5	-0.72	-1,093.58	-3.95
Water Bodies	0.31	0.00	-0.07	0.00	-0.23	0.00	0.4	0.00	-0.19	0.00

* Annual change/ ha ** annual change rate

Source: Computed from the classified LULC aerial and satellite images, 1986 to 2020

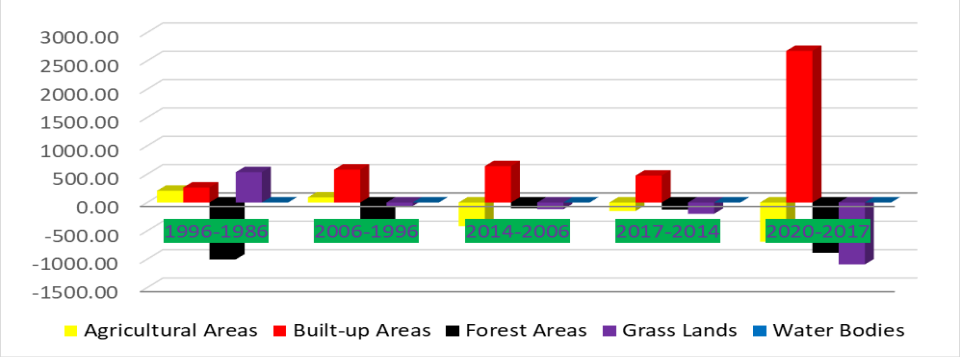


Figure 3: LULC change/ha from 1986 to 2020

Source: Computed from the classified LULC aerial and satellite images, 1986 to 2020

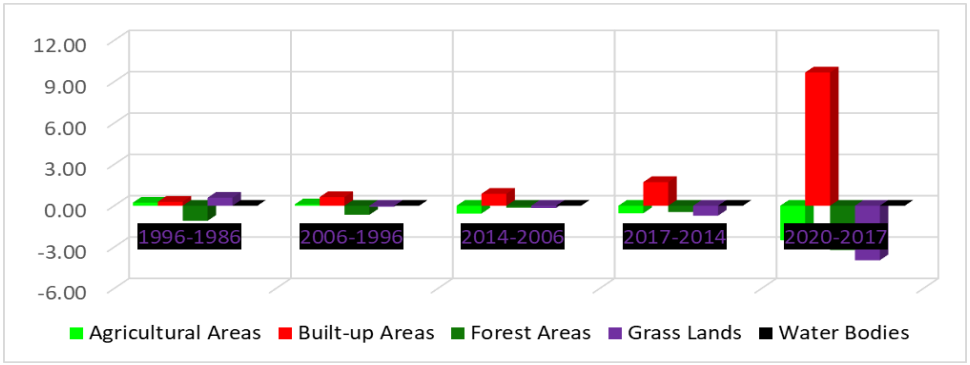


Figure 4: LULC annual change rate from 1986 to 2020

Source: Computed from the classified LULC aerial and satellite images, 1986 to 2020

3.2 Trends of LULC Change of Burayu Town

The land use land cover (LULC) change trend by 2030 is projected according to table-5 annual change rate. According to the projection depicted in figure-5, by 2030 the LULC of the town will be changed radically. Thus, the largest LULC of the town will be built-up areas, which covers 78% of the town. While, the remaining 8% of the town will be covered by agricultural areas, forest areas 7%, and grasslands will be 5%.

