Modeling Deforestation Trends Using Remote Sensing, Artificial Neural Network Techniques and its Relationship with Socio-Economic Drivers

By

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DEDICATION

Dedicated to my parents for their unwavering love and prayers, and to my siblings who have been a steadfast source of support and encouragement throughout this research

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First and foremost, I'd like to bow my head in gratitude to Allah Almighty, for enabling me to have completed this research with His blessings.

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Muhammad Ali Awan

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
LULC	Land Use Land Cover
NDBI	Normalized Difference Built-up Index
ANN	Artificial Neural Network
CA	Cellular Automata

ABSTRACT

Monitoring temporal forest changes can highlight management gaps that can help Forest department for policy-making and afforestation schemes. Many previous studies done to monitor LULC changes lacked social data. This study used high resolution remote sensing data and social data to examine trends in district Abbottabad. The study's objectives were (1) To determine the temporal trend and drivers of forest cover change (2) To predict the future Land Use / Land Cover for District Abbottabad. Landsat imagery of 2010 and 2020 was classified using supervised classification, more than 500 samples were collected for forest, agriculture, barren and urban class, and 300 samples were collected for water body class. To monitor change in forest cover, area of each class was calculated and compared. A socio-economic survey was carried out using an online questionnaire to evaluate the socio-economic conditions of the population and validated with GIS techniques to identify the drivers behind Deforestation. The cellular automata artificial neural network (CA-ANN) model integrated into the Molusce plugin of QGIS to predict future land use land cover for year 2030. The overall accuracy for the year 2010 and 2020 was obtained as 89% and 85.5%, respectively. Forest cover decreased from 48.6% to 33.3%, a net change of 15.27% in 10 years.

A significant increase of 22.27% in agricultural land was observed. Validations shows that population, urbanization and agriculture expansion were 3 major contributing factors to Deforestation. The forecast for Land Use and Land Cover (LULC) suggests that by 2030, the primary land uses in Abbottabad will be built-up areas and agricultural land 653sq.km and 315sq.km respectively. The study recommends that the Forest Department should enforce stringent measures against individuals or activities causing disturbances to forest land.

Chapter 1

INTRODUCTION

1.1 Background Information

Forests, the remarkable ecosystems that cover vast expanses of our planet, are an invaluable natural resource that sustains life in countless ways. With their dense foliage, towering trees, and diverse plants and animals, forests play a crucial role in maintaining the balance of our global environment. They act as the Earth's lungs, absorbing carbon dioxide and the world's forest cover, posing a grave danger to biodiversity, climate stability, and the well-being of human communities. We must recognize the critical importance of forests and take urgent action to conserve, protect and restore these precious ecosystems for the benefit of present and future generations, releasing oxygen, providing habitat for countless species, and regulating local climates. However, despite their immense ecological significance, forests worldwide are under severe threat. Deforestation, illegal logging, wildfires, and climate change are rapidly diminishing the.

1.1.2 Deforestation

Deforestation refers to the intentional removal of forested areas. Throughout history and into contemporary times, forests have been cleared to make space for agricultural activities, grazing of animals, and procuring wood for fuel, manufacturing, and construction purposes. The conversion of forested regions into farmland, ranches, or urban areas is a common occurrence leading to Deforestation. This widespread practice has significantly transformed landscapes across the globe.

1.1.3 Forest Degradation

When forest ecosystems lose their capacity to provide crucial goods and services to humanity and the environment, they enter a state of degradation. The alarming degradation trend is evidenced by the fact that since the 1960s, over half of the world's tropical forests have faced destruction. Shockingly, more than one hectare of tropical forest succumbs to destruction or severe degradation every second. This ongoing environmental crisis that are heavily reliant on wood for sustenance. The inherent dependency on wood resources, compounded by dynamic shifts in the ecosystem, renders these communities highly susceptible to future forest degradation. The implications of this vulnerability extend beyond the immediate loss of livelihoods, reaching into the potential erosion of essential skillsets and the destabilization of habitats. In essence, numerous households and workers in this region confront the looming threat of losing their means of sustenance and grappling with the potential dismantling of their unique skills and the habitats they call home. This multifaceted challenge underscores the urgent need for comprehensive strategies to address and mitigate the consequences of ongoing and future forest degradation.

1.1.4 Deforestation in Pakistan

With an annual deforestation rate of 4.6%, Pakistan is the second most deforested country in the world (Abbasi, Baloch, & Memon, 2011). There are several hotspots for Deforestation, including Pakistan, which has the second-highest rate of Deforestation in

Asia (Gul, Khan, & Khair, 2014). The world's forest cover areas are disappearing at an alarming rate due to overlogging and land removal for agriculture and habitation (Hansen, 2013).

Experts state that a country's forests should make up at least 25% of its total land area; Pakistan's forest cover is only 5.7%. Out of Pakistan's total area of 881,913 sq.km wood covers only 16,440 km^2. The rapid degradation of forests, especially in the highlands of Pakistan, is worrisome and threatens the environment.

Based on the total rate of habitat change, Pakistan lost 11.5 percent of its forest and woodland habitat between 2005 and 2015.

Government estimates from 1990 to 2000 showed that Pakistan's forest cover accounted for 4.2 million hectares, or 4.8 percent of the country's total land area, with an annual loss rate of 0.7 percent (Shehzad et al., 2014). The FAO estimates that the rate of decline was 2.0 percent year between 2000 and 2010 (FAO, 2010). According to Global Forest Watch, Pakistan lost 69.2 hectares of forest cover in 2020, equivalent to 26.1 kt of CO2 emissions.

According to Abere and Opara (2012), Deforestation is the deterioration of forests brought on by a process that diminishes the natural forest vegetation and resources in a certain area. The irreversible conversion of forest area to non-forest uses like agriculture, grazing, or urban development is known as Deforestation (Chakravarty, Ghosh, Suresh, Dey, & Shukla, 2012).

Pakistan has a variety of forest types, with coniferous forests being most prevalent in the northern areas of KPK, Northern Punjab, Baluchistan, and Azad Kashmir. The elevation of the forests in KPK ranges from 1,000 to 4,000 meters above sea level. These forests are found in Punjab areas like Rawalpindi and KPK districts like Abbottabad, Dir, Malakand, Swat, and Mansehra (Sheikh & Wang, 2012).

Deforestation is mostly caused by agriculture. The principal cause of Deforestation, according to the United Nations Framework Convention on Climate Change, is tree-cutting for agricultural expansion (Tariq, Rashid, & Rashid, 2014). Pakistan faces numerous issues, one of which is the rapid rate of Deforestation. Numerous analyses and assessments indicate that the overall area of woods is less than 4.6 million hectares. With a deforestation rate of about 1.5%, these woods rapidly deteriorate, particularly in steep areas, endangering and jeopardizing ecosystems (Kamal, Yingjie, & Ali, 2019). Approximately 53 percent of Pakistan's annual domestic energy needs are met by fuel wood.

Fuel wood dependency is anticipated to stay high since switching from conventional fuel to fuel wood would require a more robust economy. Both the population growth and the amount of fuel wood used are predicted to rise by 3% annually. Forests are rapidly being destroyed by the growing need for wood for home fuel (Benjaminsen and Ali, 2004). The industrialization of cities, which started with the industrial revolution, has led to an increase in settlement areas due to the rapid migration of people from rural to urban areas.

Increased access to markets and woods through roads, rivers, and trains speeds up Deforestation. While particular forests are more accessible than others, coastal and island forests are more accessible than huge, dense forests. Deforestation is decreasing in any forest two or three kilometers away from a road. Population growth requires More acreage for food, fuelwood, timber, and other forest products (Angelsen and Kaimowitz, 1999). 7–11 million km2 of forest have been removed in 300 years (Mawalagedara and Oglesby, 2012). The Forestry Sector Master Plan states that in 1993, the amount of wood consumed was 29.5 million cubic meters (Mm3).

In Pakistan's northern provinces, Deforestation exacerbates soil erosion and deterioration. According to Tariq et al. (2014), land degradation and soil erosion in Gallies Forest of Abbottabad Drose as Deforestation increased. This is because albedo makes the land more susceptible to these negative effects, whereas plants and forests serve to offset them. The provincial forest agency's incompetent methods and bad management are to blame for the Deforestation in the north. The forestry extension service provided by the agency is inadequate and fails to tackle the root causes.

One of the leading causes of Deforestation is illegal logging. The quantity of unlawfully harvested wood is calculated from the total amount of wood obtained from Pakistan's State forests and the amount of wood consumed. The value of timber obtained illegally was four times more than that of legally harvested timber. A large portion of the underground economy is derived from illegal logging (Cashore et al., 2016). Pakistan's green cover was less than 5% following Bangladesh's independence in 1971, compared to 7% when Pakistan achieved its independence in 1947.

The annual rate of Deforestation was 1.63% in 2000, in 2005 reaches to 2.02% and in 2015 it was 2.54% in, as shown in table 1.1

Pakistan is at a critical juncture with about 2–5% of its forest cover remaining (Kurosaki, 2011). Pakistan now produces approximately 14 million cubic meters of wood, expected to increase to 32.6 million cubic meters by 2016. To meet people's demands, 33 million cubic meters of wood will be required by 2016. Between 2003 and 2013, the usage of (building, furniture, village carpentry, mining timber, and industrial fuelwood) increased by 42%, from 3123000 m3 to 4434000 m3, as shown in Table 1.2.

The conceptual framework states that the growth of agriculture and infrastructure, wood removal, and other elements such as social trigger events and predisposing biophysical circumstances are the direct causes of Deforestation (Geist and Lambin, 2001). A global study on the evolution of deforestation drivers and their possible effects on the cost of deforestation avoidance techniques employed this paradigm (Shehzad et al., 2014).

Threatened forests in Khyber Pakhtunkhwa and Kashmir are at risk from armed groups engaging in illicit timber harvesting. Illegal timber is trafficked between Afghanistan and Pakistan.

After being smuggled out of Pakistan, the wood is brought back to Pakistan, pretending to be duty-free Afghan wood. The timber is transported to Karachi and, ultimately the Gulf States after smuggling into Pakistan (Nizami, 2013).

In order to save the forests, government organizations must combat illicit logging. All logging, whether legal or illegal, causes Deforestation. The government has imposed tree-cutting prohibitions in recent programs (1991, 2005, and 2010). However, the wood mafia has continued to harvest wood despite corruption, political intervention, a lack of sincere commitment, and theft on the part of the government to prosecute the criminals. Because of this, those who traffic in wood use any means necessary to sneak it in order to make quick money.

Due to existing rules and government scrutiny, only 20 wood licenses spanning 910,000 hectares of forest were granted. The government's latest strict forest conservation restrictions have resulted in a 79 percent fall in active wood permits. In response to market demands, the government incentivizes the private sector to invest in industrial forest plantations, establishing 172 such plantations over the past ten years.

