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FOREST COVER MONITORING IN SOUTHWESTERN GHANA

WITH REMOTE SENSING AND GIS

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DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

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FOREST COVER MONITORING IN SOUTHWESTERN GHANA WITH REMOTE SENSING AND GIS

ABSTRACT

Obuasi is one of the major municipalities in southwestern Ghana, Forest resources play a major significant role in the day-to-day activities of the locals due to their high dependency on it. Despite this contribution, the annual rate of current deforestation in Obuasi is about 50 hectares. At this rate the municipality may lose its substantial forest cover completely in the next 25 years. GIS and remote sensing techniques have proven to be efficient ways to monitor forest cover, especially on a large-scale using satellite imagery. In this study, a post-classification comparison change detection algorithm was used to determine the change in forest cover in the 1991-2021 period. The methodology includes a statistical analysis of rainfall and temperature variability for a period of 30years as well as the analysis of perceptions and knowledge of locals on forest modifications. MOLUSCE plugin in QGIS was used to model and generate maps of forest cover and predict future changes in land use/land cover. The land-use/landcover maps showed that between 1991 to 2000 forest areas decline at the rate of 17.1% while another class such as agricultural, built-up, and mining sites has a significant increase of 14%, 4%, and 2% respectively. Between 2000 to 2021, forest areas and agricultural lands decrease from 67% to 60% and 26% to 20% respectively while built-up and mining areas increase from 4% to 12% and 3% to 7% through forest areas remain the dominant landcover class in the area. During the same study period, there was a fluctuation in climatic conditions. Rainfall between 1991 to 2021 has reduced by an amount of 24 mm while temperature has increased to 0.037°C per annum. The majority of the locals believe that cultivated land expansion and mining are the driving forces of forest cover change in the area and the only solutions to these issues are through enrichment planting, and strengthening forest protection laws and mining regulations. Future prediction on forest cover in the area for 2030 map shows that forest areas will be the major contributor of land to other land use/landcover class, henceforth causing it to decline if no intervention is made. These findings can be used to inform conservation and management strategies to mitigate the impact of forest cover change and protect the ecological integrity of forests in the municipality.

KEYWORDS

Obuasi Municipal

Land use/Landcover

Forest Cover

Remote Sensing

Geographical Information Systems

Post Classification

ACRONYMS

ANN – Artificial Neural Network

CA – Cellurlar Automate

CA-ANN – Cellular Automate Artificial Neural Network

CRAMA's – Community Resource Management Areas

DEM – Digital Elevation Model

ETM – Enhanced Thematic Mapper

GIS – Geographic Information System

HA – Hectors

KML – Keyhole Markup Language

LULC – Landuse/Landcover

MM - Millimetre

OBIA – Object-Based Image Analysis

OLI – Operational Land Imager

QGIS – Quantum Geographic Information System

ROI – Region Of Interest

TCS – The Number Of Agreement Between The Two Raters

TIRS – Thermal Infrared Sensor

TM – Thematic Mapper

TS – The Number of Agreement by Chance

USGS – United State Geological Survey

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Introduction

1.1 Background

Human-induced modification of vegetation cover and landscapes, ecological and geomorphological processes, inter-annual climate variability, greenhouse effect, and long-term natural change in climate conditions have resulted in the loss of a substantial amount of forest cover and other landcover where natural vegetation plays a very important role in maintaining ecological balance and biodiversity, environmental purification, carbon sequestration, and sustainability in agriculture (Yadav et al., 2018). It is estimated that about 410 million people are dependent on forests, where about 10 million of them get direct employment from the forest ecosystem, also 1.6 billion people depend on it for their day-to-day activities, moreover it economic value sums up to $450 billion annually with forest product trade internationally between $15billion and $200billion (Köhl et al., 2015).

During the 2014 United Nation Secretary-General Climate Summit, the New York Declaration of the forest was launched with the ambition of halving the rate of natural forest globally and proposed strategies to end natural forest loss by 2030, but tropical deforestation and degradation continue with 15.8 million hectares of trees cover loss record in 2017 (Delabre et al., 2020). Although modification of land by anthropogenic activities to obtain livelihoods has been a reality for more than a thousand years but the magnitude, amount, and rate of change in forest cover are far larger now than ever (Hassan et al., 2016).

Deforestation has declined but forest average reduction between 2015-2020 is around 10 million hectares globally (Somuah et al., 2021). The estimation rate of tropical deforestation has taken into account that deforestation is homogeneously dispersed across regions or countries of interest but mostly such areas of interest are fixed infraction, where most knowledge about such geographical areas/regions of forest depletion is at time-poor especially in new hotspot evolving geographical areas (Roy et al., n.d.). Currently, the depletion of tropical forests has gained popularity in its increased `awareness due to its associated effect on biodiversity and the global environment, which has led to global to regional plans to limit its depletion, meanwhile, forests continued to be degraded at an alarming rate despite so many initiatives. The state of the tropical forest requires an up-to-date and timely assessment of its state, from global to local, to examine its effect on present and past dynamics of its functionality and to gain appropriate knowledge and information to understand it properly and foresee future consequences(Ustin, 2004).

Mapping different natural resources management modeling is gaining mass impetus in the current years due to the use of remote sensing and GIS data, environment studies in recent years have mainly focused most of their work on remote sensing and GIS. Most professionals in remote sensing and GIS are using these scientific techniques and their implication on forest cover change and urban planning which is now getting more attention and interest. These techniques have become very useful and important in the monitoring of forest cover mapping since they provide consistency in data, synoptic coverage, precision, maximum accuracy in data provision, global reach and readability (Sajjad et al., 2015). Capturing data from a large area and getting information within a short period with a little restriction can be achieved through remote sensing techniques (Weilin et al., 2000).

Recently government organizations and international communities have been informed about the rapid and unprecedented decline in tropical forest cover through remote sensing. Rigorous and quantitative assessments of human implications on forest cover are being acquired through advanced remote sensing technologies and data processing capabilities. Robust remote sensing tools for near-real-time operational applications are an issue due to the growing societal demands to develop more accurate and time tools for long-term natural resources studies and more effective characterization of forest disturbance and functioning. Traditional data collection methods in monitoring forest resource management like ground truth are usually time-consuming and expensive with numerous related challenges such as accessibility of study area and capacity to conduct repeated measurements over time(Huete, 2004). Furthermore, the need to maintain long-term continuity of results, methods, and output, produces workflows that are difficult to change due to their complexity which leads to a huge barrier in operating new technologies in remote sensing for natural resource monitoring due to limited capacity, high cost of tools and data types(Lister et al., 2020). Moreover, huge data storage requirements and the high cost of data acquisition are important drawbacks of very high spatial resolution data limiting their application at large scale(Pham et al., 2019). Landsat 9 and European Copernicus earth observation program includes Sentinel-2 has ensured continuity and a more robust archive in monitoring the earth's surface under a free and open data policy with multiple global acquisitions with similar spectral and spatial characteristics(Romero-Sanchez & Ponce-Hernandez, 2017).

Despite the benefit derived from the forest, several studies have documented evidence of forest resource destruction. In most countries, the difference in forest cover loss is related to several factors such as anthropogenic activities and climate change (Tuffour-Mills et al., 2020). Also, cultural, and technological development and biophysical activities can be considered as the key drivers that could significantly modify the forest cover change(Sarfo et al., 2022). Furthermore, deforestation such as proximity to infrastructure (reservoirs and roads), proximity to the previously deforested area, soil erosion, population density, slope, elevation, and flooding are major physical and socio-economic drivers of forest cover change in most countries (Sharma et al., 2020). To solve the basic problems that stem from global, regional to local without incurring unintended consequences the key drivers of forest cover change that pose threat to livelihood and ecosystem service can be examined holistically using an interdisciplinary approach. Forest management that addresses the needs of the community such as poverty alleviation through diversification of economic activities and increased off-farm employment opportunities to avoid pressure on the forest has to be studied critically, also improving forest protection, soil, and water conservation structure, financing for added ecosystem service, plating and community awareness will help to sustain forest and it ecosystem service (Sarfo et al., 2022). Moreover, the implementation of existing regulations and alternative land use opportunities for locals such as REDD+ demonstration activities will address key drivers of forest cover change (Sharma et al., 2020).

Most tropical deforestation degradation processes seem to be compatible with the Markov property of first-order dependence except for some generic paths of land-use change. The landscape change process can be simulated using linear or stochastic techniques Markov chain described stochastically processes that move in a sequence of steps since landcover conversions are mainly driven by socioeconomic factors though stationarity in landcover change data should not be expected. The Markov property as applied to landcover change is that “The conditional probability of landcover at any given time all previous use at an earlier time depends at most the most recent use and not upon any earlier ones thus a Markov chain is limited to short-term projection” (Lambin, 1997). Furthermore, the process in which the future state of a system can be simulated purely or the basis of the immediately preceding state capitalized geographical information systems, remote sensing, and Markov model techniques help to simulate landcover change. With a supervised classification approach, it is feasible to simulate land-use/landcover change based on the Markov model and remote sensing, since it indicates descriptive capabilities of trend projections, though the model finds it difficult to accommodate and predict the influence of variables such as the climate, government policies, and human disturbance, the model provides not only a quantitative description of a change in the past but also directs the magnitude of change in the future (Kumar et al., 2014). More importantly, calculating the transition area matrix of land-use/landcover in simulating time, Markov conditional probability image of simulated time, and the creation of a map of potential transition rules setting with stimulated land-use/landcover map within a period are the most important steps to implement a circular automotive model for a stimulated landuse. The model combines the Markov chain and cellular Automate approach that predicts land use/land cover for the future (Yulianto et al., 2019).

Moreover (Gemitzi, 2021) demonstrated their work where a landcover modeling was developed, tested, and validated. In their project historical landcover observation from 2010 to 2018 was modeled, created, trained, and validated using the CA-Markov model in Greece. To predict the landcover transition for the future in their project, driven variables like climate variables and socioeconomic variables were associated with observed change. The study concluded that landcover transformations were led by more natural activities than human disturbed which was indicated through the prediction. Continuous monitoring of tropical forest cover is more important than ever since the provision of up-to-date information on the status of forest cover with appropriate action for the preservation of some of the last remaining contiguous areas of intact tropical forest and obtaining a concise view of forest cover of a wider region or sub-regional to understand and address the overall effect of deforestation in the tropics in a larger geographical context, is easily accessible through satellite remote sensing(Stibig et al., 2003). Africa's biodiversity decline has not been properly assessed in terms of mapping the spatial factors causing it declined on the continent especially forest reserves (Acheampong et al., 2019). The humid and sub-humid belt of West Africa was a vast area of tropical rainforest in the twentieth century but most of these tropical rainforest areas are now lost due to unsustainable logging, slash-and-burn agriculture of food crops, tree crop farming, illegal mining and oil palm (Ruf et al., 2015).

1.2 Problem

Among researchers, policymakers, and development practitioners, tropical deforestation in Ghana has become a topic of great interest in recent times due to the continuous depletion of rainforest areas because of mining activities, wildfires, forest fires, logging, agricultural expansion, and colonization. 22% of the estimated original tropical forest remains with a depletion rate of 78% of Ghana’s tropical forest with annual destruction occurring at 1.3% every year (Appiah et al., 2009). In Obuasi one of the major Municipalities in southwestern Ghana, forest resources play a major significant role in the day-to-day activities of the rural people due to their high dependency on it. Forest as a resource provides sustenance and income for about 166,000 which is about 2/3 local population living near forest communities. Most locals in forest communities highly depend on it for their daily activities such as hunting for games, medicinal herbs, fuelwood, and legal and illegal logging to support their livelihood. Socioeconomic development in the Obuasi Municipality is centered on forest products since 38% of household materials are directly generated from the forest. Despite this contribution, the annual rate of current deforestation in Obuasi is about 506 (ha), per this rate the municipality may lose its substantial forest cover completely in the next 25 years. Past and current policymakers have not been able to face this chronic issue of deforestation due to inadequate information and a viable national mitigation plan. Lives and traditions in the rural communities are at threat so as national economic growth (Boafo, 2013). Illegal and unsustainable logging and mining with agricultural expansion coupled with land tenure insecurity are the major factors leading to deforestation in municipalities due to overexploitation of these natural resources, though all of these are subjective opinions of respondents without any factual findings (Acheampong et al., 2019). Spatiotemporal variation significance of deforestation dynamics in southwestern Ghana has been investigated, the environmental and socioeconomic impact of deforestation aspect in southwestern part has been addressed but only a few research have enumerated forest cover change in a long term and with much emphasis on deforestation on the semi-deciduous forest at the municipal levels in Southwestern Ghana (Ranagalage et al., 2020). Many agencies and organizations both government and private have pledged their support in support of natural resources restoration in Ghana. Community Resource Management Areas (CRMA's) have been developed by the government of Ghana through the local government agencies to help address conservation issues on community land and natural resources through decentralization procedures with the support of Ghana REDD+, which pledge to the Bonn Challenge, a global restoration commitment to plant 2 million hectares of trees in 2012 (Baruah et al., 2016). Though formal policies are in place to be implemented by various stakeholders, no significant change has taken place. According to the World Resources Institute, rapid uncontrolled mining, urban growth, rural-urban migration, rapid population growth, and agricultural expansion have increased due to anthropogenic disturbance which has led to the detriment of open and closed forest areas and their ecosystem. Past, present, and future geospatial knowledge about the forest cover in the area is required due to current anthropogenic activities.

