Monitoring Forest Cover Dynamics for Achieving SDGs Using Google Earth Engine : A Case Study Menagesha Forest, Ethiopia,

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Abstract

Throughout the world, the effects of climate change are becoming increasingly evident as temperatures rise, glaciers melt, greenhouse gases increase, sea level rise accelerates, and global warming approaches. This situation needs to be addressed urgently. In particular, forests play an important role in the transition to a circular economy by providing various biomass resources that are not food or feed. As well as sequestering carbon, conserving biodiversity, and providing ecosystem services, they are also a source of carbon. Forests, however, are challenged by climate change, so it is essential to enhance their resilience and ability to provide these vital goods and services.

The effects of climate change worldwide necessitate urgent action to mitigate its impacts. Forests play a crucial role in the transition to a circular economy, providing non-food biomass resources, carbon sequestration, and ecosystem services. This study characterizes the spatio-temporal dynamics of land use and land cover (LULC) in the Menagesha Forest Catchment over the past 10 years using Google Earth Engine. Preliminary findings reveal significant reductions in forest cover, emphasizing the need for afforestation initiatives and sustainable land management. Monitoring land cover dynamics in forested areas is vital in addressing climate change challenges and achieving the Sustainable Development Goals (SDGs).

Climate change poses significant threats globally, manifesting through rising temperatures, melting glaciers, increased greenhouse gases, accelerated sea-level rise, and impending global warming. These adverse effects call for urgent action. Forests, in particular, play a critical role in the transition to a circular economy by providing non-food biomass resources, carbon sequestration, biodiversity conservation, and essential ecosystem services. However, forests are facing challenges due to climate change, necessitating efforts to enhance their resilience and capacity to provide these vital goods and services amidst changing conditions.

This study focuses on the Menagesha Forest Catchment to characterize the spatio-temporal dynamics of land use and land cover over the past decade. By utilizing multi-temporal remote sensing data and field sampling, we aim to assess the expansion and contraction of the Menagesha forest area using Google Earth Engine. The study utilizes Landsat 7 imagery for 2010, Landsat 8 data from 2015, and Sentinel-2 data from 2020 to comprehensively analyze changes occurring in the Menagesha Forest Catchment. Understanding these dynamics is crucial for effective climate change mitigation and the achievement of the SDGs.

This study employs a combination of multi-temporal remote sensing data and field sampling to assess the spatio-temporal dynamics of land use and land cover in the Menagesha Forest Catchment. Google Earth Engine platform as the primary tool for data processing and analysis.

The study utilizes Landsat 7 imagery from 2010, Landsat 8 data from 2015, and Sentinel-2 data from 2020. These datasets provide comprehensive coverage of the Menagesha Forest Catchment, allowing for the observation of land cover changes over time. Pre-processing of the imagery is conducted to correct for atmospheric effects and normalize the data.

The next step involves land cover classification using Google earth engine methods on the satellite imagery. This classification is performed to distinguish between forested and non-forested land cover types, allowing for an assessment of the spatio-temporal dynamics of the Menagesha forest area over the past 10 years.

Ground-truth data collected through field sampling complement the remote sensing analysis. The field data includes information on forest cover, deforestation, and land degradation, providing validation and accuracy assessment for the remote sensing-based land cover classification.

The preliminary findings of this study indicate noticeable dynamics in forest and non-forest land cover types within the Menagesha Forest Catchment. Over the past decade, the forest area has experienced a significant reduction from 29.46 km^2 in 2010 to 22.5 km^2 in 2020. This alarming loss and conversion of forested areas emphasize the urgent need to implement afforestation initiatives and sustainable land management strategies. Collaborative efforts involving local communities and the government are essential in combating deforestatio n and facilitating afforestation and reforestation projects.