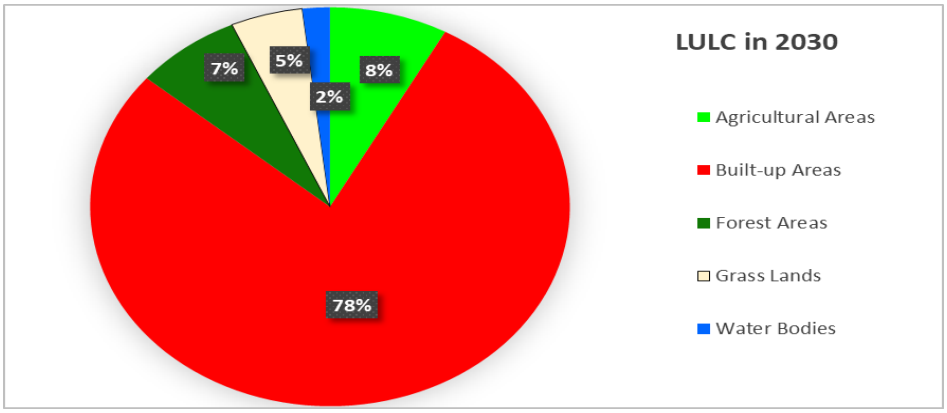


Figure 5: The LULC projection of Burayu town by 2030

Source: Computed from the classified LULC aerial and satellite images, 1986 to 2020

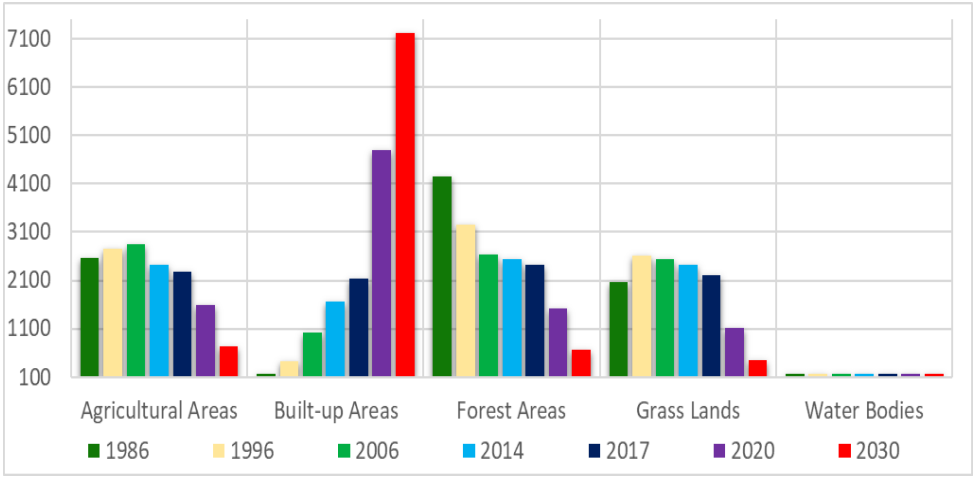


Figure 6: The LULC trend of Burayu town from 1986 to 2030
Source: Computed from the classified LULC aerial and satellite images, 1986 to 2020

As indicated in figure-6, the coverage of agricultural and grasslands increased in the earlier year but later it was decreased in coverage and the coverage of forest areas rapidly reduced from 1986 to 2030 by its coverage. This means there was a high level of deforestation from 1986 to 2020 and will have a high level of deforestation tendency by 2030. On the contrary, the coverage of built-up areas rapidly increased from 1986 to 2030. This means the coverage of grasslands, forest, and agricultural areas were converted and changed to human settlements and other built-up development activities. Whereas, the LULC change trend of water bodies is not significant (EEA, 1999; Richards et al., 2013).

4. Discussion

Finding of this study and the studies conducted by Terfa et al. show that, the forest areas decreased from 1986 (50%) to 2019 (25%).Agricultural lands and grasslands increased from 1987 to 1999 and decreased in coverage from 1999 to 2019. While, the built-up area increased from 1987 (1.25%) to 2020 (32.34%). On the other hand, the coverage of water bodies (1.06%) is similar all the time. Further, according to previous study, the coverage of forest areas even it was rapidly decreased in the early years 1990 (37.8%) to 2000 (6.7%), but it becomes slightly increased in the recent years from 2000 (6.7%) to 2019 (13.3%) (Amanu et al., 2019). Unlike forest areas, the coverage of built-up and shrub lands rise in early years from 1990 (25.6%, 33.3% respectively) to 2000 (27.8%, 56.7% respectively), and decreased in recent years from 2010 (23.3%, 42.2% respectively) to 2019 (21.1%, 18.9% respectively). Whereas the coverage of water body covers 1.1 % of the total areas in all the study period.