Currently there is the need to ascertain the swing in forest cover change. Such information would be useful in informing future policies and legislation on forest management especially in rural areas in Obuasi. Hence the study in scripted this research gap by investigating the trend of drivers and the future prediction of forest cover change from 1991 to 2021 in the semi-deciduous forest areas in southern-western Ghana. The trending complex nature and diverse interaction amongst socio-ecological system and the factors driving landuse/landcover change in forest areas makes it difficult to fully comprehend such systems using a single method approach. To provide opportunities to fully unravel the many factors that may be driving the forest cover change in the Obuasi Municipality mixed-method approach was used. This would be beneficial in contributing towards strengthening legislations and policies on forest especially in farming and mining communities and other part of

Ghana, so they can receive special attention with regards to conservation (Tuffour-Mills et al., 2020).

1.3 Research Questions

This research was intended to answer the following questions,

- What are the dispensation and pace of semi-deciduous forest cover dynamics in the Obuasi Municipality during 1990-2000 and 2000-2021?
- What are the driving forces affecting forest cover dynamics in the period from 1990 to 2021?
- How much forest area will be transformed into other land cover types in 2030?

1.4 Research Objective

The research seeks to examine the trend of semi-deciduous forest cover change and its causes in Obuasi Municipality from 1990 to 2021.
The exact objective aimed for monitoring semi-deciduous forest cover change in Obuasi Municipal are,

- To examine and map vital forest cover types for 1990, 2000, and 2021.
- To explore the interconnection between the drift of forest cover and their fundamental factors.
- To estimate the change of forest areas for the year 2030.

1.5 Organization of thesis

The thesis consists of five chapters. The first chapter contains background information, literature review, objective of the study and organization of the thesis. chapter two describes the study area, data and the methodology followed in order to conduct the current study. chapter three presents the results output while chapter four present the discussion about the finding and analyze them by relating them to the literature. Finally, chapter five describes the conclusions.

Chapter 2
Study Area

2.1 Location and Administrative Area of the Obuasi Municipal

Obuasi Municipality is bounded on the south by the Upper Dankyira District of the Central Region, West by Amansie central, East by Adansi South, and North by Adansi North as shown in figure (2). Obuasi is the administrative capital with an estimated population of about 195,000 (2020), where the famous and rich Obuasi Gold Mine, now Anglo Gold Ashanti is located. The Municipality is located between latitude 5°35'N and 5°65'N, and longitude 6°35'W and 6°90'W. it covers a total land area of 220.7 square km. it is located in the southwestern part of the Ashanti Region.

2.2 Climate conditions

The Obuasi Municipality experience semi-equatorial climate conditions where the temperature is uniformly high all year with the hottest month being March when the temperature of about 30°C. Mean annual rainfall ranges between 1250mm and 1750mm with double maxima rainfall regime. The mean average temperate is 25.5°C. The relative humidity is quite high (75% -80%) in the wet season.

2.3 Vegetation

The forest consists of limited species of hardwood which are harvested as timber. The vegetation is predominantly a degraded semi-deciduous forest. The Municipality through government laws has maintained large tracts of the teak plantation as green belts covering 12.10km within its concession. The Municipal is noted for its mineral deposit, but the main preoccupation of the majority of the people is farming. Illegal mining activities are prominent in the area.

2.4 Geology Relief, and Soils

Rocks in the Municipality are mostly upper Birimain and Tarwain (Pre-cambrian) formations which are rich in mineral deposits such as gold. The highest point is based on the Pompo range at 634 meters near Obuasi. The Municipality has an undulating terrain with most of the hills rising about 500 meters above sea level. It is drained by streams and rivers which include Akapori, Pompeo, and other perennial streams like Kyeabo, Gyimi, and Nyam. Highland ranges include Dampaia (the most extensive) in the east, Kusa in the North East, and Pompo and Sanso near Obuasi.

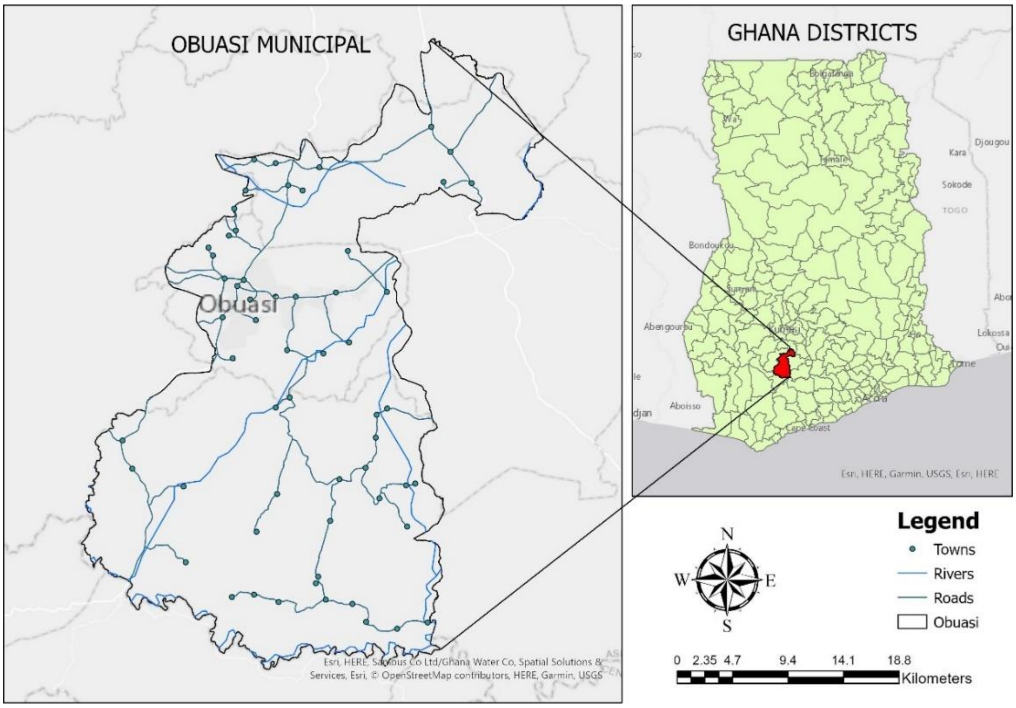

Figure 1. Location of the study area showing towns and major rivers

2.5 Land-use and Land Cover

All categories of land-use occur in the Volta Basin, including; rain-fed and irrigated agriculture, forestry, settlements, public services, wildlife preservation, University of Ghana http://ugspace.ug.edu.gh reservoirs (manmade and natural), protected lands and many more (Amatekpor, et al., 1999).Rain-fed agriculture which is based on the land rotation farming system, also known as bush fallow system, is the most common type of land-use in the area. (Titriku, 1999). The land cover of the Obuasi Municipality consists predominantly of tropical rainforest, semi-deciduous forest (UNEP-GEF, 2010). Table (2) shows the categories of LULC class in the study area.

Agricultural_Land	Describes all areas that portray sparsely located trees, shrubs, isolated thickets, and areas with non-tree crops
Built_Up	Built_up land is comprised of areas of intensive use with much of the land covered by structures, included in this category are cities, towns, villages, strip developments long highways, transportation, power, communication complex, and institution isolated from urban areas.
Forest	Forest lands have a tree-crown aerial density (crown closure percentage) of 10 percent or more that are stocked with trees capable of producing time or other wood products and extent an influence on the climate or water regime. Land from which trees have been removed to less than 10 percent crown closure but which have not been developed for other users. Example semi-deciduous, evergreen and mixed forest.
Mining	Mining sites are land where useful materials are extracted from the earth examples are gold and iron ore.

Table 1. Adapted and modified from UNEP-GEF, 2010

Chapter 3
Materials and Methods

With the opportunity to describe, acquire new insight, and discover new ideas as well as expand knowledge on the new and existing phenomenon, the study adopted a descriptive research design. This approach provided a better in-depth and understanding analysis of the topic under study, a mixed-method approach was adopted. The qualitative data collection involved conducting questionnaires and interviews with local communities, government officials, and stakeholders. The questionnaires were used to gather information on the causes of forest cover change and the perceptions of local communities on the impacts of deforestation. The interviews were used to gather information on government policies and regulations related to forest cover change. The quantitative data collected from the satellite images was analyzed to estimate the extent of forest cover change over time. The GIS software was used to calculate the area of forest cover and to identify areas of deforestation and afforestation. The data was then plotted on maps to visualize the changes in forest cover over time. The qualitative data collected from the questionnaires and interviews was analyzed using content analysis. The data was coded and categorized based on themes such as drivers of forest cover change, perceptions of local communities, and government policies and regulations. The data was then analyzed to identify patterns, predictions and trends in the causes of forest cover change and the perceptions of local communities on the impacts of deforestation**.**

3.1 Data Collection

In using remote sensing for forest cover monitoring the selection of an appropriate image data source is an important prerequisite for accurate change detection. The selection of reference data and image change detection are the two aspects to consider during the selection of appropriate data. Selecting the data is often restricted by many practical challenges such as atmospheric conditions and the availability of image data. Table (1) shows the quantitative data for Landsat satellite images and other ancillary data of forest cover were obtained for three periods 1991, 2000, and 2021 from the United State Geological Survey (USGS). The images were taken from Landsat 5

Thematic Mapper (TM), Landsat 8 (OLI & TIRS) and the Enhanced Thematic Mapper (ETM) Plus sensor of Landsat 7. These three images were selected on the quality of the satellite image and the amount of cloud cover in the image.

<table>
<tr><th>Satellite</th><th>Imagery types</th><th>Data Source</th><th>Path</th><th>Row</th><th></th><th></th><th>Source</th></tr>
<tr><td>Landsat 5 TM</td><td>1991</td><td>30</td><td>USGS</td><td>194|194|208|209</td><td colspan="2">054|055|056</td><td>USGS</td></tr>
<tr><td>Landsat 7 ETM+</td><td>2000</td><td>30</td><td>USGS</td><td>194|194|208|209</td><td colspan="2">054|055|056</td><td>USGS</td></tr>
<tr><td>Landsat 8 OLI/TIRS</td><td>2021</td><td>30</td><td>USGS</td><td>194|194|208|209</td><td colspan="2">054|055|056</td><td>USGS</td></tr>
<tr><td>Data</td><td>Source</td><td></td><td></td><td></td><td></td><td colspan="2"></td></tr>
<tr><td>DEM</td><td colspan="4">https://worldclim.org, accessed on 21 March 2021</td><td></td><td colspan="2"></td></tr>
<tr><td>Slope</td><td colspan="2">Calculated from DEM</td><td></td><td></td><td></td><td colspan="2"></td></tr>
<tr><td>Roads</td><td colspan="2">SEDAC NASA</td><td></td><td></td><td></td><td colspan="2"></td></tr>
<tr><td>Distance from roads</td><td colspan="3">Calculated from road network</td><td></td><td></td><td colspan="2"></td></tr>
</table>

Table 2 . Description of satellite imagery used for LUCC study in Obuasi Municipal

A careful decision was made considering factors that could interfere with the accuracy of mapping land use/land cover for the study area. The selected dataset was cloud-free images acquired during the drying season between December and March. Annual climatic data for the past 30 years (1991-2021) was acquired from the Ghana meteorological agency. The unit of climatic data used in this study was rainfall and temperature and thus data was from the weather station of the study area.

Ancillary data and imageries were processed to determine the LULC change pre-processing and post classification techniques was used to detect change in landuse/landcover class. CA-ANN method inside the MOLUSCE plugin in QGIS was used to model transition potential and stimulate future projections for the study area. Figure (1) shows the flow chart of the procedure for image pre-processing, enhancement, classification, accuracy assessment, change detection and future prediction.