The spatio-temporal analysis provides insights into the changes occurring within the Menagesha Forest Catchment, contributing to a better understanding of the impact of land use and land cover dynamics on the forest ecosystem. The findings help inform policy and management strategies aimed at mitigating deforestation, conserving the remaining forested

areas, and promoting sustainable forest management practices. Additionally, this research underscores the significance of ongoing monitoring of land cover dynamics, particularly in forested regions, in addressing the challenges posed by climate change and achieving the SDGs.
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The study highlights the importance of monitoring land use and land cover dynamics, specifically in forested areas, to address the challenges of climate change and the pursuit of the SDGs. Preliminary findings from the Menagesha Forest Catchment indicate a concerning reduction in forest cover, which demands immediate action. It is crucial to combat deforestation through the implementation of afforestation initiatives and sustainable land management practices. Achieving the SDGs requires collaborative efforts to promote effective forest conservation and sustainable land use, ensuring the vital role of forests in climate change mitigation and sustainable development.

Keywords : Remotes sensing ,Spatio-tempora , multi-temporal satellite, Google earth Engine

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CHAPTER ONE

INTRODUCTION

1.1 Background

Remote sensing has significantly broadened the scope of effective planning and management of natural resources. Data from satellites can provide timely and accurate information on very short repetitive periods need for monitoring. There is evidence that remote sensing data can meet most of the information needs in the forest management process in a quick and low-cost manner by various authors (Babu et al 2002 and Dengsheng Lu, 2013,)

Land cover refers to the physical and biological cover over the surface of land, including water, vegetation, bare soil, and/or artificial structures. Land use denotes how humans use the biophysical or ecological properties of land. Land use is characterized by the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it. Definition of land use in this way establishes a direct link between land cover and the actions of people in their environment. Information on land use and land cover is required in many aspects of sustainable management of land resources and policy development, as a prerequisite for monitoring and modelling land use and environmental change, and as a basis for land-use statistics at all levels (Jansen and Di Gregorio, 2004).

Land cover-land use analysis provides knowledge about landscape patterns and their changes which over time gives very important insights into the ongoing natural and human processes in the ecosystem. Human activities are a major factor contributing to global change, and they are overriding natural changes to ecosystems brought on by climate variations. Land-cover communicates to the different features on Earth’s surface (Lillesand et al., 2007) with the composition and characteristics of Earth surface elements (Karwariya and Goyal, 2011) including natural and anthropogenic features, and thus describes the Earth's physical state in terms of the natural environment and the man-made structures (Karwariya and Tripathi, 2012) which can be mapped using satellite imagery with spectral signatures. Satellite data is a significant and useful tool for monitoring and management of resources.

1.2 Statement of problem

Ethiopia is endowed with a diverse variety of fauna and flora with high level of endemism in connection with wide range of ecological variations (Tewoldeberhan, 1989,Tadesse, 2003). Yet, the country has lost most of its high forests to deforestation linked to proximate factors namely, agricultural expansion. The forest resource is competing with the expansion of agriculture as the country is largely an agrarian with over 80% of its population living in rural areas. Nevertheless, the country has not made a significant improvement in monitoring its annual loss of forests. There are reports from different sources quantifying the available forest resource and estimated annual loss. The figures given on both deforestation and remnant forest resources have significant variations. Hence, strengthening a continuous forest disturbance and deforestation monitoring is key for the sustainable utilization of the natural resources. In line with this, satellite images play pivotal role in monitoring both forest disturbance and deforestation for a better sustainable utilization of forest resources. Hence, this study utilizes Landsat8 data for mapping Menagesha forest located in Oromia region .

1.3 Objective

The main objective of the term paper is to determine expansion of the Menagesha forest area over the past 10 years and To identify the nature and extent of problem of the area.

1.4. Significance of the Study

IThe major significant of this study support the Oromia region and Addis Ababa city administrators and managers to know the extent of the Menagasha forest and identify factors affecting the frost ecosystem and valuable for decision makers related to forest management . I t may also call the attention of those who want to conduct a research in the field.

1.5. Scope of the study

1.5.1 Spatial Scope

In terms of geographical locations, the study focus Menagesha forest located in Oromia region near to Addis Ababa City, The capital city of Ethiopia . Hence the study was focus on Oromia regional state,especial zone Wolemera and Sebeta Hawas woreda, touching 10 different kebeles.

1.5.2 Thematic Scope

The Scope of this term paper is expansion of the Menagesha forest area over the past 10 years and finally to recommend possible solutions to problem.

1.5.3 Temporal Scope

The temporal scope of this study is starting from September 2021 to December 2021 .