Table 1.1. Rate of Deforestation in Pakistan went from 1995 to 2005

Variable	1995 - 2000	2000 - 2005	2005 - 2010	2010 - 2015
Total forest area in the base year (ha)	2321000	2116000	1902000	1687000
Annual forest loss (ha)	41100	42800	43000	42800
The annual rate of deforestation %	1.63	2.02	2.26	2.54

Table 1.2. Wood consumption sectors in Pakistan

Consumption (Km3)	1995 - 2000	2000 - 2005	2005 - 2010	2010 - 2015
Construction	1711	2381	3322	3930
Furniture	2216	3123	4434	5310
Village Carpentry	62.7%	57.4%	55.5%	53.4%
Mining Timber	505	742	1112	1380
Industrial Fuelwood	1320	2319	3551	4633

1.2. Literature Review

Forests impact the climate through their physical, chemical, and biological processes at local, regional, and global levels. They are a crucial resource as forests build resilient landscapes by protecting coastal areas from extreme events, soil improvement, water flow regulation and maintenance for agriculture. They are a critical part of the carbon cycle as they absorb carbon as they grow. However, when forests are cut or burnt through land use changes, they release carbon and other greenhouse gases, thus significantly impacting the climate Liang & Wang, (2020).

According to the UN's Food and Agriculture Organization, forests cover only 2.2% of the area in Pakistan, and they are also subjected to Deforestation for development and agriculture. In Pakistan, forests are a major resource of timber and raw materials such as fuel wood. However, the health and richness of forests in Pakistan are declining due to the overharvesting of wood for fuel, natural hazards, lack of management and planning, and unsustainable usage practices, which are leading to loss of forests and environmental degradation. Moreover, the forest loss is related to the specific land use practices related to converting forest land to barren, agricultural and built-up areas (Mannan et al., 019). Remote sensing and GIS have been used as powerful tools in multiple studies to monitor land use changes by providing spatial and temporal information.

Hao et al (2021) studied the land use and land cover changes in the Tibetan plateau using Landsat OLI images from 2013 and 2015. LULC information was extracted through the Landsat imagery, while DEM was used to extract the land's curved surface area and analyze the three-dimensional dynamic change. Based on field sampling and forest inventory data, the study area was divided into five cover types: broad-leaf forest, coniferous forest, shrubbery, water, and non-forest land. The results indicated that the coniferous forest area decreased by 25.14%. However, the shrubbery and broad-leaf forest increased by 14% and 12%, respectively. The study observed dynamic changes through the three-dimensional land use landcover visualization.

Hossain et al (2023) conducted a study to detect the land use and land cover changes in the Fashiakhali Wildlife Sanctuary in the Chittagong hill tracts in Bangladesh over three decades from 1994 to 2021. The Landsat images were classified using the maximum likelihood algorithm and vegetation indices were calculated and compared with the LST. The study revealed that the forested and agriculture land declined by 12% and 8%, respectively while settlements expanded by 13% due to massive human migration. The study also compared the indices NDVI and SAVI and concluded that NDVI was a more accurate measure for forest cover assessment. A negative correlation was seen between NDVI and LST which revealed that climate change had a negative impact on the study area in terms of forest loss.

Islam et al., (2021) conducted a study on forest cover loss in Nijhum Dwip National Park (NDNP), a part of Sundarbans mangrove forest in Bangladesh. The maximum likelihood classification technique was used on the 1990, 2001, 2011, and 2020 Landsat images. The study area was divided into five major land cover classes: forest, non-forest vegetation, sand, barren land, and water body. The Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) were calculated. The study further compared the forest cover changes from NDVI and SAVI-based classification with supervised classification. The results indicated that about 42% of total forest cover (1781ha) had been deforested between 1990 to 2011 while about 310ha of forest area increased from 2011 to 2020. The study also declared NDVI a better indicator of forest cover change than SAVI.

In another study by Lemma et al., (2021) worked on Temporal change of forest concerning Forest Cover Change Detection concerning atmospheric changes and Land use Land Cover change using Remote Sensing and Geographic Information System Techniques for Kaf Zone in Southwest Ethiopia. In this study, satellite images were taken at a resolution of 30m to monitor temporal forest and LULC changes. To identify different land use land cover study used classes supervised classification, then a classification comparison was made measuring the level of forest change. Results of the study showed from 1986 to 2018 change of 1168.65 ha occurred. Normalized Difference Vegetation Index (NDVI) values, due to drop of NDVI value from 0.060.064 to (–0.08)–0.12 in 1986 and 2018 respectively.

Negassa et al., (2020)I worked on forest cover change detection using the Geographic Information System and Remote Sensing Techniques for Komto Protected Forest East Wallinga Zone Ethiopia. The Results showed 23.68% annual expansion rate for agriculture land and forest land declined 4.8% annually. Their findings indicate decline in forest class and rise in other classes.

Hu et al., (2023) conducted a study on land use, land cover change detection, and NDVI estimation in the southern Punjab province of Pakistan using four images from the years 2000, 2007, 2014, and 2021. Land use changes were determined from Landsat imagery, and MODIS was used to calculate NDVI. The results of the study revealed that the forest cover decreased by 31% while settlements and barren land increased by 14.5% and 12.8%, respectively.

Remote sensing techniques have been used in various studies to classify and map the land use land cover changes, particularly in forested areas. Another such study was conducted by Philippe & Karume, (2019)where they assessed the land use land cover change in the North Kivu province in the democratic republic of Congo and analyzed the deforestation hotspots. Landsat imagery was used to detect the and land cover change through supervised classification in ArcGIS. Land use and land cover changes were detected through supervised classification in ArcGIS, and change detection was performed using ERDAS IMAGINE. The deforestation hotspots were identified through the Getis Ord spatial statistics tool of ArcGIS. The results indicated a 30% forest cover loss while the major factor identified for Deforestation was agricultural expansion in the region.

Another study was conducted in the Nandi North Forest zone in Kenya by Wachiye, (2013) to investigate the patterns of land use change and vulnerability of forests using the Remote data of 1986, 1995 and 2006. They classified the area into seven classes namely, grassland, dense natural forest, plantation forest, built up area, sparse forest, agricultural land, and tea plantation. Both supervised and unsupervised classification methods were used for land cover assessment through using false color composite images for interpretation. Various factors such as accessibility to roads, proximity to guard stations, elevation, and population were analyzed to assess the vulnerable areas that were highly susceptible to forest cover change. The vulnerability map showed that about 9300 ha of forest fell under the highly vulnerable category, about 2000 ha was moderately vulnerable and about 1900 ha fell under the less vulnerable areas. The study concluded that closeness to settlement, gentle slope, and low elevation were the driving factors of high vulnerability to Deforestation in the area.

Tariq et al., (2023) conducted a study to monitor the spatio-temporal changes in forest cover in the Khyber Pakhtunkhwa province in Pakistan using the remote sensing and GIS techniques. The study used Landsat imagery for the years 1990, 2000, 2010 and 2013 to 2017 were utilized to perform land cover classification and the images were classified into built up area, barren land, forest, snow, vegetation and water. The classification was performed using three machine learning techniques namely Naïve Bayes Tree (NBT), Support Vector Machine (SVM), and Kernel Logistic Regression (KLR) for monitoring land changes mainly for forest class. The results indicated that SVM had better accuracy than NBT and KLR in forest cover change detection.

Shah & Shah, (2023) performed a study to determine the forest cover change in Dibru Saikhowa National Park in Assam by using Landsat imagery for the years 2012, 2017 and 2021 for classification of land and examining Forest cover and pattern. Study revealed decline of forest from 223.5km^2 in 2012 to 203.4 km^2 in 2021. The main factors for the forest cover change were increased population, encroachments, and natural factors such as bank erosion from the river Brahmaputra near the southwestern part of the study region.

Developing sustainable forest management practices is essential to restore the ecosystem services and resources provided by the forests. For this purpose, it is essential to gather insight regarding the drivers that influence land use change and the conversion of forest land to non-forested area (Xiao et al., 022).

Debebe et al., (2023) conducted a study to analyze change of forest and association with drivers in National Park Semein Mountains Northwest Ethiopia. The study utilized Landsat images from 1984, 1996, 2008, and 2020 for forest cover mapping and changes in land use through remote sensing techniques. Both supervised and unsupervised classification techniques were used to classify the images and accuracy assessment was performed by using google earth images and NDVI maps. Change detection was performed by using the overlay procedure in ArcGIS and computing a change transition matrix. The drivers of forest cover change were assessed by collecting socio-economic data via questionnaires and field observations. The study's results revealed that cultivated land, built-up areas and bare land increased at higher rates while the grassland and forest cover decreased. The surveys and field observations analyzed multiple contributing drivers of forest cover change, population growth, agricultural expansion, livestock pressure, growing demand for fuelwood, and forest fires.

Another study was performed by Abebe et al., (2022) to map and quantify land use land cover changes and their drivers in Gubalafito district in Northeastern Ethiopia. The Landsat images of 1986, 2000, and 2016 were utilized, and five land cover classes were formed, including bushland, cultivated and settlement, bare land, grazing land, and forest cover. The study's results revealed that forest cover decreased from 8.9 to 2% while forest cover decreased from 8.9% to 2% while bushland, settlement, and cultivated areas increased. Various drivers for LULC changes were identified, such as agriculture and settlement expansions, population pressure, increasing wood demand for fuel, charcoal production, and livestock grazing.

Arekhi, (2011) conducted a study to determine the factors influencing forest degradation and to predict the spatial pattern of Deforestation using GIS and logistic regression in northern llam forests in Iran. Landsat images from 1988, 2001 and 2007 were processed and classified into two major classes (forest and non-forest land) to determine the deforestation factors. The logistic regression method was used to model and estimate the spatial distribution of Deforestation. Moreover, various driving factors were analyzed for and distance from road, forest fragmentation index, settlement areas, elevation, and distance from the forest edge and slope. The results indicated that more Deforestation occurred in the fragmented forests and areas near the forest/ proximity to the forest edge while the deforestation rates decreased with increased elevation.

Panigrahy et al, (2010), conducted a study on assessment of Forest Cover Change Detection of Western Ghats of Maharashtra using satellite Remote Sensing based Visual Interpretation. This study showed a decrease in the dense forest class by 610.2sq.km contributed to 10.57% of total dense forest cover in 1985-1987 of which 599.45sq.km has been changed to open forest.

Klyiola, (2014) worked on Application of Remote Sensing and GIS in Land use/Land cover mapping and change detection for Shasha Forest reserve Nigeria. The result shows that rise in Agriculture land to 30.96%, Farmland cover 22.82% and urban land to 3.09%. This study also justifies that using Remote Sensing and GIS Techniques for Land use/Land Cover Mapping and change detection are cost-effective and appropriate.