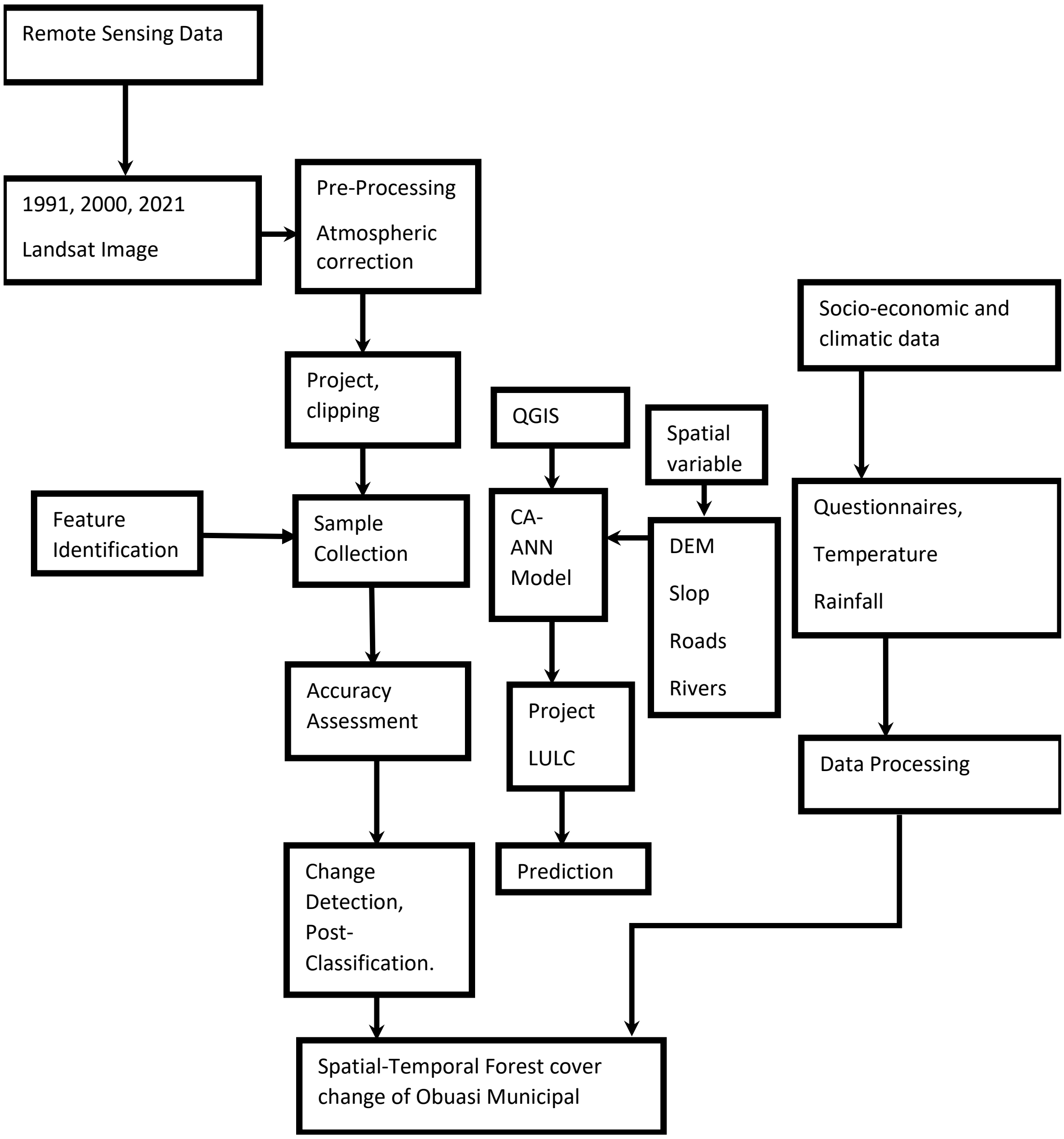

Figure 2. Methodological workflow chart. (Muhammad et al., 2022)

3.2 Pre-Processing

The initial operation was administrated to reduce or completely remove errors due to platform-specific and sensor geometric and radiometric distortion. Atmospheric defects are common defects usually associated with most optical images in the tropics including the southern areas of Ghana (Appiah et al., 2017) After image compositing filtering where the image was overlapped into a single based on aggregate function, with ArcGIS Pro the image was subset according to the defined boundary of Obuasi Municipal shapefile to reshape it to the area of interest in the process call clipping (Jeff Dacosta et al., 2019).

3.3 Radiometric Correction

So many factors can influence the radiometric conditions such as different meteorological conditions, different imaging sensors or dates, and different cover areas of cloud or rain. It may affect the accuracy of most change detection algorithms. Therefore, it is usually necessary to perform it. A relative radiometric correction was performed on the images. The histogram regularization was corrected to remove or reduce the effects of atmosphere, sensor, and other noise as shows in Figure (3) (A et al., n.d.).

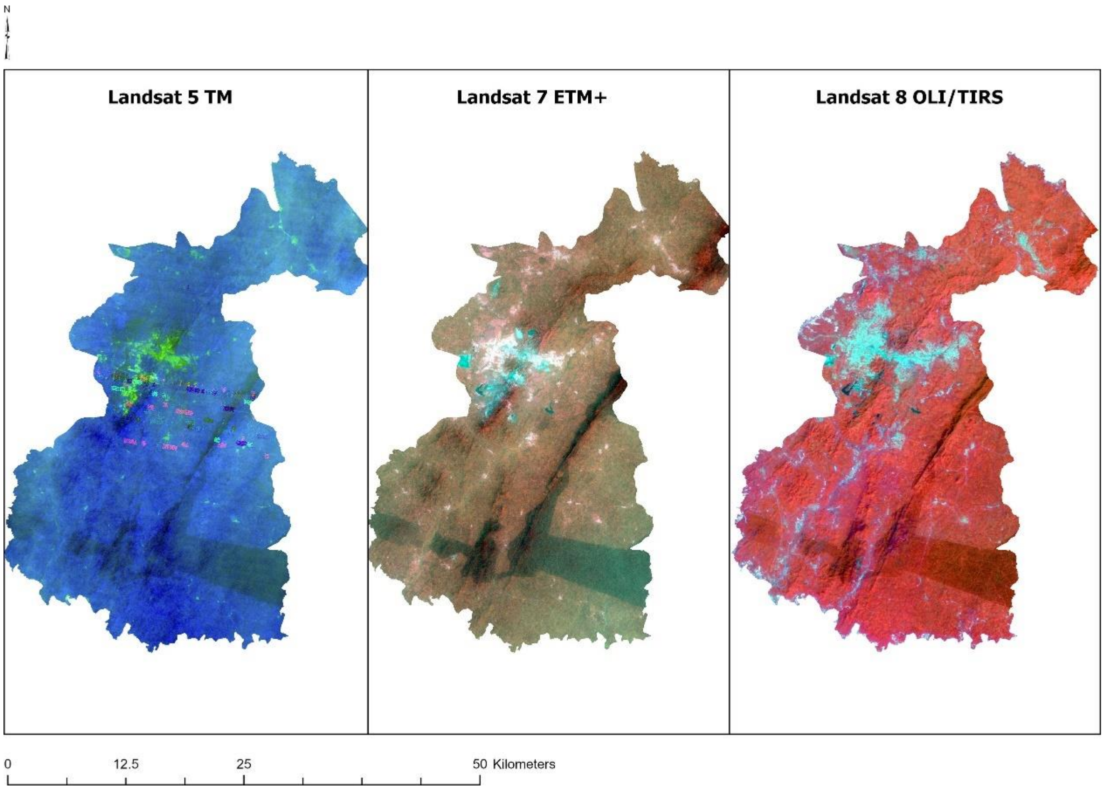

Figure 3. Study area Images displayed in RGB (colour band combination 7,6,2)

3.4 Supervised Classification

The clustering of pixels in a dataset into classes corresponding to user-defined training areas is termed as supervised classification. Training areas were selected to use as the basis for classification. In selecting the training areas, ArcGIS Pro software enables the user to make use of what is known as the region of interest (ROI). Different ROIs were carefully selected as training areas for 1991, 2000 and 2021 Landsat images, various comparison techniques were then used to verify if a specific pixel qualifies as a class member. With the broad range of different classifications, and alternatives provide under ArcGIS Pro, a supervised classification was used because it produced the best outcome for the study area and it has been used and recommended by other researchers.

3.5 Socio-economic Studies

A reconnaissance survey was conducted to have a broader understanding of the study area. A total of 50 households were selected for the household survey. We also conducted 12 group discussions with miners, experts, and farmers. In each group, 10 individuals were selected and the topic for the discussion was related to their perception of forest cover change, drivers of deforestation, their impact, existing remedies, and possible solution. Explanatory variables (drivers) of landcover change integrated into the questionnaire were based on literature and expert knowledge of the area.

3.6 Ground Truthing/Verification

Google Earth Pro was used in confirming some landuse/landcover features. Google Earth was used as post verification tool while ArcGIS Pro was used in the classification process, the coordinates of a selected landuse/lancover type in ArcGIS Pro were plot to the exact location in google earth to ensure the verification of the feature found on the satellite image. The following steps were performed during the ground verification process;

- Exporting the image to ArcGIS Pro

- Created stratified random points over the area (class) to verify the points.
- Convert points to feature to kml file type.
- Verify the kml file type by opening in Google earth.

3.7 Change Detection

Post-classification techniques were applied in determining the spatiotemporal development of the land use system in the area. The analysis was run to ascertain the regularity of the land use system and its drivers in the Obuasi Municipal. Change detection statistics for the study period were obtained using pixel count with each area in hectors and percentages analysis. This help in the generation of statistics data of change that occurs over the years for each class. LUCC was computed based on the following expression (Sarfo et al., 2022).

3.8 Accuracy Assessment

An independent stratified random sample of know pixels from the original images was assessed to check the final classified image and generate error matrices for the classified image. Error matrices indicating the concordance of the result of classification and ground truth data were constructed from the comparison. The kappa coefficient was applied for accuracy assessment between the real agreement (known pixel) and chance agree (classified pixel). Finally, post-classification was used for determining landcover change (Tuffour-Mills et al., 2020).

3.9 Accuracy Assessment Formula

Users Accuracy=(Number of Correctly Classified Pixels in each Category)/(Total number of Classified Pixels in that Category (The Row Total))×100

ProducerAccuracy=(Number of Correctly Classified Pixels in each Category)/(Total Number of Reference Pixels in that Category (The Column Total))×100

Overall Accuracy=(Total Number of Correctly Classified Pixels (Diagonal))/(Total Number of Reference Pixels)×100

Kappa Coefficient (T)=((TS×TCS)-∑(Column Total×Row Total))/(TS^2-∑(Column TotalxRow Total))×100

The Kappa Coefficient formula measures the agreement between two raters on a categorical scale. "TS" represents the number of agreements by chance and "TCS" represents the number of agreements between the two raters. The sum represents the expected number of agreements by chance calculated by multiplying the row total by the column total for each cell. The denominator represents the maximum possible agreements between the two raters, calculated by subtracting the expected agreements from the total number of observations. The result is multiplied by 100 to convert to a percentage.

3.10 Prediction and Model Validation

We used the CA-ANN technique inside the MOLUSCE plugin in QGIS to model transition potentials and simulate the future, as many scholars feel the CA-ANN approach is more effective than linear regression. For example, in a study by Li et al. (2013), the CA-ANN method was found to have a higher accuracy in predicting forest cover change in China compared to other methods such as regression analysis and decision tree analysis. Another argument for the use of the CA-ANN approach is that it can effectively incorporate multiple factors that influence forest cover change.

Simulated models are used to reduce the dynamics of composite urban structures and make them intelligible in a simple manner. The MOLUSCE plugin efficiently computes land use change analysis and is well suited for assessing land use change, spatiotemporal forest, simulating future scenarios, and predicting transition projects. MOLUSCE is a plugin for the open-source GIS software QGIS. It stands for Modeling LUng Sound Change, and it is a tool for analyzing and simulating land cover change. The MOLUSCE plugin allows users to import and analyze spatial data, such as land cover maps, to understand how land cover has changed over time. It includes a range of analytical tools, such as map algebra and change detection algorithms, that can be used to identify and quantify land cover changes.

In addition to analysis, MOLUSCE also includes tools for simulating land cover change. Users can create and test different land cover change scenarios and evaluate their potential impacts on the landscape. This can be useful for planning and decision-making in land use and natural resource management. Based on the LULC data for

1991 and 2000 transition matrices and explanatory variables we projected 2021. To validate the model prediction accuracy the MOLUSCE plugin offers a kappa validation method and comparison of actual and projected LULC images. After obtaining satisfactory results in when ANN learning process, 100 iterations and a neighborhood value of 3 x3 pixels, 0.05 of momentum, a learning rate of 0.001, and 12 hidden layers were chosen to project the LULC for 2021 employed 2000 and 2021 to forecast the LULC for 2030 (Muhammad et al., 2022)

Chapter 4
Results

4.1 LandUse/Landcover Classification and Change Analysis

Reference ground truth regions of interest were created from the original images before the classification to assess the accuracy of the classified images. Support vector machine-supervised classification was performed on all three images. All the classified images were usually compared with the original images and ground truth regions of interest generated from the original images are used to assess the accuracy of the classification. The error matrix was generated for the respective classified images with the help of the created region of interest to deduce overall, user, and producer accuracy. The confusion matrix in Table (3) indicates the classification accuracy of four classes for the 1991 image classification. The producer accuracy ranges from 83% to 95% with forest cover having the highest producer accuracy. The user accuracy for 1991 classes also ranges from 80% to 97%, were built up and forest cover had the highest of 97% and 90% respectively. The overall accuracy is 92% for the four classes that were accurately classified.

Class	**Agricultural Land**	**Built-up**	**Forest Cover**	**Mining Site**	**User**
Agricultural land	40	1	6	3	50
Built up	1	40	0	2	43
Forest Cover	3	0	106	0	109
Mining Site	4	1	0	48	53
Producer	48	42	112	53	
Overall Accuracy (%)					92

Table 3. LULC Accuracy Assessment 1991

For 2000 image classification, the confusion matrix in the Table (4) shows four features that were classified accurately as well. The producer accuracy ranges from 86% to 91%. Forest cover still had the highest producer accuracy of 91% with built-up recording the lowest at 77%. The user accuracy also ranges from 81% to 94%. The overall accuracy of the classification for 2000 was 86% for the four classes and Kappa Coefficient 98.9%.