CHAPTER TWO

2. STUDY AREAND METHODOLGY

2.1 Description of the Study Area

Menagesha suba forest which was originally protected by Zera Yacob (1399 – 26 August 1468) was the Emperor of Ethiopia the total area of the park is around 2500 hectare and the forest have a natural big trees like juniper us and Eric arboreal and is one of the tourist destination for a day trip from Addis Abeba because of its remarkable natural indigenous tree species and some endemic birds with some species mammals like endemic antelopes of Minilk Bushbuck.

A total of 150 bird species has been recorded at this site, five of which are Ethiopian endemics, and many more are Afro tropical Highlands biome species. Of interest among the biome species are Bostrychia carbuncular, Agapornis taranta, Tauraco leucotis, Lybius undatus, Zoothera piaggiae, Pseudoalcippe abyssinica, Parophasma galinieri, Parus leuconotus, Oriolus monacha, Corvus crassirostris, Poeoptera stuhlmanni, Onychognathus tenuirostris, Cinnyricinclus sharpii, Cryptospiza salvadorii and Serinus nigriceps. Chilimo forest supports populations of many other important birds including Accipiter melanoleucus, A. tachiro, Buteo buteo, B. oreophilus, Aquila pomarina, A.verreauxii, the poorly known Kaupifalco monogrammicus and the forest specialist Stephanoaetus coronatus.

Non-bird biodiversity: A significant number of Afro-montane endemic tree and shrub species occur at this site, along with the Ethiopian endemics Erythrina brucei, a tree species which occurs in more open and inhabited areas,

2.2 . Data sources

The Research used Remote sensed data in addition ,the study uses 1:25000 scale topography (from the Ethiopian Mapping Agency) . Landsat satellite images were acquired from United State Geological Survey (USGS) official website to estimate changes for the forest area .In general, the following data and materials are needed to achieve the objectives of this research:

I . **Data**

- Multi-temporal Landsat images (2005, 2010 and 2020)

- Topographic map

ii).Software packages

-Google Earth Engine

-Arc GIS 10.1and above

- ERDAS imagine

- Global Mapper and Ex cell

iii).Instruments

-Handheld GPS receives

- Camera.

2.3 Methodology

This proposal used an integrated analysis of Landsat images acquired at different times (2005, 2010 and 2020) and topographic map of the study area to detect changes in the Forst surface area during the past 15 years.

For this study, suitable Sentinel-2 and Landsate images are selected and were reprocessed with GEE (https: //code.earthengine.google.com/). GEE includes both a web-based JavaScript language code editor and a Python application programming interface (API) for analyzing data outside the web environment (Tamiminia et al., 2020). All analytical steps in this study will be performed using the GEE Python API (https: //colab.research.google.com/) to allow code to run directly from a web browser with minimal configuration. The study area is queried in GEE with a maximum haze pixel percentage of 10 according to the metadata.

32.2 Atmospheric Correction

The pre-processed images for Sentinel 2 contained 10 spectral bands ranging from visible and NIR to SWIR wavelengths. Among the 13 spectral bands acquired by Sentinel-2, Band 1(Coastal and Aerosol), bands 9 (water vapor) and 10 (cirrus) will be eliminated as they do not contain water surface information. Many algorithms have been proposed for retrieving water quality parameters from remote sensing reflectance. But, calibrated with in situ observations is needed. (Tian et al., 2014; Yoon et al., 2019; Flores-Anderson et al., 2020).

The difference in spatial resolutions among spectral bands is not an issue in GEE which uses scale specified by the output to determine the appropriate level of input image pyramids. Per-processioning steps will done using GEE includes both a web-based Code Editor in JavaScript language and a Python application programming interface (API) for data analysis outside the web environment (Tamiminia et al., 2020). Corrected image, a cloud mask will applied based on the s2cloudless dataset, which is a machine learning-based cloud detector precomputed on GEE (Zupanc, 2017).

The methodology uses four stage processes. The first stage is to eliminate measurement noise from satellite data, in this case recovering the effect of the atmosphere from the real environmental signal coming from different land use/land cover types. This involves the task of processing Landsat and Sentinel Image for geometric error correction using image stacking technique to enhance multispectral information of the environmental signal wit google earth Engnie.