Awan et al, (2018) his Study aimed at Forest change detection and its environmental impact for District Abbottabad over 9years of time (2000-2009). Results showed that 1% decrease occur in forest in 9years and vegetation increased about 36%. Change of maximum 9 and minimum -10 observed in land surface temperature.

Mohamed, (2021), Study focused on working with multi-temporal Landsat images to identify and assess changes in the dynamics of forest cover and its density between 2010 and 2020. The study suggested that several diverse variables contributed to the change in forest cover. The rise in cultivated land, population growth, and urbanization were all associated with a loss of forest.

Osman et al, (2022) his Study aimed to evaluate LULC changes in the Gedaref state, Sudan for the past thirty years (1988–2018). Moreover, the study aimed to predict future Land Use Land Cover outlook for 2028 and 2048 using Cellular Automata-Artificial Neural Network (CA-ANN). Results showed drastic LULC dynamics were driven mainly by cropland and settlement expansions, which increased by 13.92% and 39.61%, respectively, between 1988 and 2018. In contrast, forest and grassland declined by 56.47% and 56.23%, respectively. Future LULC predictions showed a slight increase in cropland area from 89.59% to 90.43% and a considerable decrease in forest area (0.47% to 0.41%) between 2018 and 2048.

Ahmet Salih, (2023) aimed to examine spatial and temporal change of LULC for the year 1990. 2006 & 2022, by using Landsat Images, moreover cellular automata–artificial neural network (CA-ANN) model integrated in the MOLUSCE plugin of QGIS were used to predict LULC of years 2038 and 2054 for Duzce City Turkey. Results of this study suggested that artificial surfaces grew by 100% between 1990 and 2022, from 16.04 to 33.10 km2, and are projected to be 41.13 km2 and 50.32 km2 in 2038 and 2054, respectively. Artificial surfaces, which covered 20% of the study area in 1990, are estimated to cover 64.07% in 2054, consequently resulting in 1st-class agricultural lands massive loss.

1.3 Rationale and Scope of the study

This work contributes to our understanding of the social and economic activities that lead to Deforestation, the nature of those activities, and the extent to which human livelihoods depend on forests. There is growing socioeconomic concern over Deforestation's influence due to its varied repercussions, including positive and negative socioeconomic outcomes, especially in this century. Positively, the world's forest resources are running out, improving household livelihood security and providing extra socioeconomic, cultural, and spiritual advantages. In the past, estimates of the effects of socioeconomic factors and forest cover studies were made for the Abbottabad district of KPK, Pakistan. Focused in prediction of future LULC analysis for year 2030 by highlighting significant factors causing forest cover loss Abbottabad. The study was conducted with an understanding of how much forest lost occurred in ten years from 2010 to 2020 and how much of the population depends on agriculture. In the past, estimates of the effects of socioeconomic factors and forest cover studies were made for the Abbottabad district of KPK, Pakistan. Objective is to have clear understanding of land classes in 2030. The study was conducted with an understanding of how much forest lost occurred in ten years from 2010 to 2020 and how much of the population depends on agriculture.

1.4 Objectives

The objectives of the study were to:

1. To determine the temporal trend and drivers of forest cover change

2. To predict the future Land Use / Land Cover for District Abbottabad

Chapter 2

MATERIALS AND METHODS

2.1 STUDY AREA

2.1.1 Geography and Landscape

Abbottabad city of KPK Province was founded in 1853. Abbottabad is located in the captivating Hazara division of N.W.F.P, Pakistan (Figure 2.1). The picturesque district of Abbottabad spans an expansive area of 1,967 square kilometers. The latitude of Abbottabad is 34.15 and the longitude is 73.21. Abbottabad is situated at 1256 meters above sea level. This district is very rich in Biodiversity. District Abbottabad has a very pleasant climatic condition. Abbottabad's weather attracts people which results into population increase. District Abbottabad is bordered by Muzaffarabad district in the east, Mansehra district in North, Rawalpindi in South and Haripur district in West. Abbottabad district lies within the active monsoon zone. Most of the land is rain-fed, with 60% of average precipitation received during the July–August period and the remaining 40% unevenly distributed between September and June.

2.1.2 Climatic Variations

The average rainfall reaches 1366.16mm. The maximum rainfall is received in the month of august (261.27mm) closely followed by July (258.26mm) (IUCN,2004). The surface of Abbottabad is hilly, this district is at base of hills which makes it temperature low most of the time. Abbottabad city is famous for beautiful weather, and it attracts the people from all over country for tourism and this city is also known as city of schools. Renowned for its pleasant climate and breathtaking landscape, this region is a magnet, attracting visitors from all corners of Pakistan. Some come here for tourism, seeking refuge from the scorching summer temperatures that soar above 45 degrees in the country's plains, while its esteemed educational institutions draw others. Indeed, tourism plays a vital role in Abbottabad's economic activity.

In spite of its fame and allure, district Abbottabad is not immune to the challenges of population growth, which have begun to impact its environmental conditions. Over the past few years, the area has undergone significant land use changes. Once adorned with lush pine trees and only a few residential and commercial areas, free from the pressures of rapid population growth, Abbottabad's idyllic climate and natural beauty are gradually being altered due to a combination of natural and socio-economic factors. The most prominent drivers of land use change in this region are the 2005 earthquake, the appealing weather, and the advancements in higher education, which have led to increased migration to the area. As a result, the demand for residential and commercial spaces has soared, leading to escalating land prices. Unfortunately, Deforestation has resulted in deforestation and converting forested, grassland, and agricultural areas into residential colonies and commercial zones, housing hotels, restaurants, and markets.

Regrettably, the lack of appropriate land use planning and sustainable development measures has given rise to several pressing issues. The plummeting water table, contamination of drinking water, inadequate water drainage systems resulting in flood-like situations during heavy rainfall, and an influx of vehicles leading to recurrent traffic congestion and air pollution are among the challenges now faced by the once-traditionally unspoiled district of Abbottabad. The gravity of these changes threatens the long-term harmonious relationship between the people and surroundings. Hence it’s hard to gather information on land’s patterns, explore opportunities within their optimal utilization to meet the escalating demands of the growing population's basic human needs and welfare. Such information is also vital for monitoring land-use dynamics due to the changing demographics. These powerful tools have proven effective in detecting land-use and land-cover spatial and temporal dynamics (LULC). RS provides abundant, cost-effective, and real-time multi-spectral and multi-temporal data, which can be transformed into valuable information for understanding and monitoring land development patterns and processes, thereby building comprehensive land use datasets.

Meanwhile, GIS can store, analyze, and display geo-referenced data essential for change detection. This study delves into in-depth analysis of the land use changes in district of Abbottabad, utilizing these advanced techniques of Remote Sensing. This study aims to provide invaluable insights, especially if there is ever a consideration for city planning that prioritizes the preservation of Abbottabad's natural beauty and sustainable development.

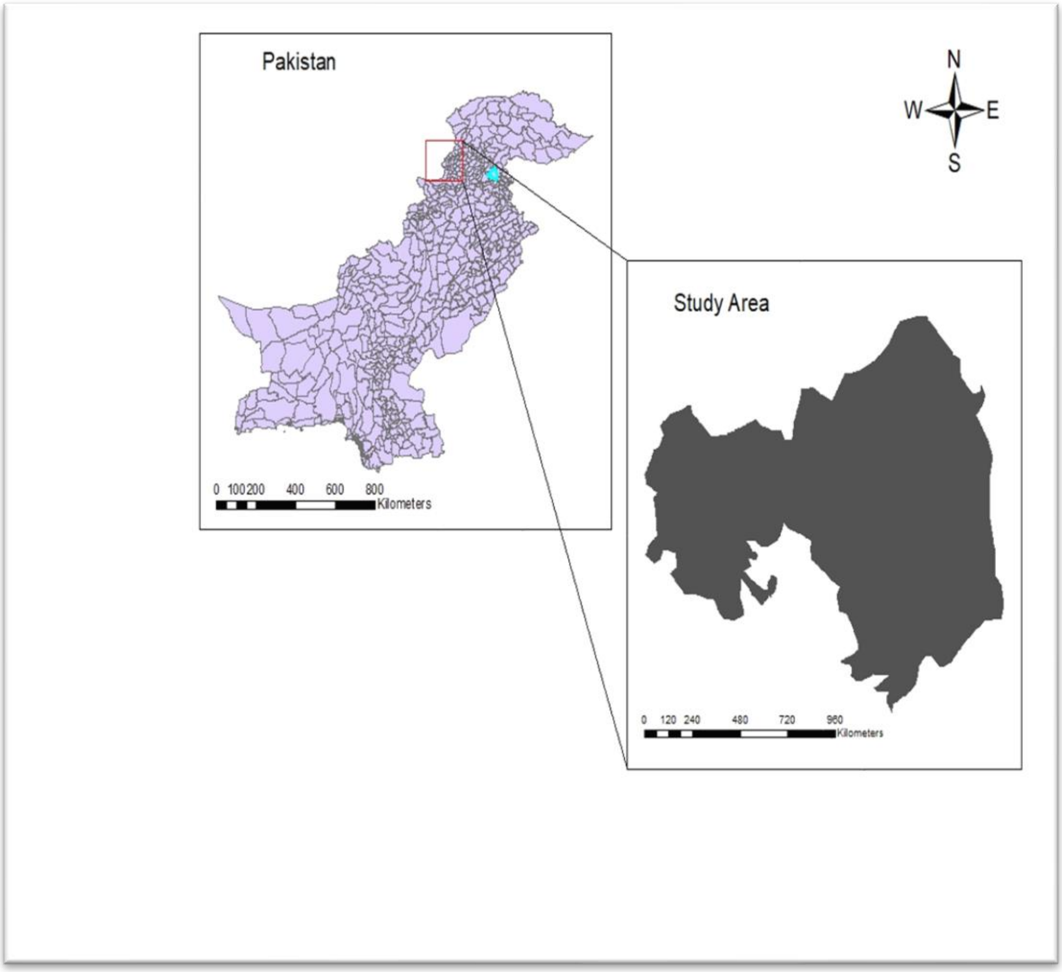

Figure 2.1. Study area map of District Abbottabad

2.1.3 Data sets

The main data set was remote sensing data, including imagery from 2010 and 2020 with a resolution of 30 meters. It was acquired from USGS, as shown in Table 2.1. Imagery of year 2010 was of Landsat 5 while image of year 2020 was of Landsat 8, both the images were of same April season to reduce chance of miss-classification, Moreover Digital Elevation Model (DEM) was downloaded from USGS server with a resolution of 1arc.

The second important data set was ground data, which consisted of road, river, river, and population data. Road data was extracted from Open Street Map using extract.bbbike.org, which is a gateway that provides OSM data in vector form. River and stream data was downloaded from www.hydrosheds.org, explaining every stream and river flowing near or in the study area.Landscan.ornl.gov, which provides population data yearly in this study population record of the year 2010 and 2020, was downloaded.