Class	Agricultural Land	Built-up	Forest Cover	Mining Site	User
Agricultural land	39	4	3	2	52
Built up	4	36	1	3	44
Forest Cover	1	3	100	4	108
Mining Site	1	4	4	44	53
Producer	45	47	108	53	
Overall Accuracy (%)					86

Table 4. LULC Accuracy Assessment 2000

The confusion/error matrix for 2021 image classification in the Table (5) shows accurately classified features of four classes. The user accuracy varies from 64% (agricultural), 76%(built-up), 92% (forest cover), and 82% (mining site). On the other hand, producer accuracy ranges from 66% to 91% where agricultural land recorded the lowest with mining sites recording the highest of 91%. Table (6) shows the overall accuracy and Kappa Coefficient for all maps that were accurately classified.

Class	Agricultural Land	Built-up	Forest Cover	Mining Site	User
Agricultural land	32	0	12	3	47
Built up	6	32	4	0	42
Forest Cover	6	5	100	1	109
Mining Site	4	1	5	44	54
Producer	48	38	116	48	
Overall Accuracy (%)					82

Table 5. LULC Accuracy Assessment 2021

Year	Overall Accuracy	Kappa Co-efficient
1991	92	88.3%
2000	86	98.9%
2021	82	80.2%

Table 6. Overall accuracy and Kappa Coefficient of the LULC maps

Land-use/Landcover change map for Obuasi Municipal was created for 1991, 2000, and 2021. In 1991 forests recorded the highest area with a total area of 13975.1(ha) representing 84% of the entire study area as shows in Figure (4), while agricultural lands, built-up and mining sites recorded the lowest which represents 13975.1(ha) (14%), 1601.98ha (2%) and 562(ha) (1%) respectively.

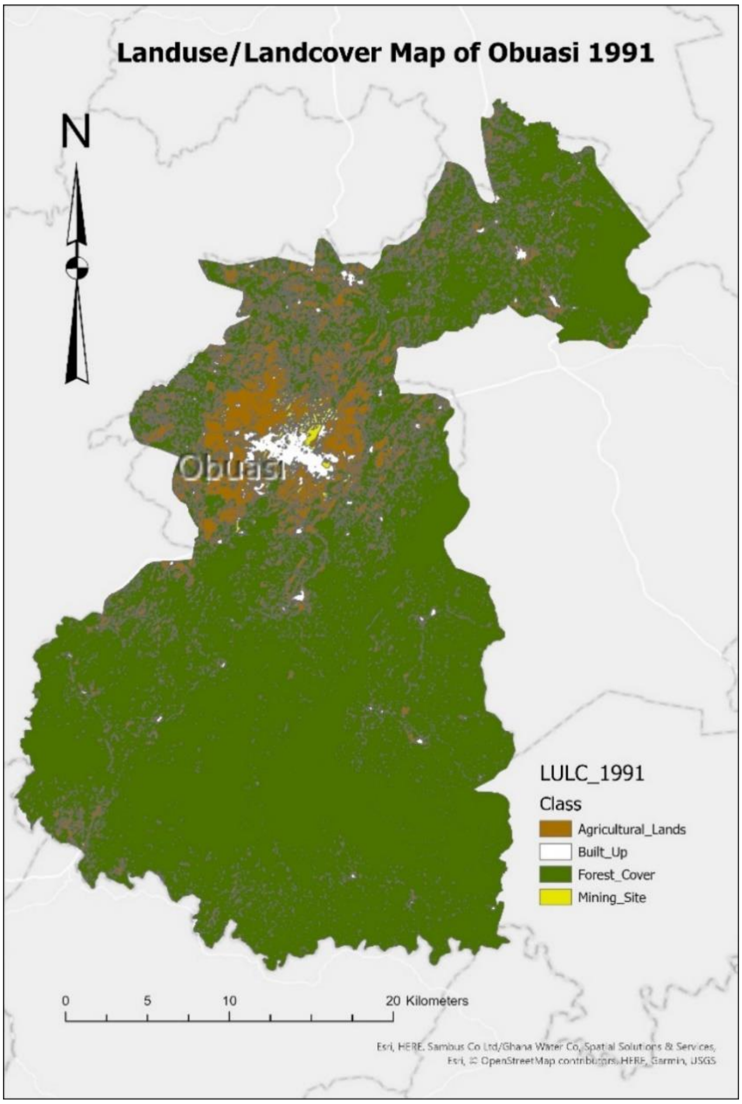

Figure 4. Obuasi LULC map for 1991

In 2000 as shows in Figure (5), the forest declined as compared to 1991. Its total area decreases from 85858ha (84%) to 68275ha (67%). Agricultural land saw a massive increase in 2000 as compared to 1991. The total area for agricultural land increased from 13975ha (14%) to 27018ha (27%). Built-up also had a slight increase in area from 1602ha (2%) in 1991 to 3973ha (4%) in 2000, while mining site has a significant increase in 2000 as compared to the 1991.

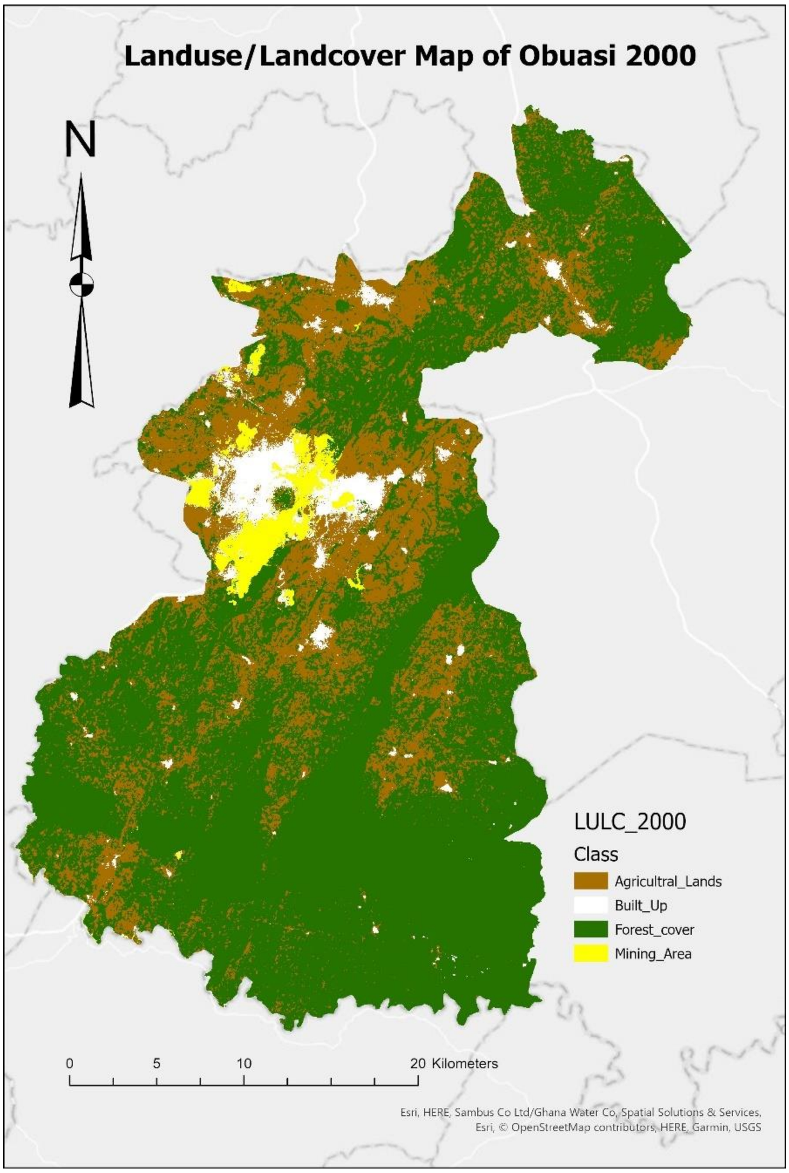

Figure 5. Obuasi LULC map for 2000

In 2021 there was a massive decline in forest cover and agricultural land area as shows in Figure (6). Forest cover decline from 68275 ha (67%) in 2000 to 63371 ha (60%) in

2021 while agricultural lands also decline from 27018 ha (26%) in 2000 to 20666 ha (20%) in 2021. Built-up and mining sites had a significant increase from 3973 ha (4%) in 2000 to 10840ha (12%) in 2021 and also from 2729ha (3%) in 2000 to 7116ha (7%) in 2021 respectively.

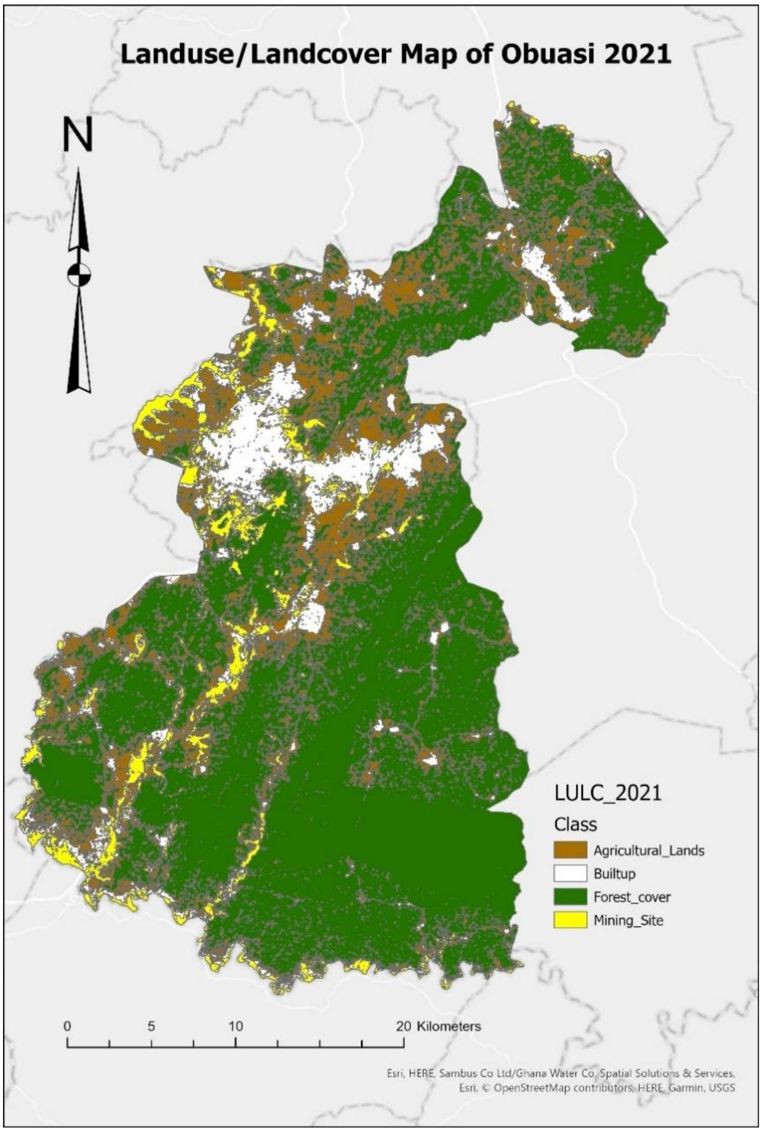

Figure 6. Obuasi LULC map for 2021

Forest areas had a massive decline while built up and mining sites has an increasing rate throughout the study due to human inflated activities as predicted in the hypothesis. Table (7) below shows the statistics analysis of the change

Class	Area (ha)1991	Area (ha)2000	Area (ha)2021	(Area Diff (ha)) 2000-1991	(Area Diff (ha)) 2021-2000
Agricultural Land	13975.1	27017.9	20665.94	13042.8	-6352.76
Built up	1601.98	3972.74	10840.41	2370.76	6867.67
Forest Cover	85857.19	68274.52	63370.54	-17582.67	-4903.98
Mining Site	561.89	2729.24	7115.54	2167.35	4386.3

Table 7. Temporal changes 1991–2021.

4.2 Change Detection

In 1991 agricultural land was 13975 (ha) built up 1602ha, forest cover 85858 (ha) and mining site 562 (ha). Forest cover recorded the highest land cover of about 84% of the total land area whiles agricultural and mining sites represent the second highest and the least with a total area of about 14% and 1 % respectively. In 2000 agricultural lands had a significant increase in size to about 27018 (ha). Forest cover was still the highest land cover in 2000 but there was a progressive decline as compared to 1991 as shows in Figure (7). Both built-up and mining sites had a massive increase in land area as compared to their initial state in 1991. Between 2000 to 2021, forest and agricultural lands has a massive decline in size from 67% to 60% and 26% to 20% while built-up areas and mining sites increase from 4% to 12% and 3% to 7%, though forest remains the dominant landcover class in the area.