The second stage is to delineate watershed for Forest region from topographic map byemploying terrain analysis techniques.

The third stage is to determine deferment land use/land cover types including based facilities using supervised classification technique. The study used supervised classification techniques to classify the images into Forest , Road , urban area ,grazingland and farm land. Supervised classification can be used to cluster pixels in data set into classes corresponding to user defined training classes. Supervised classifications require a prior knowledge of the scene area in order to provide the computer with unique training classes. In this method, the user defines the original pixels that contain similar spectral classes representing certain land cover class. It identifies and locates land cover types by combining the previous personal experience, and fieldwork (Jensen 2005). This classifier considers not only the cluster centers but also the shape,size and orientation of the clusters.

The fourth stage is to change detection using standard approach such as Post classification change detection. A post classification change detection method has applied between the years of the study period. Post-classification comparison is a common method used for change detection. This method produces independent spectral classification results for different epoch of selected interval of period on a pixel by pixel basis to detect changes in cover type. A complete matrix is obtained and change classes can be defined by the proper coding of the classification results. The major advantage of this method is the capability of providing a matrix of change information and reducing external impact from atmospheric and environmental differences between the multi-temporal images (Noha Samir Donia1,2012).

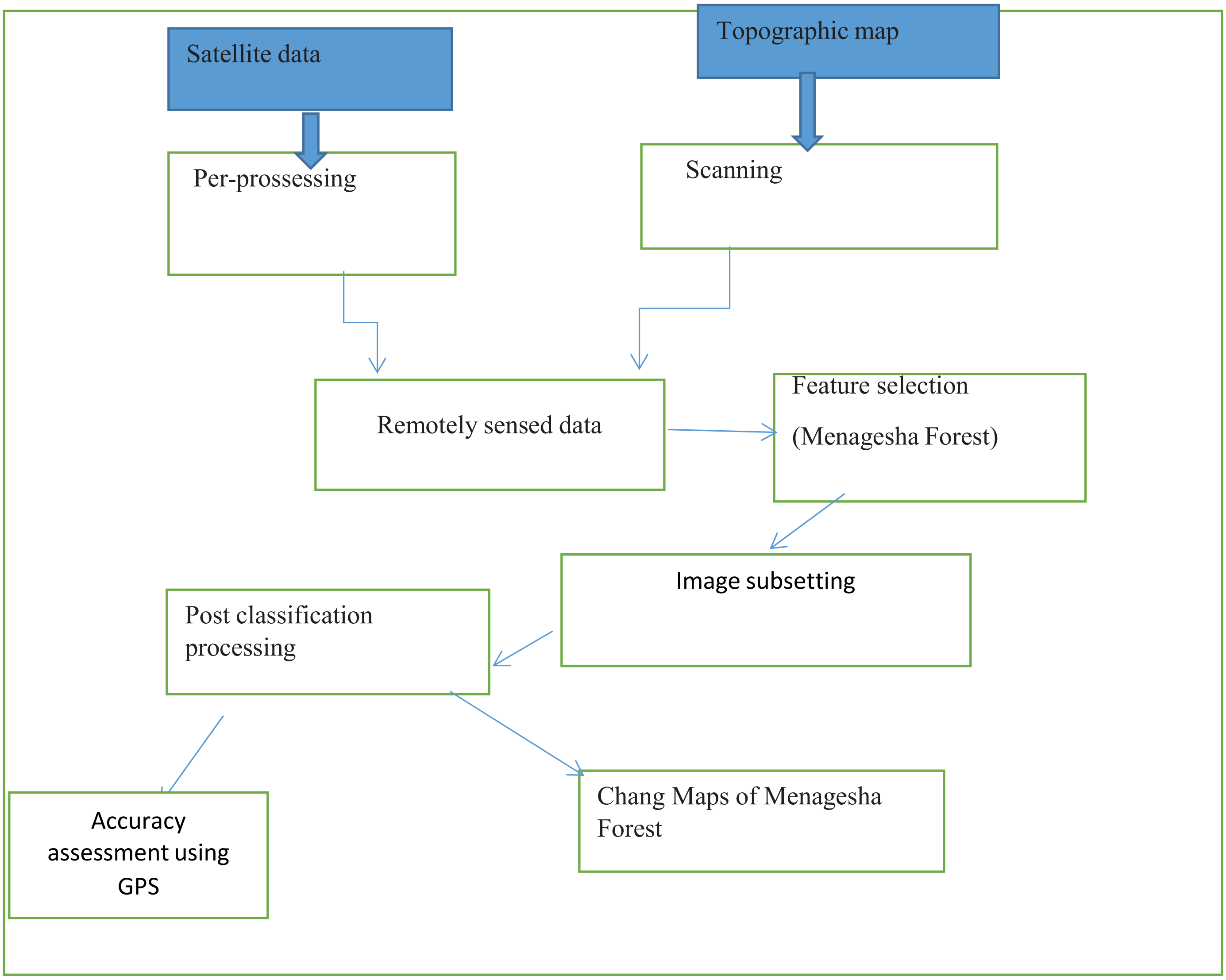

FIg1 General methodology Follow Chart.

CHAPTER TREE

3 .Forest Change Dynamics

The proportion of Forest change changes in time as a result of various factors. These temporal changes in Forest change can be determined by subtracting two or more images taken over the same area at different epochs. With the advancement of Earth observation satellite technologies, remotely sensed datasets have been providing repetitive images of the Earth& surface, enabling us to detect temporal changes in the patterns of LULC (Singh, 1989). From the Landsat series, the highest resolvable spatial scale of change