This study used an online survey that provided the data of Agriculture Involvement & Trend, Livestock and grazing, Wood Consumption, Fuel wood Consumption, Trends & Role of Urban Land and Population. Residents of Abbottabad filled survey.

Table 2.1. Dataset used in current study along with their specifications

Raster data	Description	Source
Satellite Imagery	Landsat-5 Date (2010/04/15) Resolution (30*30)	USGS
Satellite Imagery	Landsat-8 Date (2020/04/10) Resolution (30*30)	USGS
SRTM DEM	Resolution 1 Arc	USGS
Ground Data	Description	Source
Road Data	Road Network (OSM)	bbbike.org
River Data	River, Streams, Lakes	hydrosheds.org
Population Data	Yearly Population data of 2010 & 2020	Landscan.ornl.gov
Survey Data	Description	Source
Agriculture Involvement & Trend Livestock & Grazing	Survey conducted to estimate, which area has more agriculture activities and livestock.	Online Survey
Wood Consumption	Survey filled by people to show their dependency on forest & actions reducing forest	Online Survey
Fuel wood Consumption	Survey conducted to check people are not using SUI gas for domestic use	Online Survey
Trends & Role of Urban Land and Population	Survey conducted to estimate Construction & Pop being cause for Deforestation	Online Survey

2.3 Methods

Prior to interpretation, digital images were processed using standard procedures. First, Atmospheric correction, radiometric correction and image enhancement performed using ArcMap software. After that all the layers were combined using layer stacking method to have single image consist of multiple bands. Both the imagery was stacked in ArcMap. After that image was clipped for study region Abbottabad using Extract by mask method. Moreover, the Methodological Framework shown in figure 2.2 explains data acquisition, preprocessing, analysis, and results.

2.3.1 Image Classification

Classification applies to each pixel in an image. LULC refers to the characteristics present on the Earth's surface, encompassing both elements that occur naturally and those that humans create. Identifying and mapping land use and land cover (LULC) is crucial to global and local monitoring studies, resource management, and planning operations. A classification scheme that defines the LULC classes was utilized to create the LULC map using satellite imagery. More than 2300 samples were taken for classification, keeping in mind the accuracy of the classification if the number of samples are taken. Classes In order to create the LULC map using satellite imagery, a classification scheme that defines the LULC classes was utilized.

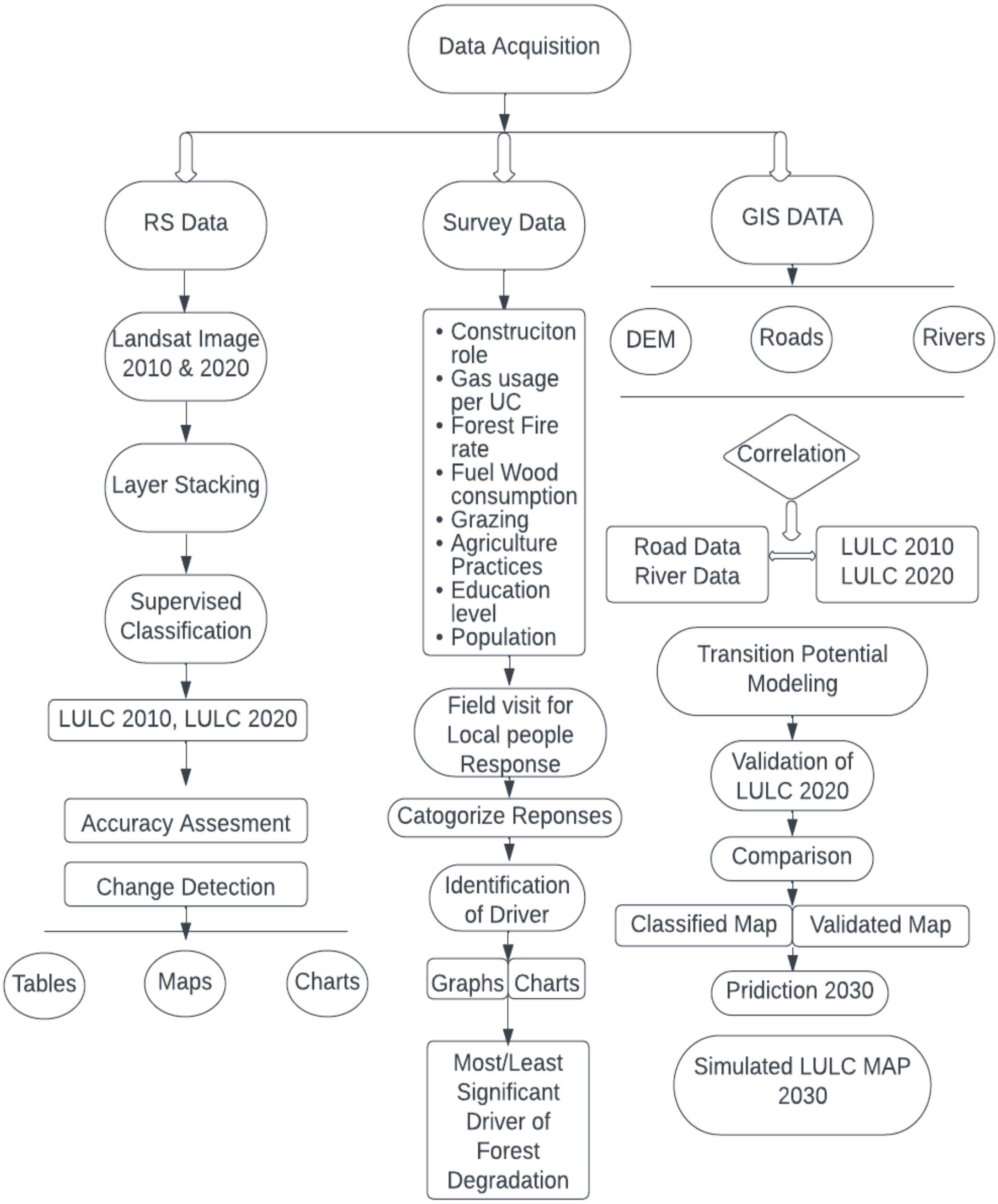

Figure 2.2. Methodological Framework showing data acquisition, data preprocessing and data analysis and results

2.3.2 Sample Collection

Considering the scope of this study, 500 samples were collected from agricultural and forest land. For barren land and urban land, 500 samples were collected separately. Water bodies usually do not show much change so 300 samples were taken for water body class. All these samples were collected by drawing a polygon after that, polygons were merged to identify each class for land use type. All these 2300 samples were used to identify 5 major land use land cover (Water body, Agriculture Land, Forest Land, Barren Land and Settlement Land)

2.3.3 Supervised Classification

Out of two primary ways of picture classification, Supervised classification is best chosen when use possess vast information of subject. Training samples need to be chosen individually for each class. Maximum likelihood classifier used in this study. The chance of pixels belonging to specific class is fundamental factor maximum likelihood classifier. The probability for each class is equiprobable.

2.3.4 Accuracy Assessment

After classification, an accuracy assessment was performed for LULC map of 2010 and 2020. This suggests the producer accuracy, user accuracy and over all accuracy for classified maps. Moreover, Kappa value was monitored to clearly understand these prepared LULC maps for district Abbottabad.

2.3.5 Online Survey

Using googles maps online survey was generated to collect response from resident of Abbottabad, consists of several questions about fuelwood consumption, livestock grazing etc. Half survey was filled out online by people of Abbottabad and half was filled by manually reaching them in their home places. After gathering, all the responses were categorized in sequence, which helped identify the most significant and least significant factors affecting the Abbottabad Forest.

Normalized difference indices are utilized to analyze and classify surface cover

types. The premise of the Normalized Difference Built-up Index (NDBI), proposed by Zha in 2003, shown in equation 2.1, is a method used to extract urban surfaces. It is defined as...

$$\text{NDBI} = \frac{Band\ 4 - Band5}{Band + Band5} \quad \text{----------------------- Eq (2.1)}$$

2.3.6 Future Prediction

CA-ANN model used to find out the analysis for the future years i.e., for the year 2030, the study predicted the LULC for 2030, figure 2.3 represents the model methodology.

To forecast, predict and simulate the datasets using AI technology Cellular Automata Artificial Neural Network is required (Faisal et all 2021). This model is very cost effective for prediction as it consists of various hidden layers to train model (Abdullah-Al-Faisal et all 2021). It predicts results automatically when input data is given, all hidden layers are trained by classified maps with multiple iterations. Hence, valid results are predicted using high accuracy data, described in table 2.2.

CA-ANN model is model of plugin Molusce, needs to be installed in QGIS 2.8. Firstly, to identify the input which trains the model and data simulation is done by measuring the transition trend starting first to last year.

For validation of prediction model, required to datasets map of 2010 and 2020 as initial and final year respectively, to predict for 2030, model consists of various iterations value of 0.1 to 0.4 as minimum and maximum values in graph explaining validation and iterations as shown in figure 2.4

To encourage accuracy and performance of model other factor were fetched like Digital Elevation Model, Distance form roads and rivers etc.