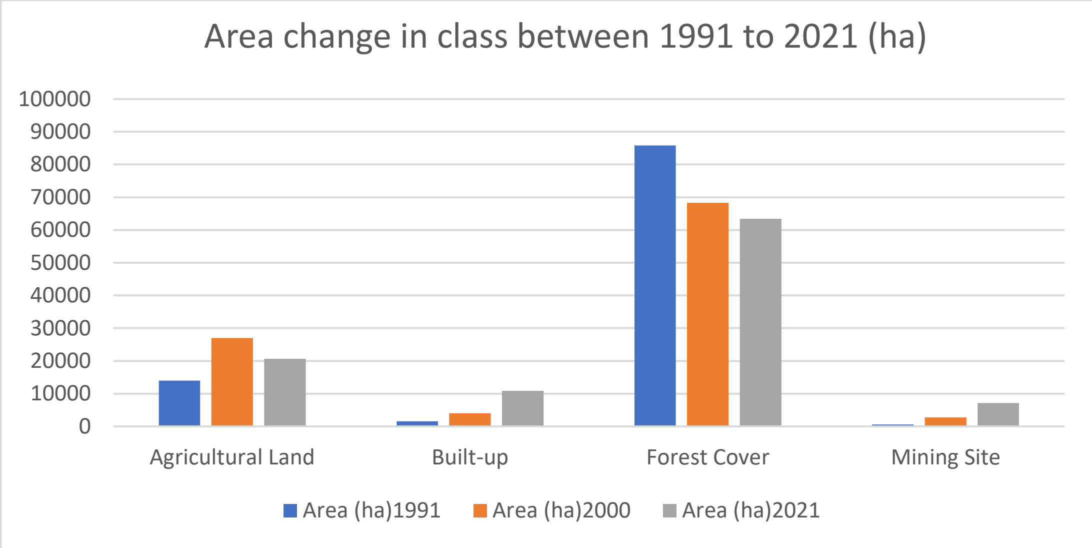

Figure 7. LULC area from 1991–2021 (ha)

Between 1991 to 2000 there was a massive change in most land use/landcover classes in the study area either at a declining or an increasing rate as shown in figure (8). Initial agricultural lands in 1991 were about 1398ha covering about 14% of the total area but within a period of 9 years, only 7697 (ha) of initial agricultural lands were maintained. 2175 (ha) of agricultural lands were changed into built-up, 310 (ha) changed into forest cover and 1013 (ha) change into mining sites. Within the same period built-up maintain an initial state of 979 (ha) where 150ha of its total area was changed into agricultural lands, 19 (ha) into forest cover, and 454 (ha) into a mining site. So, between 1991 to 2000 most of the built-up area was lost to the mining site and agricultural lands. The Forest area recorded the highest land cover within the study area between 1991 to 2000. 64925 (ha) of forest cover was maintained within the 9years period. About 19010 (ha) of forest cover was turned into agricultural lands, 786ha into built-up, and 1013ha of it into mining sites.256 (ha) of mining site was maintained between 1991 to 2000. Most mining sites were converted into forest cover, 33 (ha) into agricultural, and 44ha into built-up.

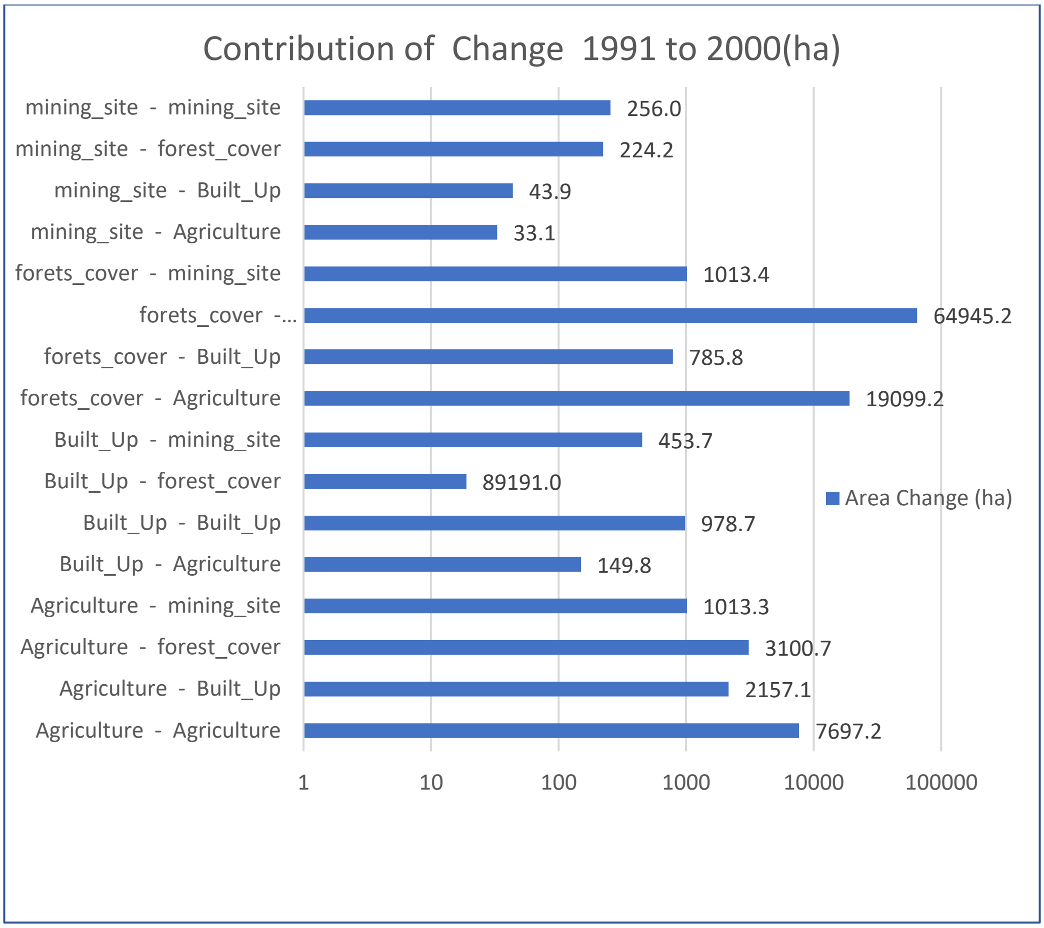

Figure 8. Contribution of LULC categories to change 1991–2000 (ha)

Between 2000 to 2021 agricultural lands were able to maintain their initial state of about 10022ha. 5081 (ha) was converted into a built-up area, 9598 (ha) was changed into forest cover and 2278 (ha) was changed into a mining site. Most agricultural lands during this period were converted to forest cover and built up. 2344 (ha) of forest cover was converted to the built-up area per the change detection statistics as shows in Figure (9). 9128 (ha) was changed into agricultural lands, 3906 (ha) was a change into the mining site, only 52884 (ha) of the initial forest cover for the period between 2000 to 2021 was maintained.

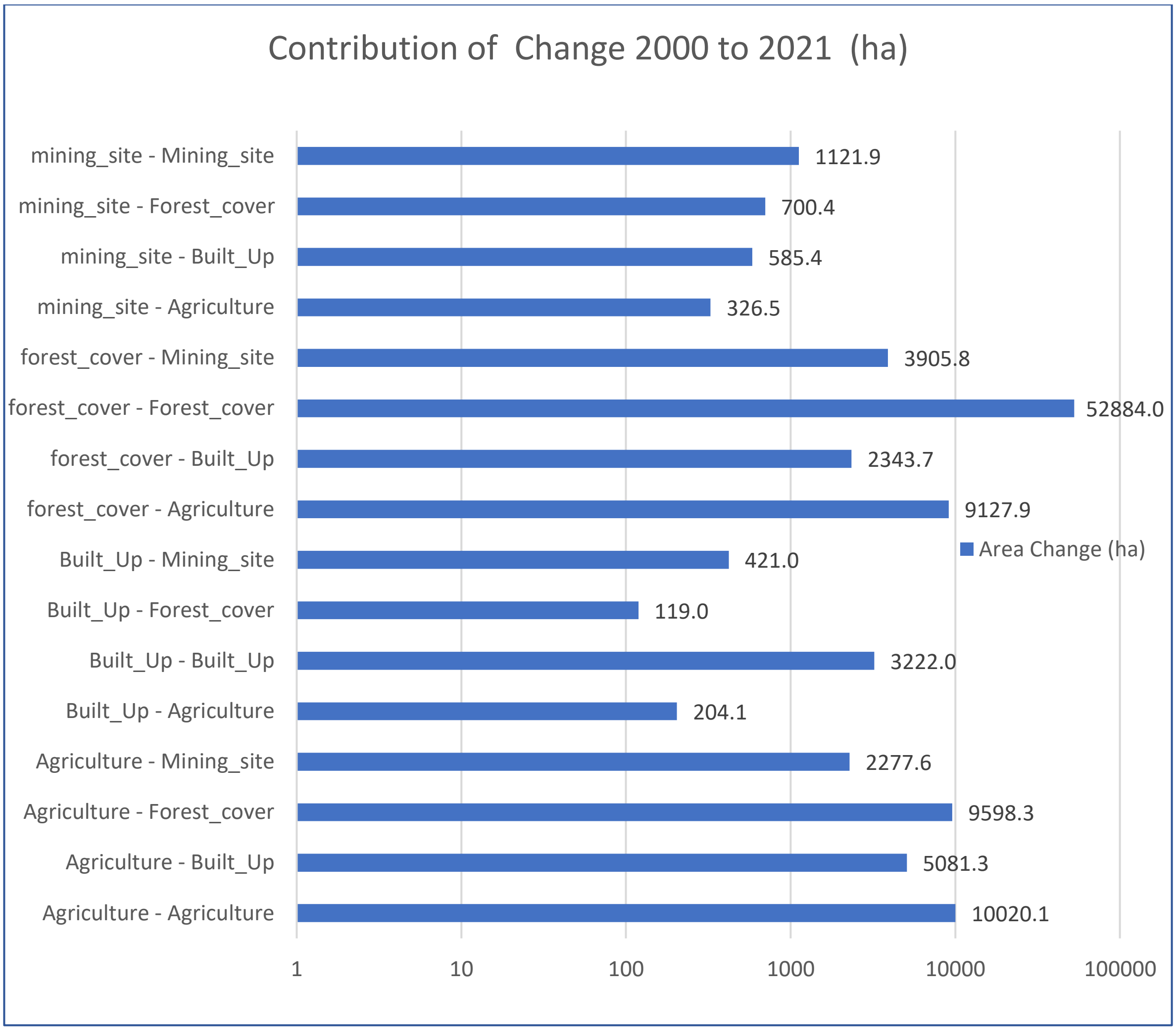

Figure 9. Contribution of LULC categories to change 2000–2021 (ha)

The impact of the change was less on mining sites as compared to other landcover classes between 2000 to 2021. 1121 ha of initial land of mining site maintained, 327 (ha) were changed into agricultural lands, 700 (ha) were converted into forest cover and 585 (ha) were changed into the built-up area. Built-up also had a progressive growth between 2000 to 2021 through 119 (ha) were converted into forest cover, 421 (ha) were changed to the mining site, and 204 (ha) into agricultural lands. But the initial state of 3222 (ha) was maintained as a built-up area

4.3 Rainfall

The average annual rainfall in the Obuasi Municipal for the period 1991 to 2021 was 1325 mm. The maximum and minimum rainfall recorded over the period were 1593 mm and 1011mm respectively. From 1991 to 2000 the study area experienced generally high rainfall recording the highest rainfall of about 1410,8 mm for the entire 9 years. The regression equation of the rainfall data indicated that despite a considerable increase in rainfall from 1993 to 1995 with an average amount of 1271mm. there was a decline in rainfall between 1996 to 2000 with an average of 1217mm of rainfall. Between the entire period of 30 years, the data indicate that there was a reduction in the amount of rainfall at the rate of 2.4 mm per year which can be seen in Figure (10). Within the entire study period, 1998 recorded the lowest amount of rainfall of 1011 mm while 2019 recorded the highest amount of 1594 mm of rainfall.