detection is 15m (available from Landsat 8 panchromatic band) while the lowest resolution for multi spectral Landsat 1 payload is 57m. In general, the technique of quantifying temporal changes of LULC is called LULC change detection. In essence, the change detection techniques should eliminate temporal effects that are .This study has used dynamic index approach to estimate Forest change between multi-temporal images taken at three different epochs: 2010, 2015 and 2020. The method is also useful to reduce the effect of atmospheric and environmental differences between the images acquired at different epochs (Wang and Bao, 1999). The formula for the computation of the dynamic index K is given by:

$$\frac{Ub-Ua *100}{Ua*T}$$

Where Where Ua,Ub are the area of a certain LULC type at the beginning and end of the study period, respectively, T is the length of time, and K is the dynamic index representing rates at which each LULC type changes in time. Statistically, the dynamic index method examines spectral difference on a pixel-by-pixel basis to detect changes of LULC types over a given temporal resolution. The magnitude of change refers to the expansion or reduction in the extent of LULC. Negative values indicate decrement in the extent of LULC, while positive values show increment in contrary.

3.1 Forest change

The the forest area changed/converted to none forest area during the period from 29.46 Km^2 to 25.63km^2 in year 2010 to 2015, and 25.63 to 22.5 KM^2 in 2015 to 2020. As shown in table 2, In 2010,the forest is the dominant land cover type accounting for 95 percent of the area, while Non forest land only contributes about 5 percent in year 2010.However ,in 2015 year the forest cover change in to 83 percent and 2020 year covers 71.75.Where as non in 2015 forest cover increase by 17 percent and 28.25 percent in 2020. This implies the forest land has decreased by 23.25 percents from the year 2010 to 2020 and non forest increase by 32 percents from the year 2010 to 2020.

Class type	Area coverage in 2010(km2	Area coverage in 2015(km2	Area change (2010-2015) KM^2	Area coverage in 2020(km2	Area change (2010-2020) Km^2	Remark
Forest	29.46	25.63	-3.83	22.25	7.21	
Non Forest.	2.47	6.23	3.87	9.56	7.52	
Total area	31.86	31.86		31.81		

Fig 2. Forest area change

As shows in fig 2 the forest area coverage was high decreased wheres as the non non forest are was increased. This implies deforestation is highly increase time to time.