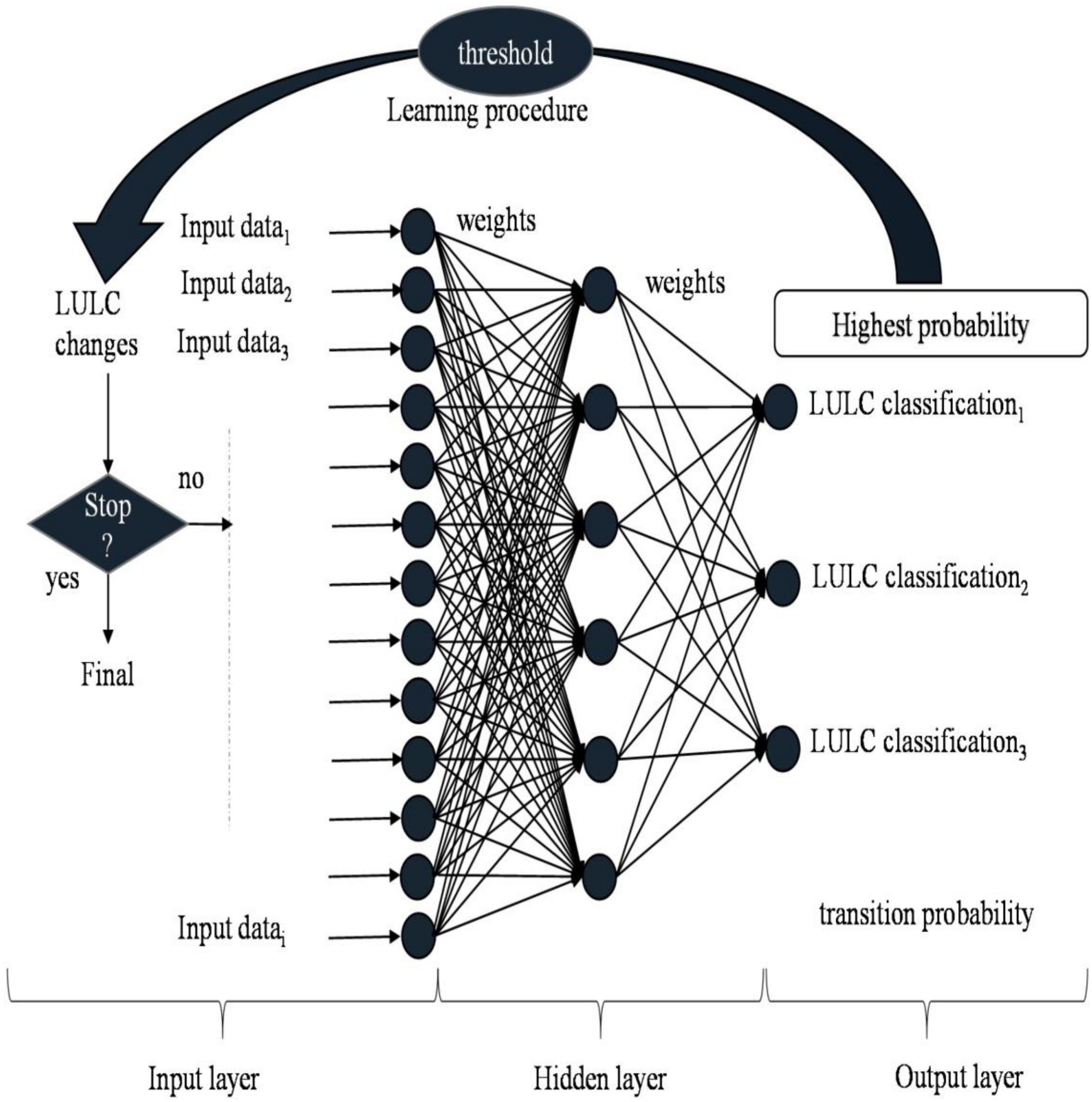

Figure 2.3. Methodological framework for Model Cellular Automata Artificial Neural Network (CA AN)

2.3.7 Validation of referenced maps

Spatial variables were road data, river data and DEM and their validation with land use land cover maps is shown in figure 2.4. LULC was obtained as the input extent, and the LULC for 2020 was obtained as the output extent. Correlation was performed for spatial variables and classified maps. Further, using Cellular Automata- Artificial Neural Network model provides a predicted map after a selective number of iterations, the model shows overall error and kappa coefficient and other factors as shown in table 2.2

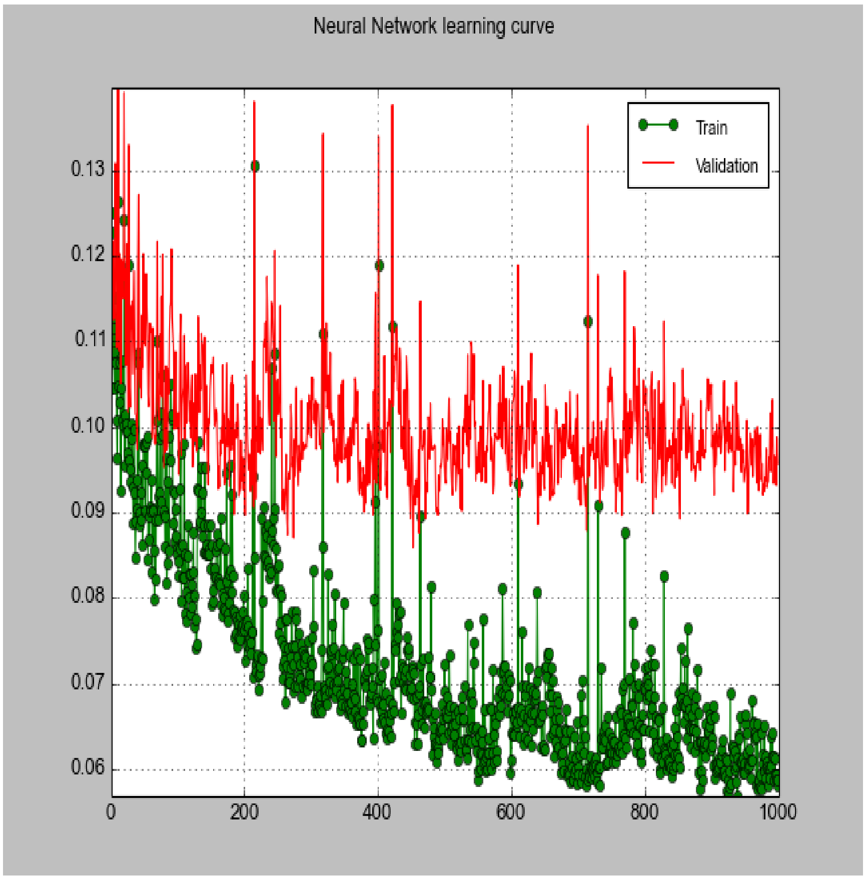

Figure 2.4. Model training with the validation of the input data as LULC

Table 2.2 Model training samples

1	Max Iterations	[50]
2	Hidden Layers	[3]
3	Momentum	[0.050]
4	Learning Rate	[0.100]
5	Min Validation Overall Error	[0.023]
6	Current Validation Kappa	[0.81]

Chapter 3

RESULTS AND DISCUSSIONS

3.1 Land Use Land Cover Withdrawal

Maximum Likelihood Classifier Technique was used for classification of images. Equalized random technique was considered for validation of sample points. Google Earth images of high resolution was used as reference data for validation of sample points.

Five hundred samples were taken for each class. Using satellite image for change detection is very affective as it describes various features on earth plus patterns describe classes and their changes with time to monitor change of one class to another

3.2 Change Detection

To examine change over time five different classes were. Figures 3.1 (a) and (b) represent the result of LULC maps for both years. Noticeable decrease occurred in forest land due to increase in agriculture land in 10 years. Agriculture area gained from 302 sqkm to 609 sqkm resulting decrease in forest land from 657 sq. km (2010) to 450sq.km (2020). The decrease in District Forest was about 15.27% from 2010 to 2020 and then the trend increased by 22.27% for agriculture land.

Table 3.1 shows temporal change in classes. All five classes changed overtime with an intensive rise in Agriculture and a massive decrease in Forest. Urbanization in 2010 was 7.02% & 11.82% for 2020, 4.8% rise was noticed in Urban Land. Barren land also showed a noticeable decrease in 10 years, 13.76% in total, from 301 sq.km (2010) to 116sq.km (2020), consequently decreasing to 185 sq.km. In the case of water bodies in the district Abbottabad, slight change occurred in 10 years; initially, water bodies consisted of 19sqkm in (2010) and 14sqkm in (2020) with total change of 4sqkm.

Forest land from 657 $km^2$to 450sq.km shown in figure 3.2 2010(a), 2020(b). The decrease in District Forest was about 15.27% from 2010 to 2020.

Major conversion of forest land into other types include Forest to Urban Land and Forest to Agriculture as shown in Figure 3.3, specific area converted from Forest to Urban Land (a) and specific area converted from Forest to Agriculture Land in 10 years (b). Area covered by each Land Use Land Cover (LULC) class in square kilometers and the percentage for both 2010 and 2020, as illustrated in figure 3.4 (a), (b) figure 3.5 (a), (b).

(a) (b)

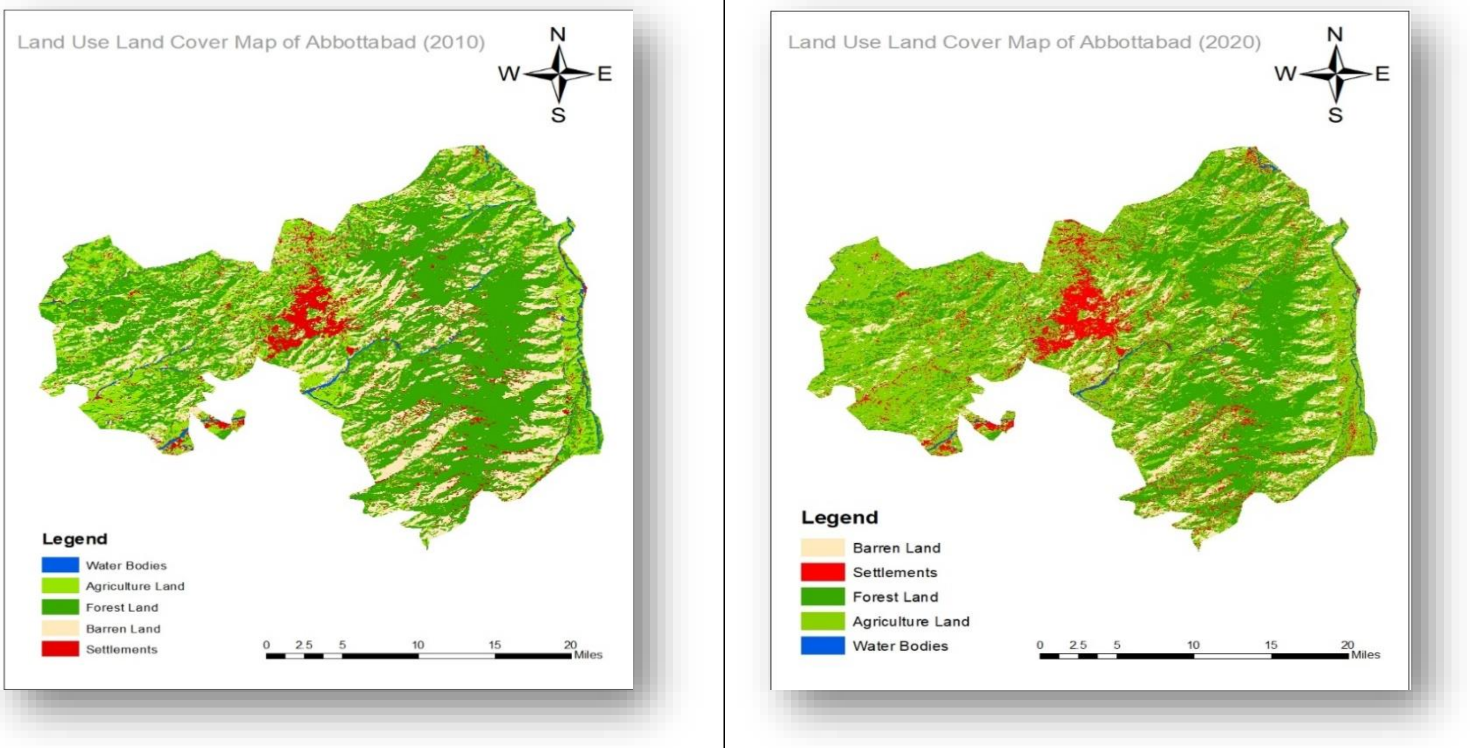

Figure 3.1. Presenting Land Use Land Cover for the year 2010 (a), 2020(b)