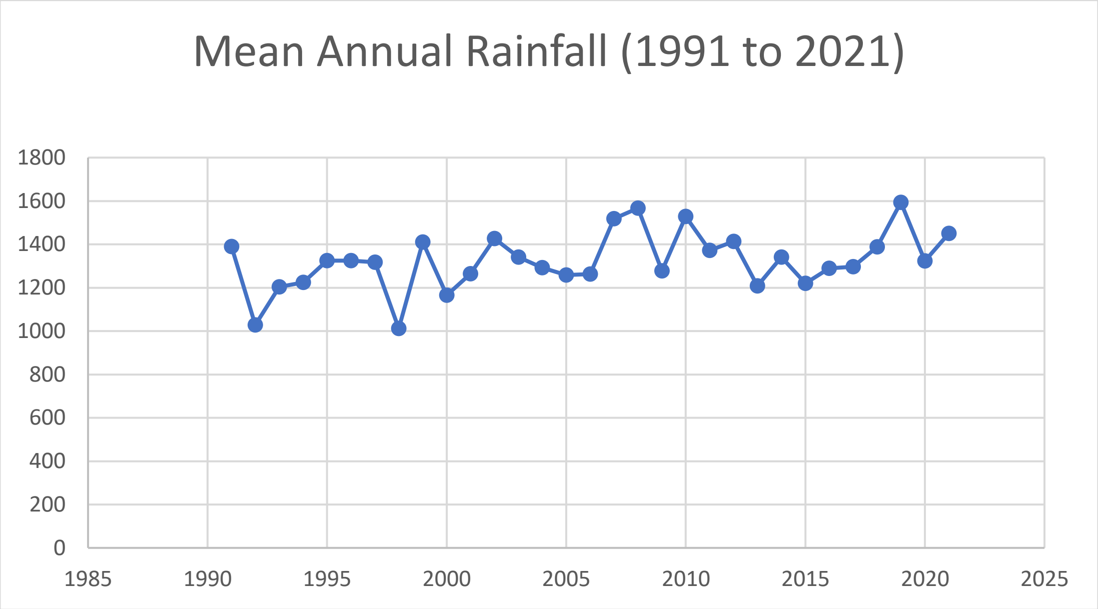

Figure 10. Main annual rainfall between 1991 to 2021

4.4 Temperature

The mean annual temperature of the Obuasi Municipal ranged from 24°C to 28°C as shows in figure (11). The maximum temperature was 28.1°C and the minimum temperature was 26.6°C. The value for the mean annual temperature was 26.1°C. The maximum temperature of 27.5°C was recorded in 2016 while the minimum annual temperature for the entire period of study was 26.46°C in 1992. The time between 1991 to 1994 recorded an index which is below the average temperature of 26.6°C, this shows that those years were relatively cold. The period between 1995 to 1998 had a sharp increase with 1998 recording as high as 27.4°C compared to the average temperature for the entire study period. Figure (11) shows the chart

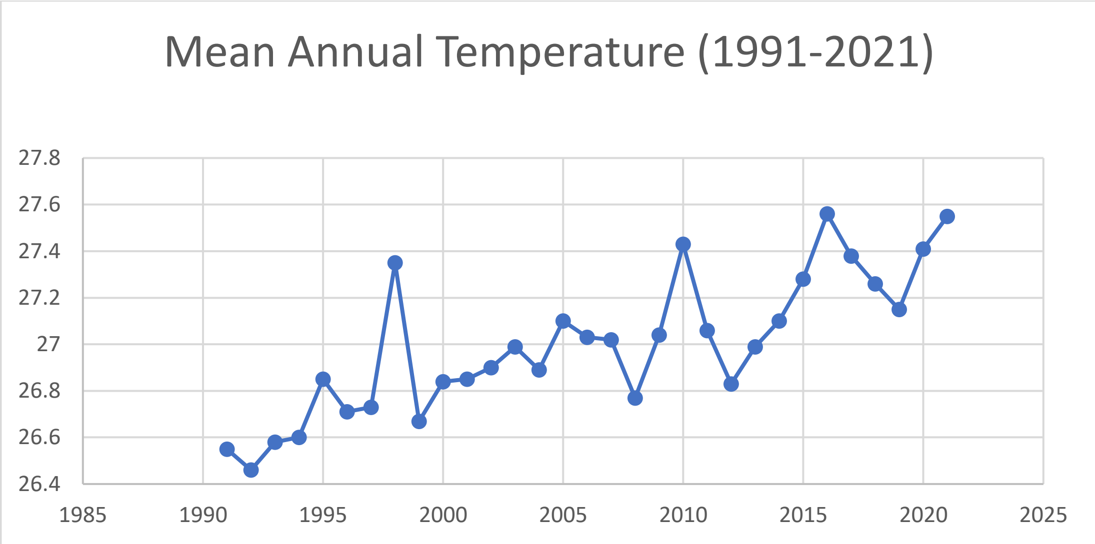

Figure 11. Main annual rainfall between 1991 to 2021

Again, there was a sharp rise in temperature from 2013 (26.1°C), 2014(27.2°C), 2015(27.28°C), and 2016(27.56°C) though there was a drop in temperature from 2017(26.45°C) and 2019(26.83°C) it was above the average temperature for the entire study period. In the succeeding years from 2020 to 2021 experienced generally warm temperatures. It can be shown on the chart that there has been a progressive increase in temperatures from 2000 to 2021. Moreover, there was a generally increasing trend in average annual temperature at the rate of 0.037°C per year in the study area.

4.5 Socioeconomic characteristics of respondents

The majority 72% of the sample household and stakeholders were between the ages of 23 to 57. The household size was between 0-5 (67%), 6-10 (20%), and 11-20 (3%). 75% of the respondents were male while 25% were females. The mean household size was 5 persons, while the smaller land size was the largest proportion of most households. The average land size for farm cultivation and mining concession was about 0<7 and 0<1 per household in the municipality. 63% were farmers, 20% were miners and only 3% of the respondents depended on another income source like wood collection and vegetable trade. (Table 8)

House Attribute	**Value**
Education (Literate %)	35
Gender (Male %)	75
Average household age	39
household occupation (family %)	63
Average household size	5
Average Land hold size	0.5
Average household income($/year)	150

Table 8. Sample household characteristics in the studied landscape

4.6 Perception towards forest cover change in the Municipality

83% of the respondents believe that the forest was in a critical condition and it needed urgent attention from the community stakeholders and the government else the forest's declining rate may worsen shortly while 17% signal that the forest was increasing in size. Table (9)

Increase	**Decline**	**No Change**
49	237	0

Table 9. residents' perception of forest cover changes at the landscape level.

4.7 Perception of residents on the impact of deforestation

As shown in Figure (13), according to the respondent deforestation has led to the following environmental issues in the municipality. Flooding (5%), water cycle disruption (10%), drought (4%), soil erosion (50%), and shortage of wood for fuel (31%) were the immediate impact of deforestation in the study area. (Table 9)

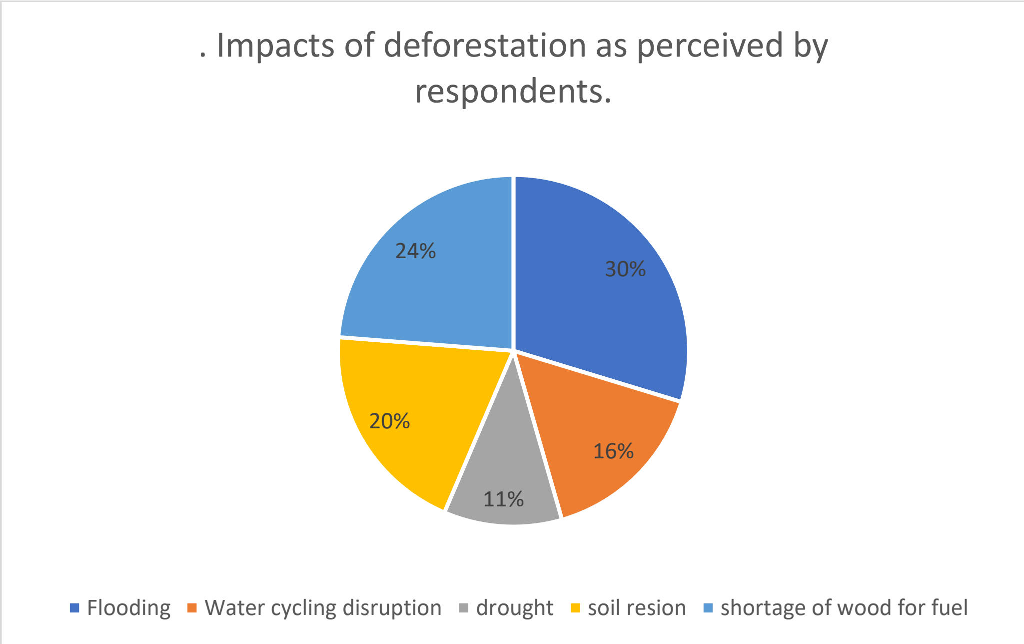

Figure 12. Impacts of deforestation as perceived by respondents.

4.8 Source of household income

Illustration from our respondents shows that forest cover plays a very crucial part to the household income of the people in the municipality since it provides employment opportunities and forest products. About 85% of the respondents view forest products as very important since forest products have been extracted for subsistence and cash income, followed by laboring about 90% of the respondents because they also relied on work from the agricultural sector and logging services. The average household income for all the interviewed households was $150 (GHC2000) The results suggested that the main source of income of the municipality are forest produces, mining, laboring, cropping, and livestock.

4.9 Drivers of Forest Cover Change

The respondents from the survey show that deforestation is the main cause of forest cover change and the majority of these cases are mining, drought, agricultural expansion, and infrastructural development because of rapid market demand for commercial timber for construction, firewood for domestic use, and gold for foreign exchange. Also, the increase in the number of economic migrants and land speculation. Forest is clear to claim land for settlement and then possible to be later sold. With inefficient agricultural productivity, limited access to modern equipment, and seeking the potential of agro-industry, the locals need more land to cultivate crops by clearing more forest. According to the respondents, major drivers of deforestation are fuel wood collection (16%), population growth (15%) mining (18%), logging for income generation (11%) drought (6%) construction (14%), and agricultural (20%) are the consequent that has had a very huge impact on forest cover change and Figure (13) shows the chart.

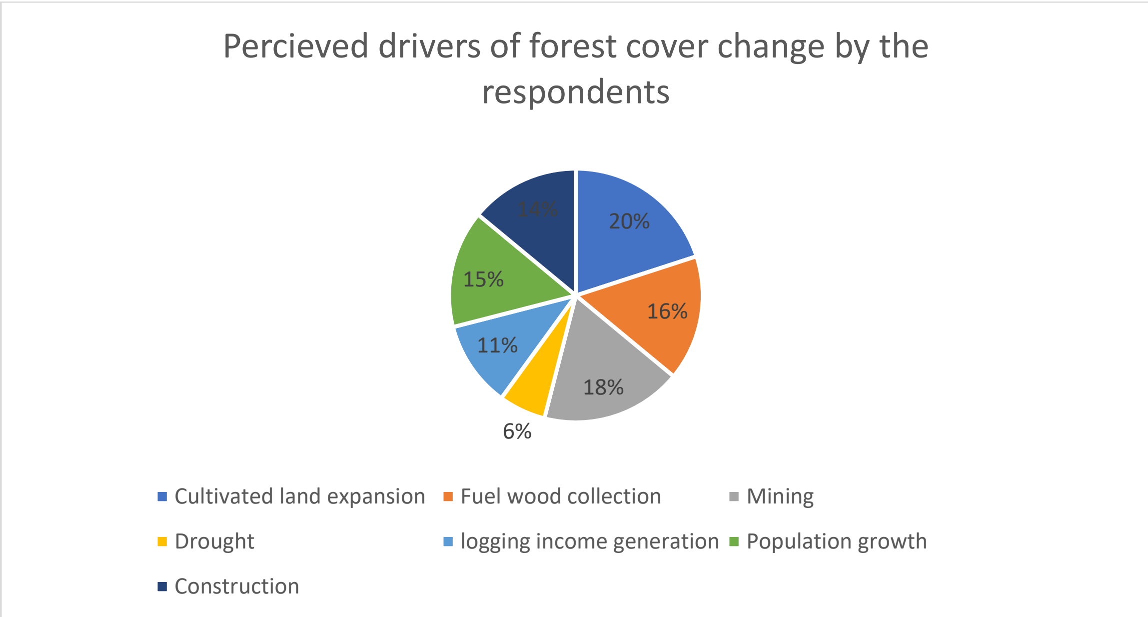

Figure 13. drivers of forest cover change as perceived by respondents.

4.10 Existing Remedies and Potential Solutions

According to the respondent, to maintain areas undergoing long-term forest decline, a massive measure needed to be taken, enrichment planting (25%), financing for adding ecosystem service (21%), awareness creation (18%), strengthening forest protection (20%) and zero grazing mechanism (17%), as shown Figure (14). This meant that respondents' understanding and skills on natural resource management were paramount.