5. Conclusion

The aim of detecting the land use land cover (LULC) change is to manage the improper LULC changes. As discussed above follow-up the LULC change of towns is very essential for town administration and policymakers to manage the process of urbanization and the ecology of the town as well as the region. The LULC change of Burayu town was examined between 1986 to 2020 and projected for 2030 using geospatial techniques. As the study shows, by 2030, the built-up areas will cover 78% of the town, whereas, agricultural areas, forest areas, grasslands, and water bodies will cover 8%, 7%, 5%, and 2% of the town respectively. This implies that the coverage of grasslands, agricultural, and forest areas rapidly converted or changed to built-up areas.

Therefore, for managing the rapid LULC change, the administration of the town and the policy-makers should formulate the right strategies to manage the rapid deterioration of forest areas and land invasion and associated issues. Unless managing the change of LULC of the town there will be difficulty in planning and controlling urban growth. However, the role of high resolution and time serious aerial and satellite imagery is very cost-effective and vital for urban planning practice and urban management. Future studies should research the socio-economic and ecological implications of rapid LULC change on the town and the surrounding environment.

Recommendations

Based on the results of this study, the following suggestions were forwarded:

- As the study has shown, the rapid LULC change of the town was the effect of the rapid growth of the population. Hence, there should be a policy to manage the growth of the population.
- Even though the town has prepared a structured plan, there is a proper implementation gap. Thus, the town administration should allocate the required resources, appropriate organizational structure, and supports to achieve the desired goal.
- To reduce the LULC change, the town administration should promote the green belt principles and a mixed-use approach.
- The town administration should plan to acquire aerial photography of the town every three years. Because of the use of high spatial and temporal resolution, aerial imagery has a vital role for certainly detecting the LULC change, and for follow-up urban planning implementation.
- The policymakers should promote green belt principles to protect the forest areas and to maintain the ecology of the town and the surrounding area. To sustainably achieve the growth of the town and maintain the ecology there should be an optimal environmental impact assessment (EIA) practice and mitigation measure for those rapid LULC changes.

References

Alemu, Genanaw, 2008, Forest Cover Change Detection and Fire Risk Susceptibility Mapping Using GIS and Remote Sensing: Case of Goba Woreda. Addis Ababa : Addis Ababa University, July 2008.

Amanu, Lencho, 2019, Modeling Spatio-Temporal Urban Land Use Changes: A Case Of Burayu Town Using Remote Sensing And Gis Techniques. Addis Ababa, Ethiopia : Addis Ababa University, October 2019. 23https://medium.com /@SunnyKulkarni/ city-expansions -and-the-vertical -urbanization -approach-10280a05a01

Ancot J.P, Kuiper J.H, Paelinck J.H.P., 1983, Long-term urban trends in developing countries: some further econometric results. Rotterdam, The Netherlands, July 27, 1983, Environment and Planning, Vol. 15.

Andarge, Abebaw, 2017, Monitoring the urban growth of Debre Markos Town (1984-2012), Ethiopia: Using satellite images and GPS. Academic Journals, April 2017, Journal of Geography and Regional Planning.

Anupam, Anand, 2017, Accuracy Assessment. Processing and Classification of Remotely Sensed Images. s.l. : ResearchGate, 14, Pp. 59 -78.

Bekele, Firew, 2010, The Impact of Horizontal Urban Expansion on Sub-Urban Agricultural Community Livelihood: The Case of Tabor Sub-City, Hawassa city, SNNPRS, Ethiopia. Addis Ababa : Addis Ababa University.

Bhatta, B., 2010, Causes and Consequences of Urban Growth and Sprawl. Analysis of Urban Growth and Sprawl from Remote Sensing Data. s.l. : Springer-Verlag Berlin Heidelberg.

Britannica, 2019, The Editors of Encyclopaedia. Encyclopaedia Britannica. [Online] [Cited: December 06, 2019.] https://www.britannica.com/topic/urbanization.

Burayu Town Administration. [Online] 2018. [Cited: December 25, 2019.] http://www.oromiyaa.gov.et.