Table 3.1. Total Area Covered by Each Land use land cover class

	Class Name	**2010 (sqkm)**	**2020 (sqkm)**	**Δ (sqkm)**	**2010%**	**2020%**	**Δ%**
1	Water	19.07	14.23	-4.84	1.41	1.05	0.36
2	Barren Land	301.96	116.27	-185.69	22.38	8.62	13.76
3	Forest	656.80	449.11	-207.69	48.69	33.29	15.39
4	Agriculture	276.23	609.72	333.48	20.48	45.20	24.72
5	Settlement	94.70	159.44	64.74	7.02	11.82	4.8

(a) (b)

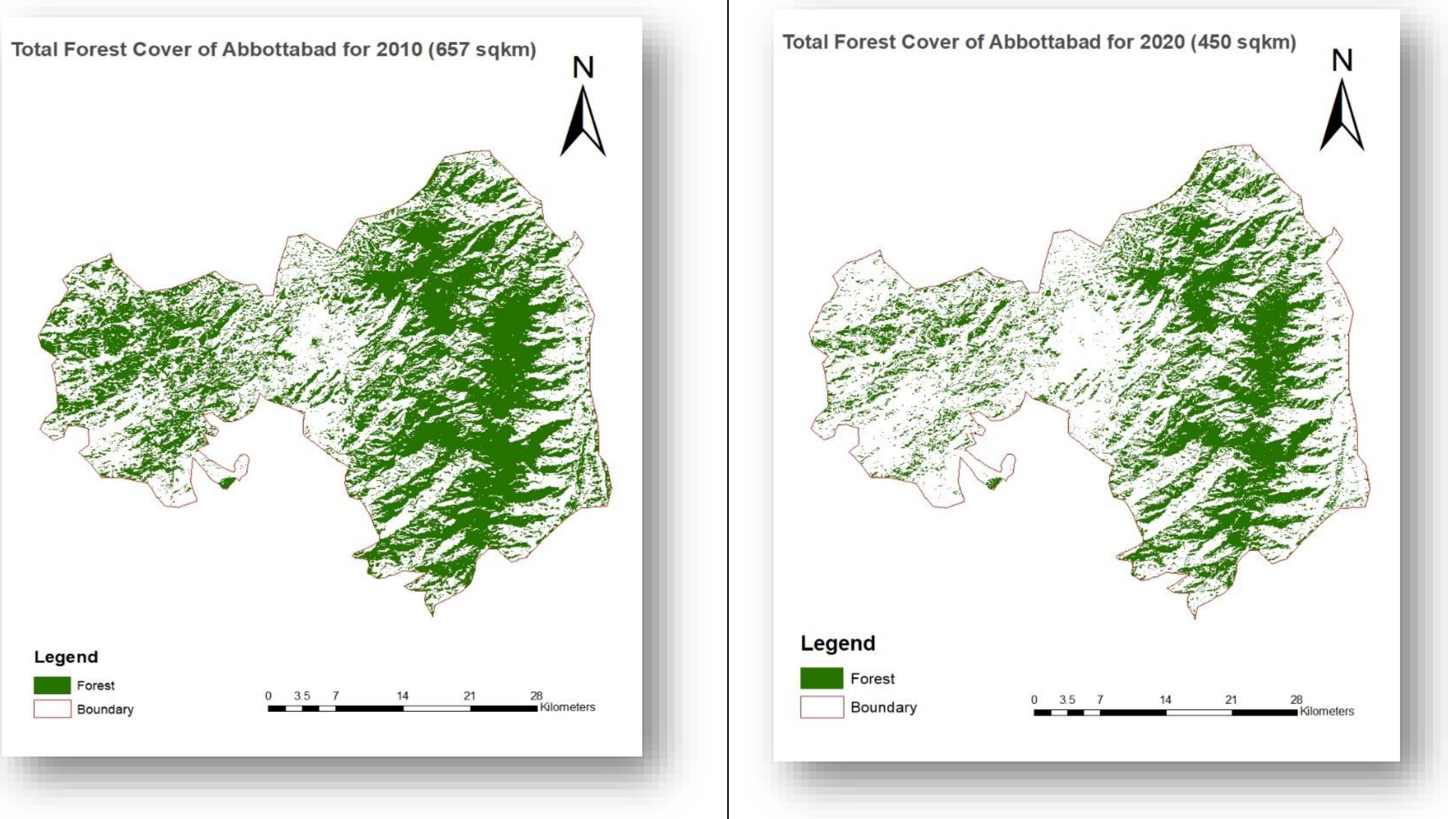

Figure 3.2. Displaying total area covered by forest 2010(a), 2020(b)

(a) (b)

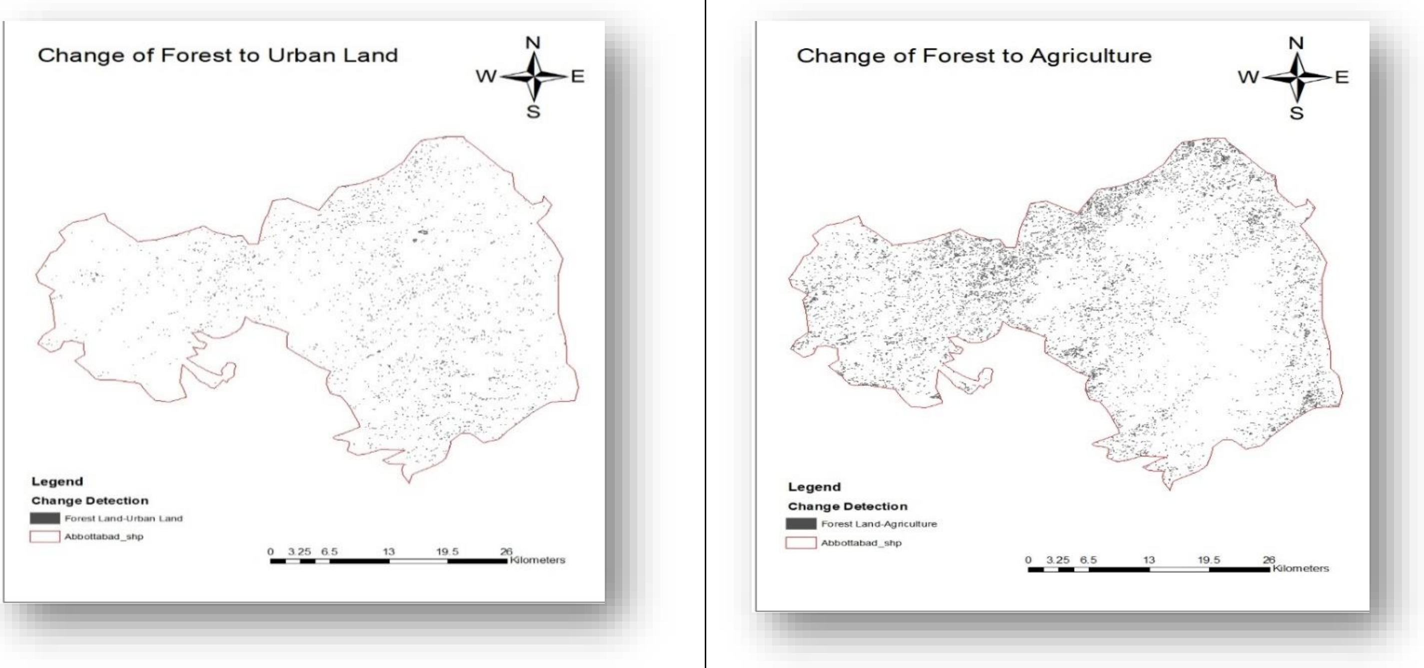

Figure 3.3. Showing forest area converted to urban land (a) and agriculture land (b) from 2010 to 2020

(a) (b)

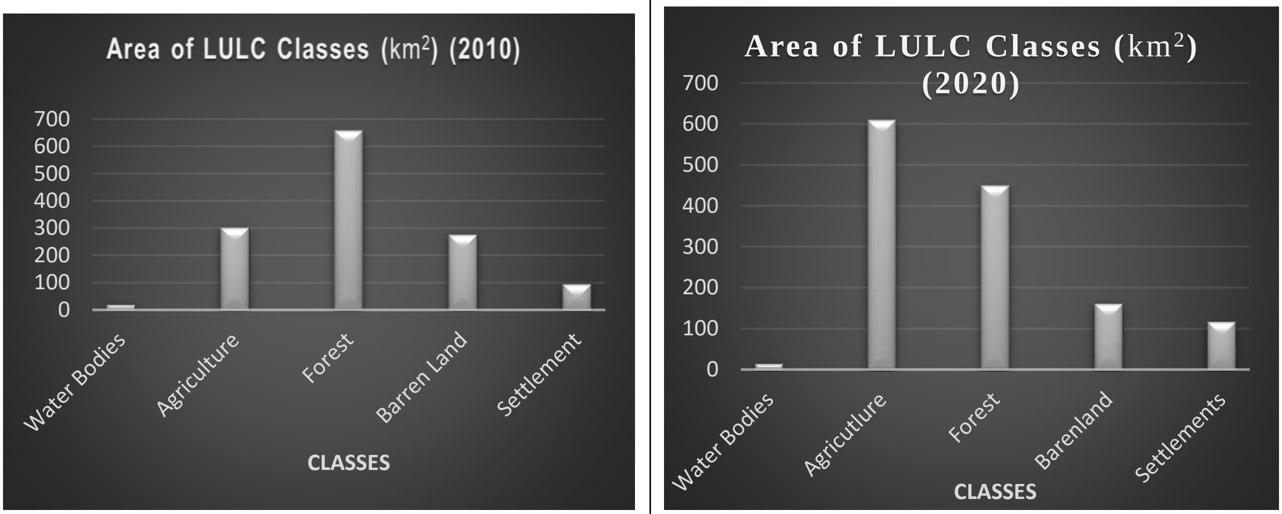

Figure 3.4 Presenting difference between area of land use land cover classes in **(**km^2**)** 2010 (a), 2020 (b)

(a) (b)