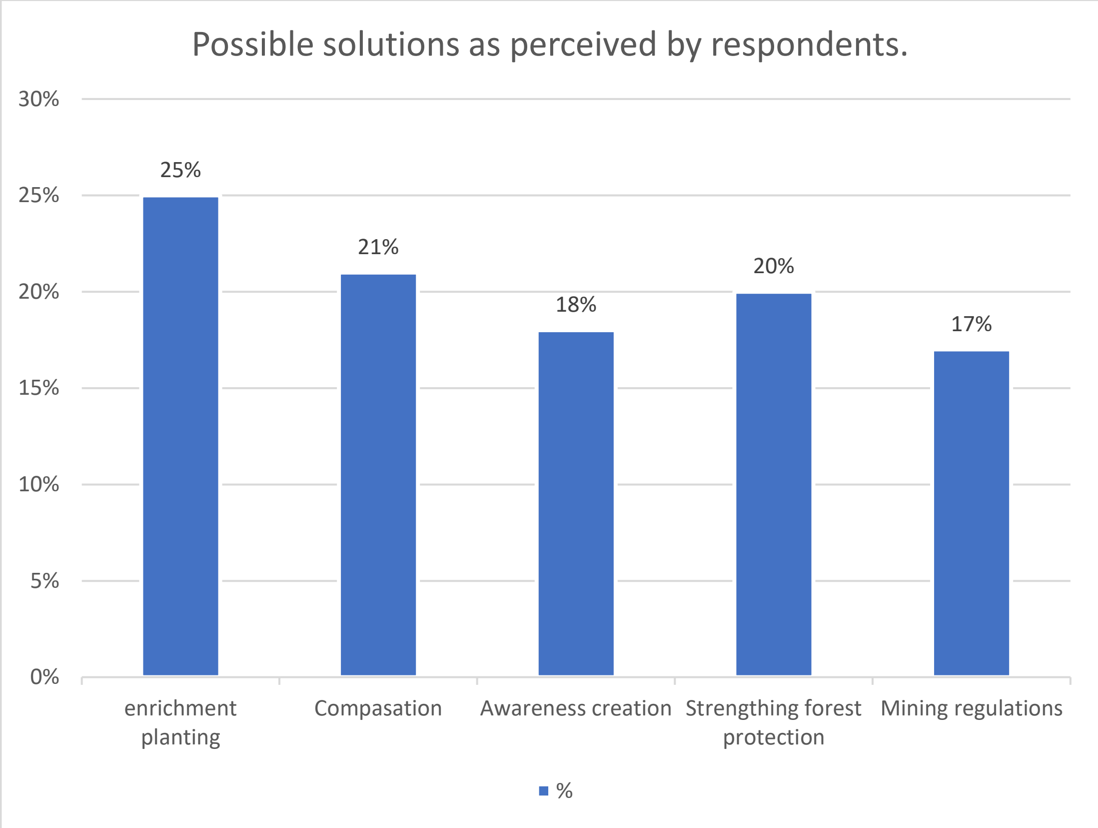

Figure 14. Possible solutions as perceived by respondents

4.11 Selection of Spatial Variables

There was an observation that the significant growth in built-up and mining areas according to the transition matrix. This was highly influence by agricultural and forest land fragmentation, these transitions were based on socio-economic and physical factors. Most current literatures use these spatial factors to investigate LULC. The use of Digital Elevation Models (DEMs), slope, distance from major roads, and distance from major rivers is a common methodology for investigating landuse/landcover change. These variables are often used in combination to identify patterns and trends in land use and land cover change over time. The justification for using DEMs is that they provide a detailed representation of the topography of a landscape, which can be used to identify areas that are more or less suitable for different land uses. For example, areas with steep slopes may be less suitable for agriculture or urban development. Distance from major roads and distance from major rivers are also important variables in landuse/landcover change studies. These variables can indicate the accessibility and connectivity of an area, which can influence land use patterns. For example, areas that are farther away from major roads or major rivers may be less accessible and less likely to be developed, while areas that are closer may be more accessible and more likely to be developed. Overall, the use of these variables in combination allows for a comprehensive understanding of the factors that influence land use and land cover change. By identifying patterns and trends in these variables, researchers can gain insights into the drivers of landuse/landcover change and develop strategies for managing and conserving landscapes. Table (10) indicates the prospective, Cramer's V values.

Spatial Variables	**Cramer's V**
DEM	0.42
Slope	0.32
Distance from major roads	0.52
Distance from major rivers	0.09

Table 10. Cramer's V value of spatial variables.

Cramer's V is a measure of the association between two categorical variables. It is similar to the Pearson's correlation coefficient, which measures the strength of the linear relationship between two continuous variables. However, unlike Pearson's correlation coefficient, which can only range from -1 to 1, Cramer's V can range from 0 to 1, with values closer to 1 indicating a stronger association between the variables. When Cramer's V is used with spatial variables, it can be used to measure the association between the categorical variables and the spatial locations they are observed in. For example, Cramer's V could be used to measure the association between the type of land use (e.g., residential, commercial, agricultural) and the location of a particular piece of land. A high Cramer's V value would indicate a strong association between the type of land use and the location, while a low Cramer's V value would indicate a weak association. The selected variables are showed in Figure (15) and Figure (16). In this study the variables values were more significant hence the variables were ideal for the transition potential modeling. Physical and socio-economic explanatory variables were more effectual per the values that was generated. Slope 0.32V, Distance from major rivers 0.09V, Distance from major roads 0.52V and DEM 0.42V.

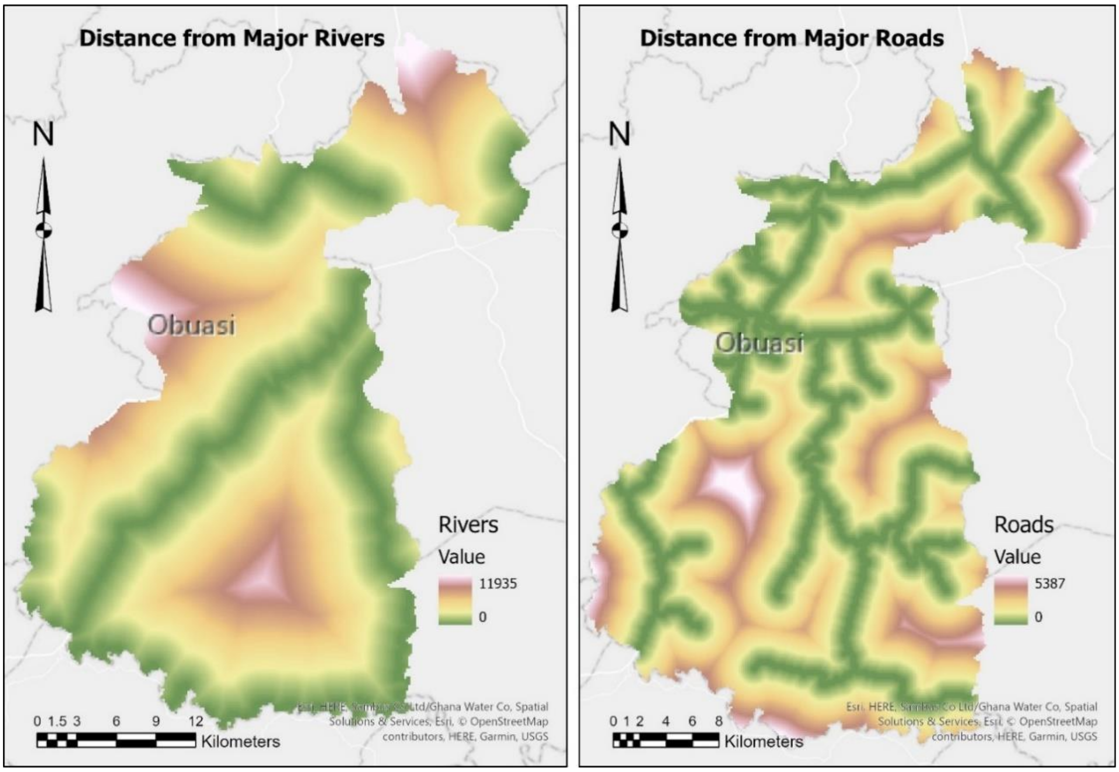

Figure 15. Spatial variables used in the study (Rivers and Roads)

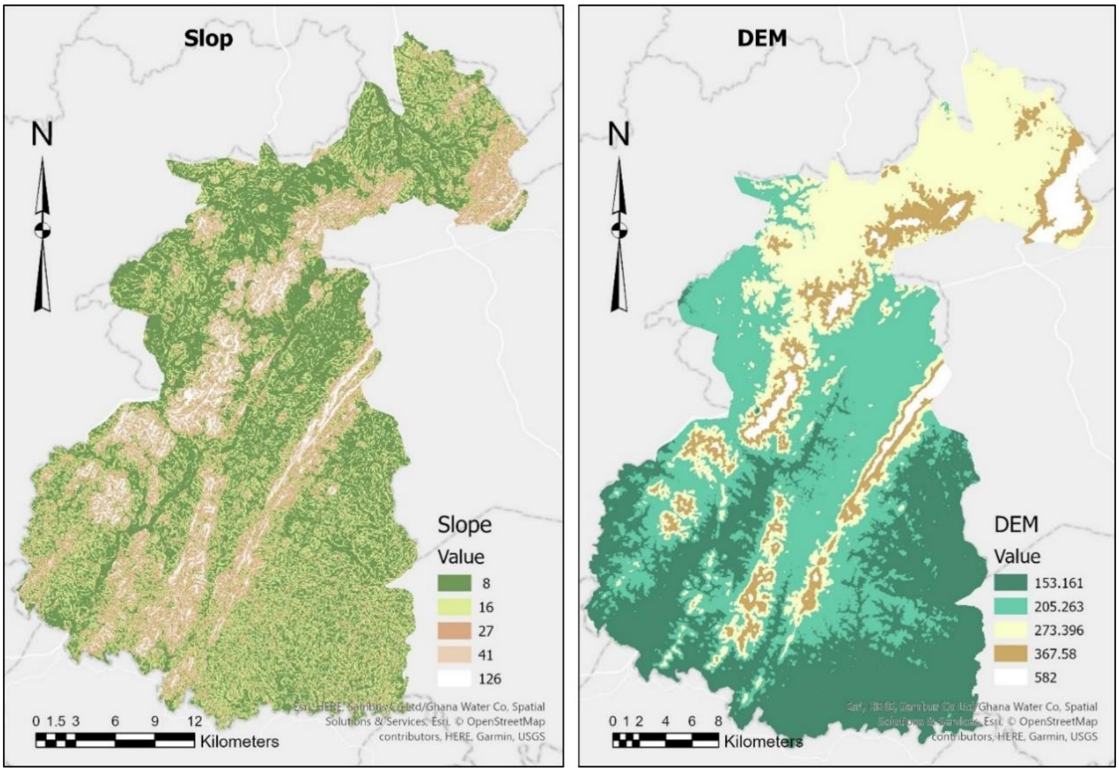

Figure 16. Spatial variables used in the study (Slope and DEM)

4.12 Prediction of LULC

MOLUSCE plugin in QGIS integrated with some well-known algorithms for transition potential, modeling such as multicriterial evaluation, logistic regression, the weight of evidence, and CA algorithms to stimulate future changes were used. CA-ANN technique for transition potential modeling and prediction were employed. LULC data from Landsat from 1991, 2000, and 2021 along with spatial variables to project LULC for 2021 and obtained a validated value. After securing the projected LULC the genuine LULC is compared with the projected data to help obtain the overall accuracy and forecast the map and statistics for 2021. Relative strong associations with LULC were done through spatial variables for modeling calibration. LULC Landsat data from 2000 and 2021, spatial transition probability matrix, and variables were employed to produce the LULC for 2030. 2030 LULC was predicted after obtaining a satisfactory outcome from the model validation. The spatial dynamic variations in the LULC pattern during the study were analyzed. The results from 2021 to 2030 indicate a notable expansion in built-up and mining sites and a huge decline in forest cover and agricultural lands. The spatiotemporal area and percentage changes in all LULC categories. Table 11 and Figure (16) show the map.

LULC Categories	**Hectors**	**%**
Agricultural Land	17566	18
Built up	16204	17
Forest cover	51267	53
Mining Site	11825	12

Table 11. Predicted area statistics (2030)

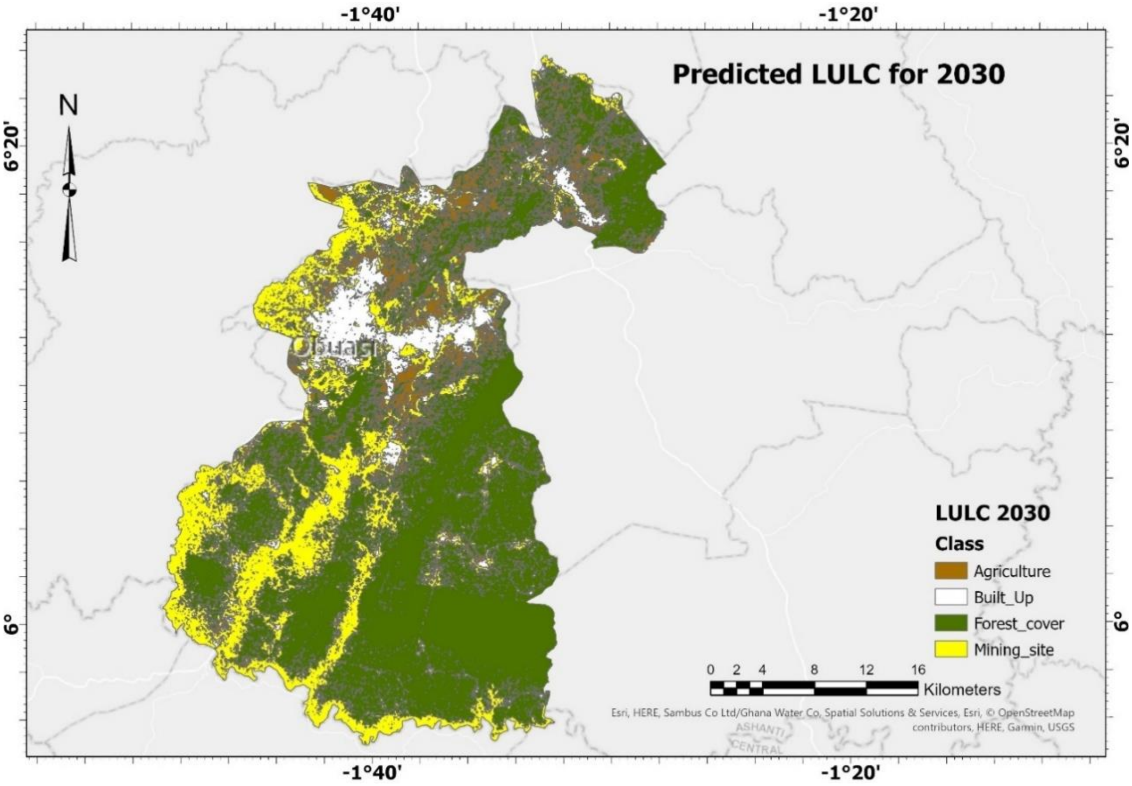

Figure 17. LULC prediction 2030

Agricultural and forest cover contribute about 17% and 21% to built-up and mining sites respectively. Forest cover is the largest contributor to the changes from 2021 to 2030 with 25% to mining and 19% to built-up areas, while agricultural lands contributed 12% to the mining site and 6% to built-up areas table 12 shows the change statistics.