Christiane, Schmullius, 2011, Land Cover Classification. Jena, Germany: Friedrich Schiller University. Earth System Monitoring and Modelling.

Coffey, Ryan, 2013, Michigan State University MSU Extension. [Online] Extension, Michigan State University, January 18, 2013. https://extension.msu.edu.

Congedo, et al., 2012, Development of a Methodology for Land Cover Classification in Dar es Salaam using SPOT Imagery. Sapienza University, May 18, 2012.

CSA. 2013, Population Projection of Ethiopia for All Regions at Wereda Level from 2014 – 2017. Addis Ababa : Federal Demographic Republic of Ethiopia, Central Statistical Agency (CSA).

Dinsa, Melkamu N., 2016, Powers of Urban Local Government on Land Administration and the Challenges of Illegal Housing: The Case of Burayu City Administration, Oromia National Regional State. Addis Ababa : Addis Ababa University, May 24, 2016.

Donna, Roberts, 2012, MathBitsNotebook. Algebra 1. [Online] 2012. [Cited: July 29, 2020.] http://mathbitsnotebook.com/.

Earth Observing System, 2019, Earth Observing System. [Online] Earth Observing System, April 12, 2019. [Cited: August 8, 2020.]

EEA, 1999, Land use footprints. [prod.] Europian Environmental Agency.

ERDAS Imagine, 2016, Accuracy Assessment.

European Environment Agency, 1985, European Environment Agency. [Online] 1985. https://www.eea.europa.eu/publications/COR0-part1/download.

Fisher, Jonathan R. B., et al., 2017, Impact of satellite imagery spatial resolution on land use classification accuracy and modeled water quality. John Wiley & Sons Ltd on behalf of Zoological Society of London, July 19, 2017, Remote Sensing in Ecology and Conservation, pp. 137–149.

Gemechu, Samual, 2018, The Trend and Level of Squatter Settement in Burayu City. Addis Ababa : Addis Ababa University.

Hannah, Ritchie and Max, Roser, 2015, Our world in Data. [Online] November 2019. https://ourworldindata.org/urbanization.

Haregeweyn, Nigussie, et al., 2012, The dynamics of urban expansion and its impacts on land use/land cover change and small-scale farmers living near the urban fringe: A case study of Bahir Dar, Ethiopia. Elsevier B.V., March 22, 2012, Landscape and Urban Planning, Vol. 106, pp. 149-157.

Humboldt State University, 2014, Humboldt State University Geospatial online. [Online] Humboldt State University, in Arcata, California, 2014. [Cited: July 22, 2020.] http://gsp.humboldt.edu/OLM/Courses/GSP_216_Online/lesson6-1/unsupervised.html.

Ibrahim, Rizk H., Mosbeh, Rashed K., 2015, Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. Gulf Organisation for Research and Development, Pp. 117-124.

Jain S.K., Singh V.P., 2003, Chapter 3 - Emerging Techniques for Data Acquisition and Systems Modeling. Developments in Water Science, Vol. 51, Pp. 123-205.

Jambally, Mohammed D., 2013, Land use and cover change assessment using Remote Sensing and GIS: Dohuk City, Kurdistan, Iraq (1998-2011). International Journal of Geomatics and Geosciences , Vol. 3, ISSN 0976 – 4380 .

James R., et al., 1976, A Land Use And Land Cover Classification System For Use With Remote Sensor Data. Anderson, Washington : US Geological Survey.

Jason, Karl and Anne, Axel, 2019, The Landscap Toolbox. [Online] 2013. [Cited: December 21, 2019.] https://wiki.landscape tool box.org/doku.php/ remote _sensing_methods: change_detection.

Karen, Schuckman and Jarlath, O'Neil D., 2018, PennState college of Earth and Miniral Scince. Remote Sensing Image Analysis And Applications. [Online] College of Earth and Mineral Sciences, The Pennsylvania State University, https://www.e-education.psu.edu/geog883/node/496.