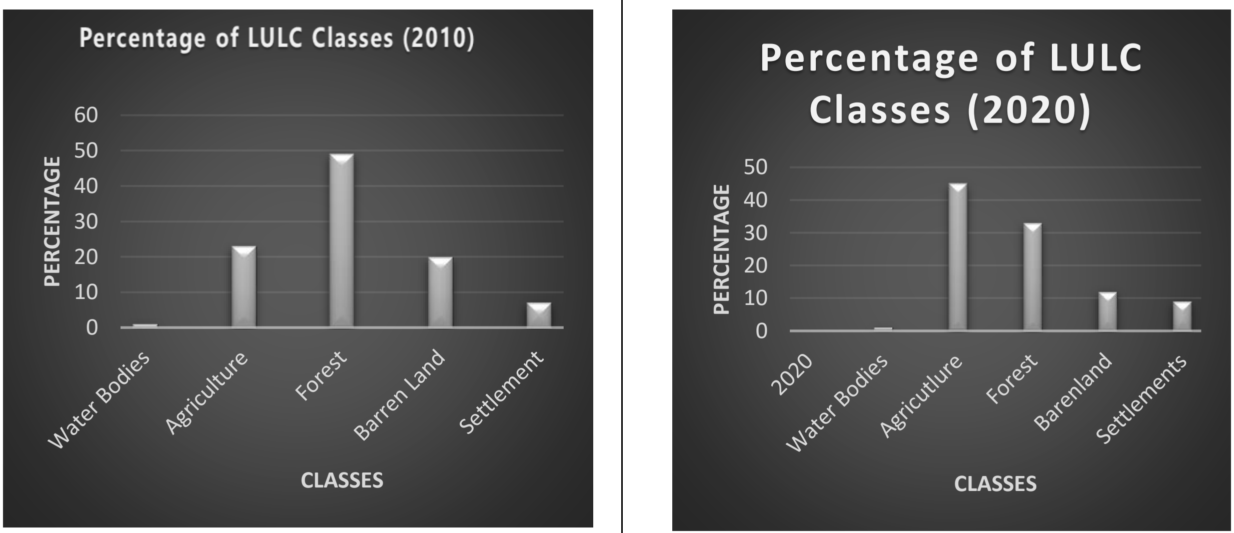

Figure 3.5 Presenting difference between area of land use land cover classes in percentage 2010 (a), 2020 (b)

3.3 The Accuracy Assessment

By using the confusion matrix evaluation of the LULC classification was estimated. Primary aspects of the classification outcome were accuracy and reliability of the classification results. Overall Accuracy, User Accuracy, Producer Accuracy and Kappa Coefficient are shown in tables 3.2 for year 2010 and 3.3 for year 2020.

Result indicated that Overall Accuracy for 2010 image of Landsat was 89% and the kappa coefficient value was 85.5%. Whereas the overall accuracy for LULC classes in Landsat 8 image of the year 2020 was 85.45% and the kappa coefficient value was 81.23%.

Table 3.2. Accuracy Assessment for the Year 2010

Classes	**Water Bodies**	**Agriculture land**	**Forest Land**	**Barren Land**	**Urban Land**	**Total**	**User's Accuracy**
Water Bodies	9	0	0	1	0	10	90%
Agriculture land	0	26	3	0	1	30	86.66%
Forest Land	0	3	27	0	0	30	90%
Barren Land	0	0	0	18	2	20	90%
Urban Land	0	1	0	0	9	10	90%
Total	9	30	30	19	12	100	
Producer's Accuracy	100%	86.66%	90%	94.7%	75%		
Overall Accuracy	89/100) *100=**89%**	Kappa Coefficient	=**85.5%**				

Table 3.3. Accuracy Assessment for the Year 2020

Classes	Water Bodies	Agriculture land	Forest Land	Barren Land	Urban Land	Total	User's Accuracy
Water Bodies	8	0	0	2	0	10	80%
Agriculture land	0	24	2	3	1	30	80%
Forest Land	0	0	30	0	0	30	100%
Barren Land	0	3	0	16	1	20	80%
Urban Land	0	1	0	3	16	20	80%
Total	8	28	32	24	18	110	
Producer's Accuracy	100%	85.71%	93.75%	66.66%	88.88 %		
Overall Accuracy	89/100) *100=**89%**	Kappa Coefficient	=**85.5%**				

3.4 Socioeconomic survey

Agriculture practices in Abbottabad are in the daily lives of residents. This activity is causing a reduction of forests, and this is on alarming condition. The socioeconomic survey consisted of multiple questions stating from overall forest-reducing factors in Pakistan. Conversion of Forest land into another type of land highly depends on social behavior and the economic situation of people; some of the factors of deforestation in Pakistan are Agriculture Expansion, Construction development Fuel wood Consumption, Population Growth, and Forest Fires. Out of all recorded responses showed that 32% of the people said the Construction of roads and houses is the main reason for Deforestation in Pakistan, whereas 31% claimed population growth as main reason, 25% agreed with mentioning agricultural expansion, while 8% and 3% contributed for Fuel wood consumption and Forest Fires respectively. As shown in figure 3.6 (a).

The conversion of Abbottabad Forest land into the urban area is highly influenced by massive increase in Population. Some of native areas population increase results into agriculture activities sacrificing forest land. Using wood for domestic and commercial use also plays a vital role in reducing forest land. When it comes to Deforestation in Abbottabad out of all recorded responses showed 45% of the people says Population growth is the main reason for Deforestation in Abbottabad, whereas 44% claimed Urbanization as the main reason for Deforestation, 27% agreed with mentioning agriculture expansion and Fuel wood consumption. In comparison, 20% and 16% contributed for wood selling and Furniture use, respectively. As shown in figure 3. 6 (b).

One of the questions in survey was about the involvement of people in agriculture responses showed a significant percent (57.5) of people are involved in agriculture and (69) % use agriculture as a source of income, ultimately reducing forest. Miss-managed agricultural activities lead to Deforestation. As shown in figure 3. 6 (c) and (d).

Animal grazing also contributes to forest loss, (66%) of people of Abbottabad claimed they have livestock which somehow effect nearby forests. As shown in figure 3. 6 (e). Due to poor access to the market in backward areas, most people have livestock, and their role is alarming for disturbance in Forest land. Forest clearing was less probable among families with more members working off the farm.

According to a survey, in the past 10 years, construction development is done in the district and has played a role in reducing forest land. A massive count of responses (96.5%) says rapid construction was done in the district of Abbottabad from 2010 to 2020. As shown in figure 3. 6 (f).

Urbanization is a severe threat to Abbottabad Forest; more than 60km increase in urban land is recorded in the past 10 years. According to survey 88.5% of people claim urbanization is a cause of Deforestation in Abbottabad as shown in figure 3.6(g).

Fuel wood consumption is a daily activity of people and continuously affecting Forest from many years. According to survey 62% use sui gas for domestic use, whereas 37% of local people rely on LPG /cylinders, As shown in figure 3.6(h).

Population growth also plays a vital role in consuming natural resources. According to the survey, most people (45%) considered population growth a significant driver of forest loss in Abbottabad. As shown in figure 3.6(I). Population growth leads to multiple factors such as the conversion of land into Agriculture and other types, More land requirement for living, More food requirement, and Limited availability of resources.

Figure 3.6. Showing the results of socio-economic survey

3.5 Validation of Socioeconomic Survey with GIS Analysis

First involves the identification of drivers and first driver is population. Population Map 2010 suggested that total population of Abbottabad was 10500754 in year 2010 shown in figure 3.7 (a) whereas Population Map 2020 suggested that total population of Abbottabad was 1482472 in year 2020 as shown in figure 3.7(b). The overall population increase in district Abbottabad from 2010 to 2020 was 9,018,282. Whereas Online survey suggested that majority of Local people considered Population growth **(44.7%) as** a **Significant** Factor of Forest Loss in District Abbottabad from rest of the Factors. Thus, this validation suggests both sources (Online survey & GIS Mapping) identify population growth as a 1st major significant driver of forest loss in the district Abbottabad between 2010-2020.

The second driver was urbanization in remote sensing Normalized difference indices are utilized to analyze and classify surface cover types. Normalize Difference Built-up Index 2010 displayed less built-up density areas in Abbottabad for the year 2010, as shown in figure 3.8(a). Meanwhile, the Normalize Difference Built-up Index 2020 displayed high built-up density areas in Abbottabad for the year 2020, as shown in figure 3.8(b). The difference in urbanization is observed by comparison of both NDBI Maps. An online survey suggested (96.5%) agreed that rapid construction was done in Abbottabad between (2010-2020); moreover (88.5%) think that this development is reducing forests. Overall **(43.7%)** as a **2nd Significant** Factor of Forest Loss in District Abbottabad from rest of the Factors. Thus, this validation suggests that both sources (Online survey & NDBI) identify Urbanization as a 2nd primary significant driver of forest loss in district Abbottabad between 2010-2020

(a) (b)

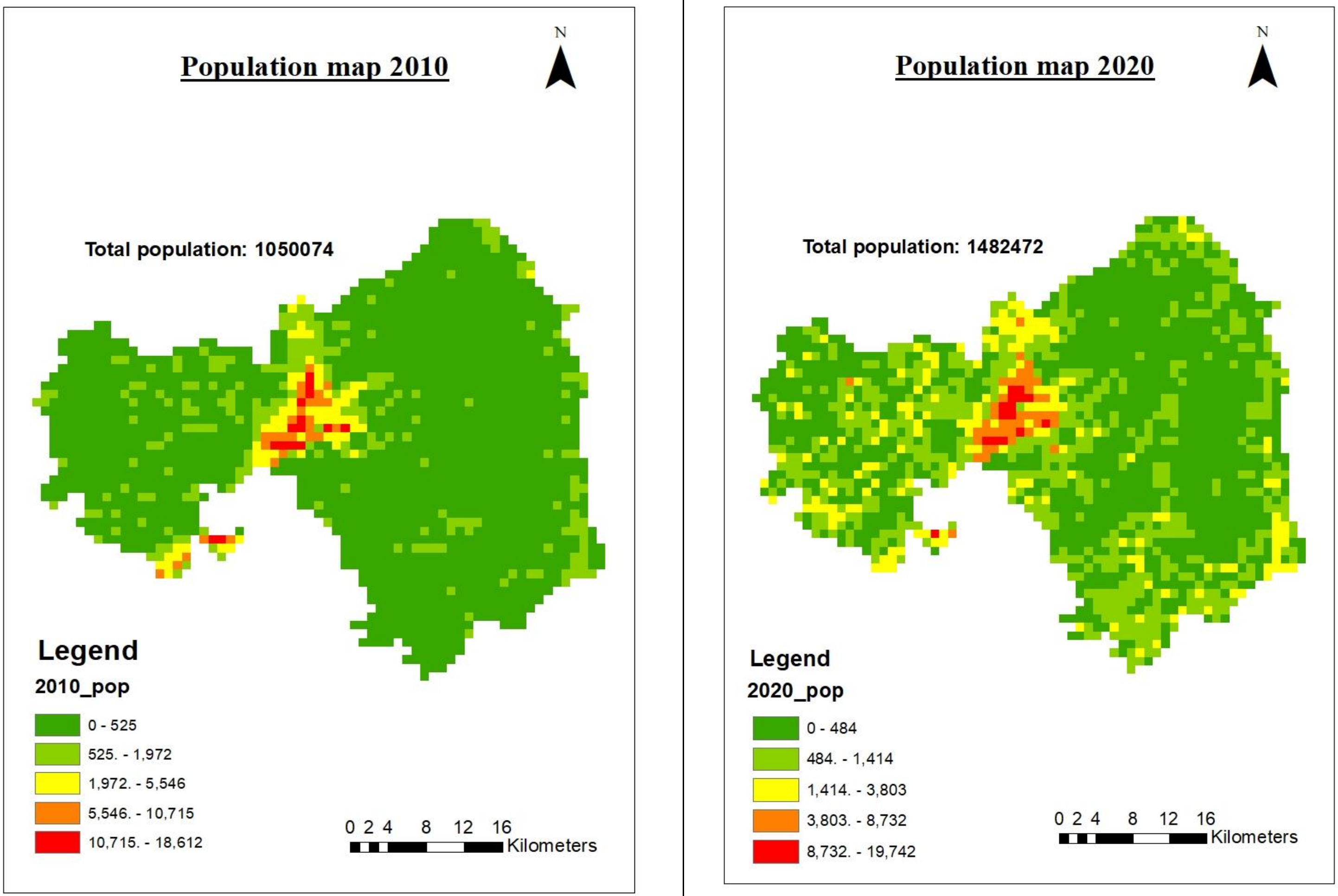

Figure 3.7. Total population of Abbottabad in year 2010 (a) and year 2020 (b)