LULC Categories	**Area change (2021-2030)**	**%**
Agricultural Land	-3110	-3
Builtup	5364	6
Forest cover	-12103	-13
Mining Site	9096	9

Table 12. Temporal changes 2030

In conclusion, our research findings indicate that forest cover has been significantly impacted by human activities such as logging and land development. These changes have resulted in a loss of biodiversity and a decrease in the overall health of forest ecosystems. Furthermore, the impact of climate change is expected to exacerbate these negative trends.

Chapter 5
Discussions

5.1 Remote Sensing For Forest Cover Monitoring

Researchers have routinely employed remote sensing and GIS tools to examine forest cover change. These technologies enable huge volumes of data on land cover, vegetation, and land use to be collected at vast geographical and temporal dimensions, giving significant information for understanding and managing forests.

A study conducted by (Ropars et al.,2017) utilized satellite images to track changes in forest cover in the Congo Basin from 2002 to 2014. The authors discovered that forest cover decreased by 3.4% throughout this period, with the biggest losses occurring in regions with heavy logging and road building. According to this study, the integration of remote sensing and GIS methods enabled an accurate and thorough investigation of forest cover change in this region, giving valuable information for conservation and management activities. Moreover, other studies have emphasized the value of remote sensing and GIS techniques in understanding the determinants of forest cover changes. For example, (Gibbs et a.,2007) examined land cover change in the Amazon Basin between 2000 and 2005 using satellite photography. They discovered that while deforestation was a primary driver of forest cover change, other causes such as fires and illicit logging also contributed to forest loss. According to the authors, the use of remote sensing and GIS techniques enabled the discovery of these many causes of forest cover change, giving vital insights for conservation and management activities.

5.2 Land Use/Landover Change of Obuasi Municipal

During the research period, the Forest area shrank dramatically. Several reasons have led to the reduction of forest cover in Obuasi Municipality. One of the key drivers is the increase in agriculture, notably the production of cocoa, which is the country's principal export crop. Since there is high demand for cocoa, forests have been converted to agricultural land, and existing cocoa fields have been expanded. According to published research by (Yaw et al.,2013), cocoa beans were originally introduced in Obuasi in 1879 before spreading throughout the country, therefore cocoa cultivation is a part of people's everyday lives. Also forest decline was attributed to the growth in logging, the high demand for charcoal, and timber by the native people (Jiménez et al.,2018). Obuasi's depleting forest cover has had major ramifications for the ecosystem and residents. Soil erosion caused by deforestation can have a severe influence on agricultural output and water quality. It can also result in the extinction of plant and animal species due to habitat loss. Moreover, local populations who rely on forests for a living may suffer as a result of the loss of these resources. According to (Adjei et al.,2017), deforestation in Ghana's Atewa Forest Reserve resulted in increased soil erosion and decreased soil fertility. The researchers asserted that the loss of trees exposes soil to erosion-causing elements including rainfall and wind, resulting in the loss of topsoil and nutrients. They also stated that soil erosion can have a detrimental influence on agricultural output by reducing the soil's ability to sustain crop development. Likewise, (Amponsah et al.,2018) discovered that deforestation in Ghana's Asante Akim South District enhanced soil erosion, which in turn increased sedimentation in streams and rivers. They went on to suggest that sedimentation might have a detrimental influence on water quality because it affects the quantity of light that reaches the aquatic plants that produce oxygen to the water, resulting in lower oxygen levels in the water.

Agricultural fields increased in size between 1991 and 2000 as a result of significant policies adopted by the then government. (According to FAO 2002), the government of Ghana implemented some critical programs to support farmers in the country during the late 1990s, such as financial assistance, irrigation, and water management projects, adoption of modern farm techniques and technologies, seed improvement, affordable fertilizers, and efficient infrastructure development, such as an efficient transportation system and increasing availability of ready markets. Furthermore, the adoption of more efficient and sustainable farming technologies, such as conservation agriculture, contributes to increasing production while reducing agriculture's environmental effects. In addition, the growing demand for agricultural goods both locally and globally contributed to a rise in agricultural productivity in southwestern Ghana in the late 1990s (Danquah et, al.,2001). Between 2000 and 2021, agricultural lands decreased significantly from 27017.9 (ha) to 20665.94 (ha), losing around 6442 (ha) of the total area to other land use/landcover classes. Most researchers agreed that

climate change, land degradation, and a lack of government assistance for small-scale farmers were the primary causes of the drop in agricultural productivity in southern Ghana in the mid-2000s. Climate change, according to (Cline.,2010), has been a major contributor to the reduction of agricultural productivity in southern Ghana.
Since mining has been a key contribution to the economy of southern Ghana for many years, with various minerals such as gold, diamonds, and bauxite being mined from the region, the total land size of the mining site expanded massively from 1991 to 2021. There has been a significant rise in mining activity in the area recently, with new mines being created and current businesses growing. This increase may be ascribed to several causes, including increased worldwide demand for minerals, technical advances in mining processes, and favorable government policies. Most scholars believe that the growth rate of mining in Obuasi Municipality is driven by a variety of variables. One important aspect is the region's high concentration of gold reserves, which has drawn investment from mining corporations looking to utilize these resources Owusu et al., (2018). Another element is the region's favorable government policies and regulatory environment, which have made it simpler for mining corporations to operate (Bampo et al.,2020).

According to (Adu-Amankwah et al.,2017) the technical developments in mining processes, such as open-pit mining and heap leaching, have led to the growth in mining in Obuasi Municipality. These processes have made mineral extraction more cost-effective and efficient, resulting in increased output and profits for mining firms. Furthermore, the increased worldwide demand for minerals has contributed to the development of mining in Obuasi Municipality. With the rising industrialization of emerging economies such as China and India, demand for raw resources such as gold has increased significantly Dzansi et al., (2019). This has resulted in higher gold prices, attracting investment from mining companies seeking to exploit the riches located in Obuasi Municipality. It ought to be noted that the increased mining in Obuasi Municipality has had a slight effect on the region and its population. Mine growth has resulted in environmental damage, such as deforestation and contamination of water supplies Agbesi et al., (2016).

Mining firms and local people have also clashed over issues such as land rights and compensation (Yeboah et al., 2020). Similarly, Amoah et al., (2013) discovered that the increase in mining in Obuasi has resulted in huge amounts of forest degradation, notably in the Amansie West District. According to the authors, the area's loss of forest cover has had a severe influence on the local climate, including higher warmth and decreased rainfall, which can affect agriculture output and lead to water scarcity. According to Zomer et al., (2015) and Masakure et al., (2018), several reasons have contributed to the rise of built-up areas in Obuasi. One aspect is the presence of a substantial mining sector in the area, which has drawn a considerable inflow of migrants and resulted in the growth of urban centers. Another consideration is the government's strategy of encouraging urbanization and industrialization, as well as the availability of infrastructure and services in the municipality. This has prompted many to relocate from rural to urban regions in quest of greater economic possibilities and a higher quality of life.

However, there is a growing body of scholars that analyzes the rise in Obuasi's built-up areas and their consequences on forest cover. According to Adjei (2018), the growth of urban areas in Obuasi has resulted in severe deforestation and loss of forest cover. He emphasizes how, as cities have grown in size, more land has been converted for residential and commercial development, resulting in the loss of natural ecosystems and flora. As a result of this process, carbon sinks have been reduced and greenhouse gas emissions have increased, leading to climate change. Some scholars have also suggested that Obuasi's fast urbanization has had a negative influence on the environment and the local community. According to (Mabula et al 2015), urbanization has resulted in the loss of agricultural land and natural ecosystems, as well as increasing air and water pollution. Obuasi's rising urbanization has had a substantial influence on the region's forest cover. As more land is converted for urban expansion, there is a commensurate reduction in the amount of wooded area. Several studies undertaken in the region have established this pattern.

Moreover, Adjei et al., (2017) examined the changes in land usage in southern Ghana between 1992 and 2014. They discovered a large rise in built-up areas, as well as a decrease in forest cover. The study concluded that over 22 years, forest cover diminished by 7.5% while built-up areas rose by 10.5%. This trend was detected in all five districts of the area, with the biggest losses in forest cover reported in Ahanta West and Obuasi.Furthermore, experts such as Adjei et al., (2017) have emphasized that

Obuasi's fast urbanization has resulted in insufficient housing and basic amenities for the growing population, resulting in social and economic inequities and a lack of access to resources for many citizens. Likewise, Oduro (2019) emphasizes the harmful effects of urbanization on forest cover in Obuasi. The study claims that urbanization has reduced the availability of natural resources such as lumber and has altered the ecosystem functions given by forests such as water management and soil stability. This has had severe ramifications for local populations that rely on these resources for a living.However, Asante (2020) provides a distinct viewpoint on the link between Obuasi's urbanization and forest cover. they contend that, while urbanization has had a negative influence on forests, it has also resulted in constructive developments. For example, urbanization has produced new economic possibilities and introduced new types of infrastructure, such as roads and hospitals, which have transformed the lives of local citizens.

5.3 Incidence and Trend of Climate

According to Asare et al., (2012), climate change was a significant influence on the region's loss of forest cover. The scientists examined changes in forest cover using satellite data between 2001 and 2010 and discovered that temperature and rainfall were the most important causes of forest cover change. Greater temperatures and lower rainfall were linked to increasing deforestation, whereas lower temperatures and higher rainfall were linked to increased forest cover. Moreover, Owusu et al., (2016) investigated the influence of climate change on the distribution and abundance of tree species in southern Ghana. The scientists discovered that some tree species were more sensitive to climate change than others and that their distribution and abundance were likely to shift in the future. Temperature increases and erratic rainfall patterns have made it more difficult for farmers to cultivate crops and rear animals. This has been especially difficult for small-scale farmers, who frequently lack the resources to adapt to these changes. Climate change, for example, has lowered agricultural production in Ghana by an average of 5.5% every year, according to research conducted by the International Food Policy Research Institute. Deininger et al., (2003)

Chapter 6
Conclusions

Through in-depth interviews with local stakeholders, including government officials, community members, and environmental experts, we aim to understand the underlying drivers of landuse/landcover change and their ecological implication on forest cover change in the Obuasi Municipal. Satellite imagery and spatial analysis techniques were used to measure the extent and rate of forest cover change and investigate its potential drivers. The results of this study provided a comprehensive understanding of the dynamics of forest cover change and a useful for developing effective strategies for conservation and sustainable management of forest areas. In this regards both quantitative and qualitative research approach was employed for the study (Boateng & Mensah, 2021). For the entire study period forest areas had a massive decline of about 39.2% in it total land area. Built up and mining site has a significant increase in it total area of about 7% and 5% respectively, while agricultural areas has had a progressive decline from 2000 to 2021, due to unpuplar government policies on agriculture. For the same study period there was a dynamic fluctuation in rainfall and temperature. There was a reduction of amount of 2.4mm in rainfall while temperatures has a progressive increase from 2000 to 2021. Average annual temperature had an increase of 0.037 per in the study area. These changes has been as a results of anthropogenic activities in the study area. Acoording to the locals the major drivers of forest cover change in the municipal is cultivating land expension and mining while infrastructural development and population growth remain a minor trajactory impact. We modeled and predicted landscape patterns using solely physical and socio-economic elements in this study, although development policies, climatic conditions, developmental policies, immigration and migration may all have an effect on the landscape pattern. Demands for fundamental human needs and wellbeing are growing. As a result, regulatory actions to prohibit traditional chiefs from selling agricultural lands to estate developers and mining contractors are urgently needed to protected the remaining forest areas in the Municipality. Also, decentralization of policy to the regional and Municipal levels must be taken seriously in order to reduce the migratory canker.

6.1 Recommendations

Most of the land use/landcover research that has been done in the Obuasi Municipal focuses on illegal mining with very little attention given to forest area. It is however important to track, frequently map and document land use/landcover changes that occur in forest area through remote sensing techniques for proper land management planning and other policy interventions. It would therefore be necessary for researchers to conduct Land Use/Cover change studies often using Landsat satellite images which do not cost yet gives accurate information.

1. Implementing sustainable forest management practices: This includes activities such as selective logging, agroforestry, and community-based forest management. These practices can help to ensure that the forest is used in a way that maintains its ecological integrity and provides long-term benefits to local communities.
2. Promoting reforestation and afforestation: Planting new trees can help to replace those that have been lost due to deforestation. This can be done through programs such as community-based reforestation, in which local people are involved in the planting and management of new trees.
3. Reducing illegal logging: Illegal logging is a major contributor to deforestation in Obuasi. To address this, efforts should be made to strengthen law enforcement and improve monitoring of logging activities.
4. Increasing the use of alternative energy sources: One of the main drivers of deforestation in Obuasi is the use of wood as a source of fuel. Encouraging the use of alternative energy sources such as solar, wind, and biogas can help to reduce the demand for wood and thus reduce the pressure on forests.
5. Supporting livelihoods diversification: Many people in Obuasi rely on forest resources for their livelihoods, so efforts should be made to diversify livelihood options to reduce dependency on the forest and provide alternative income streams.

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