Kassa, Fekadu, 2014, The Rates and Effects of Urban Sprawl in Developing Countries : The Case of Addis Ababa, Ethiopia. Arba Minch University : DG GRUYTER, 2014, International Journal of Area Studies, Pp. 135-151.

Kyle, Frankel D., et al., 2019, Encyclopedia of Food Security and Sustainability. Science Direct, Science Direct, Vol. 3, Pp. 14-20.

Lingli, Zhu, et al., 2008, Georeferencing Multi-temporal and Multi-scale Imagery in Photogrammetry. ResearchGate.

Mark, Joshua J., 2014, Ancient History Encyclopedia. [Online] April 07, 2014. [Cited: December 19, 2019.] https://www.ancient.eu/urbanization/.

Mark, Swilling, 2016, The Guardian. [Online] The Guardian News & Media, July 12, 2016. https://www.theguardian.com/cities/2016/jul/12/urban-sprawl-how-cities-grow-change-sustainability-urban-age.

Naif, Alajlan, et al., 2011, A Cluster Ensemble Method for Robust Unsupervised Classification of VHR Remote Sensing Images. Riyadh, Saudi Arabia: IEEE, IGARSS.

Nijhoff, Martinus, 1986, Urbanization in Developing Countries, Report of a symposium, held in December 1967 at Noordwijk, Netherlands. [Business Media Dordrecht] [prod.] International Union of Local Authorities. Noordwijk, The Hague, Netherlands in 1986, Netherlands: Springer Science, December 1968. Urbanization in Developing Countries.

NOAA, 2018, NOAA (National Oceanic and Atmospheric Administration). [Online] NOAA, 2019, US Department of Commerce, July 25, [Cited: May 18, 2019.] https://oceanservice.n oaa.gov/facts/lclu.html,.

Oxford, Food Climate Research Network (FCRN), 2018, University of. FCRN food Source. [Online] February 06, 2018. https://www.foodsource.org.uk/building-blocks/what-land-use-and-land-use-change.

Pengfei Xu, et al., 2016, Evaluating Urbanization and Spatial-Temporal Pattern Using the DMSP/OLS Nighttime Light Data:A Case Study in Zhejiang Province. October 24, 2016, Hindawi-Research Article, Vol. 2016, p. 8.

Richards, John A., 2013, Supervised Classification Techniques. Remote Sensing Digital Image Analysis. Berlin: Springer-Verlag Berlin Heidelber, 2013, Chapter 8, pp. 247 - 318.

Setyawan, Eric, 2019, INTERMAP. [Online] Intermap Technologies, August 12, 2019. [Cited: August 8, 2020.] https://www.intermap.com/blog/satellite-imagery-resolution-vs.-accuracy.

Terfa, Berhanu Keno, et al., 2020, Urbanization in Small Cities and Their Significant Implications on Landscape Structures: The Case in Ethiopia. MDPI, February 8, 2020, Sustainability.

UN, 2019, World Urbanization Prospects 2018 Highlights.

Wang, Fangju, 1990, Fuzzy Supervised Classification of Remote Sensing Images. Transactions on Geoscience and Remote Sensing, Vol. 28, Pp. 202.

Weixing, Zhang, et al., 2017, Detecting horizontal and vertical urban growth from medium resolution imagery and its relationships with major socioeconomic factors. Informa UK Limited, trading as Taylor & Francis Group, March 24, International Journal of Remote Sensing, Vol. 38, Pp. 3704–3734. 12.

Wihbey, John, 2017, Boundary Issues: The 2016 Atlas of Urban Expansion Indicates Global Dedensification. Northeastern University : U.S.

Department of Housing and Urban Development, November 2, Cityscape: A Journal of Policy Development and Research, Vol. 19.

World Bank Group, 2015, Ethiopia Unbanization Review. Urban institution for a middle income thiopia.

Yao, Yao, et al., 2018, A time series of urban extent in China using DSMP/OLS nighttime light data. PLoS ONE, May 24, PLoS ONE.

Yass, Bushra A., 2017, The Urban Expansion: Policies And Solutions. Global Scientific, Vol. 5.