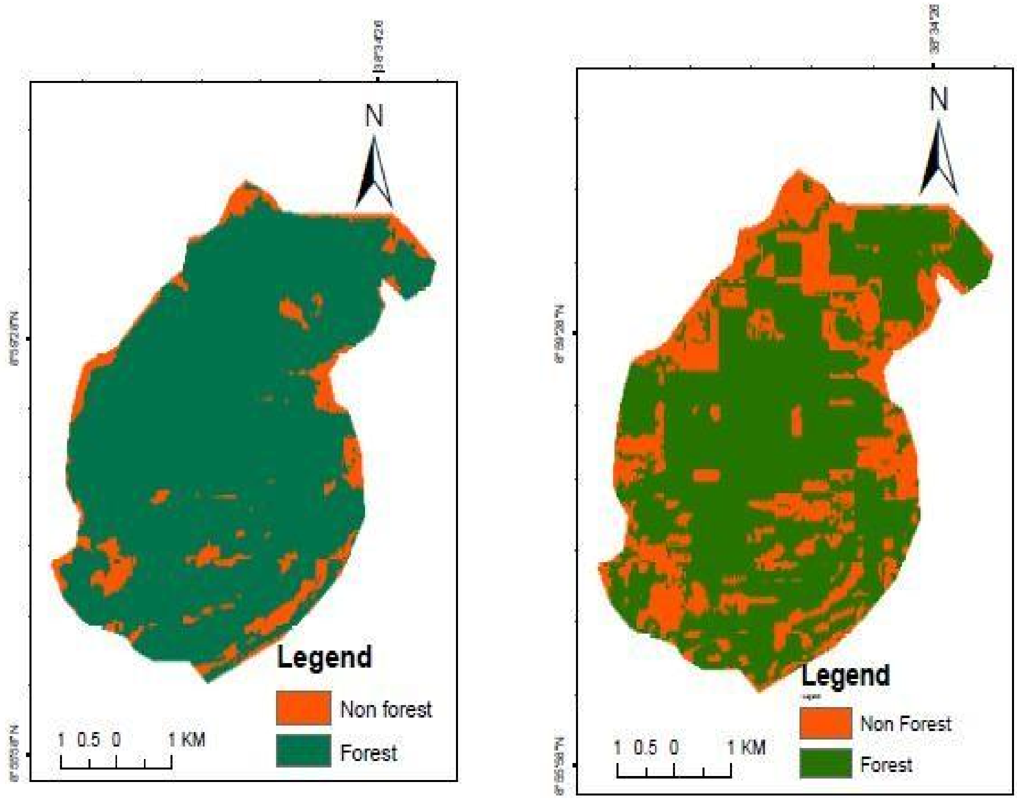

Fig 3 A. Forest map of 2015 year. B. Forest map of 2020 year

As we can see clearly in fig 3 and b the forest coverage was converted in to non forest area.The main cause of the decrease in forest cover has been the clearing of trees for charcoal production, timber production, and firewood.

Consequently, the forest ecosystem was disrupted, as the animals started migrating to another part of the forest and the number of tourists decreased. In addition, the indigenous plants were eliminated.

4 .Conclusions and Remark.

The consumption of Remote Sensing and GIS tools were kindly in detecting the extent of Forest change that has taken place in Menagesha forest over the range of 10years. The land cover/land use change can be driven by different factors such as climate change, and anthropogenic effect. The forest change can be driven by different factors such as climate change, and anthropogenic effect. In the Menagesha forest area, there were the of rapid alteration of forest change. The the forest area changed/converted to none forest area during the period from 2010 to 2015, and 2015 to 2020. In 2010,the forest is the dominant land cover type accounting for 95 percent of the area, while Non forest land only contributes about 5 percent in year 2010 ,in 2015 year the forest covers 83 percent and 2020 year covers 71.75.Where as non in 2015 forest cover 17 percent and 28.25 percent in 2020. This implies the forest land has decreased by 23.25 percents from the year 2010 to 2020 and non forest increase by 32 percents from the year 2010 to 2020.The government and local community should be implement afforestation to decrease the forest lost problem.

Based on the land use land cover change detection algorithms used for the classification, the supervised classification was found to be very effective with overall accuracy of were 85.84%, 87.53% and 89.47%, and a Kappa coefficient of 0.85, 0.87 and 0.85, for the year 2010, 2015 and 2020 respectively. The classifications met the minimum overall accuracy of 85% as set by the Anderson classification scheme.

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