(a) (b)

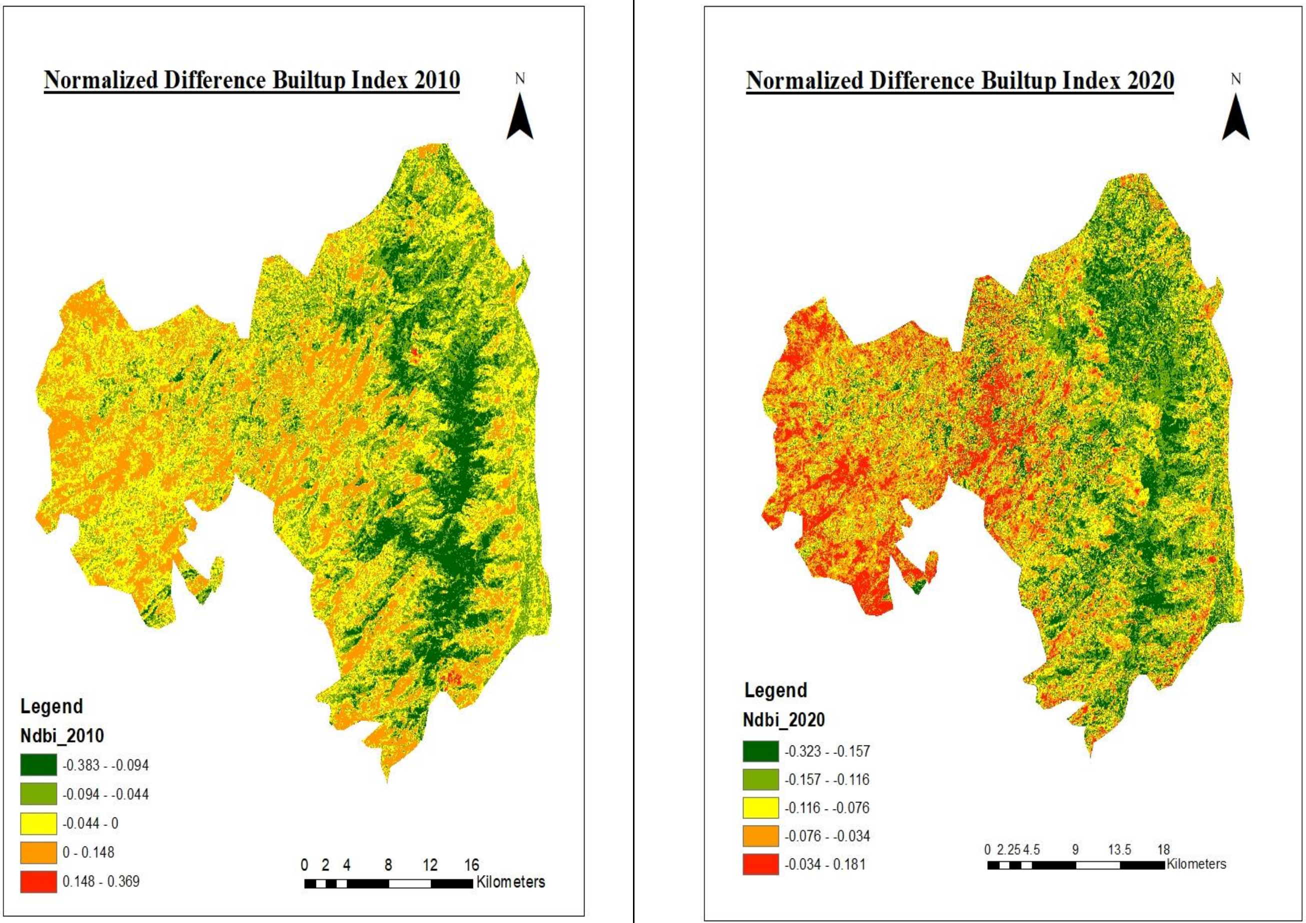

Figure 3.8. Displaying Normalized difference index for the year 2010 (a), 2020(b)

3.6 Prediction of Land Use Land Cover for 2030

The results of our study concluded that the trend of rising in agriculture, urbanization and population has increased from the year 2010 till 2020, due to construction of roads and expansion of agriculture and massive increase in population leads to loss of forest as every class affects forest class to grow.

Change detection between 2010 and 2020 by the CA-ANN Model suggest each class will show variation related to its area as shown in figure 3.9. This model will predict land use land cover in the basis of this change map prepared by Molusce tool in QGIS.

After the model provides the change map using neurons of Artificial Neural Network predicts the LULC of year 2030. Significant increase in Built-up consequently affecting Forest Land. Agriculture Land increment is also noticeable results into Deforestation as shown figure 3.10.

Predicted area of Land use Land Cover for district Abbottabad in year 2030 showed much variation in coming 10 years from 2020 to 2030. Forest land accounts 450sq.km in 2020 and 257sq.km in 2020 with loss of 193sqkm. Agriculture land doubled between 2010-2020 showed a slight increase of 44sq.km which rose from 609sqkm to 653sq.km in 2030. Water body remains the same. Barren land covered 160sqkm in 2030 and prediction resulted in to decline of 48sq.km with final area coverage of 112sq.km in 2030. Urban Land for year 2030 by CA-ANN Model shows a massive increase, 117sqkm in 2030 reached to 325sq.km in 2030 with net increase of 198sqkm in just 10 years consequently reducing forest land at alarming condition for district Abbottabad as shown in table 3.4.

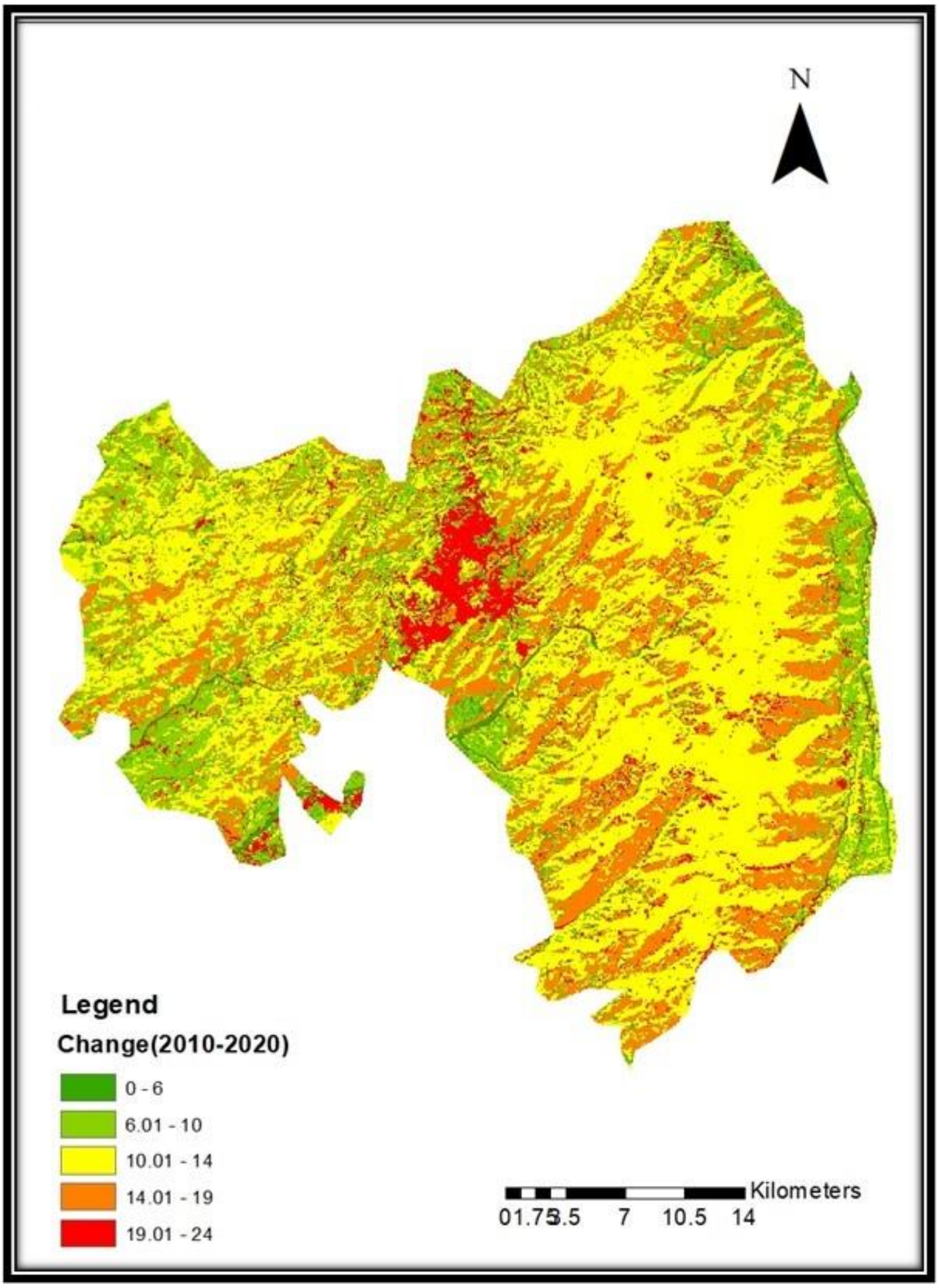

Figure 3.9. Change detection map for 10 years

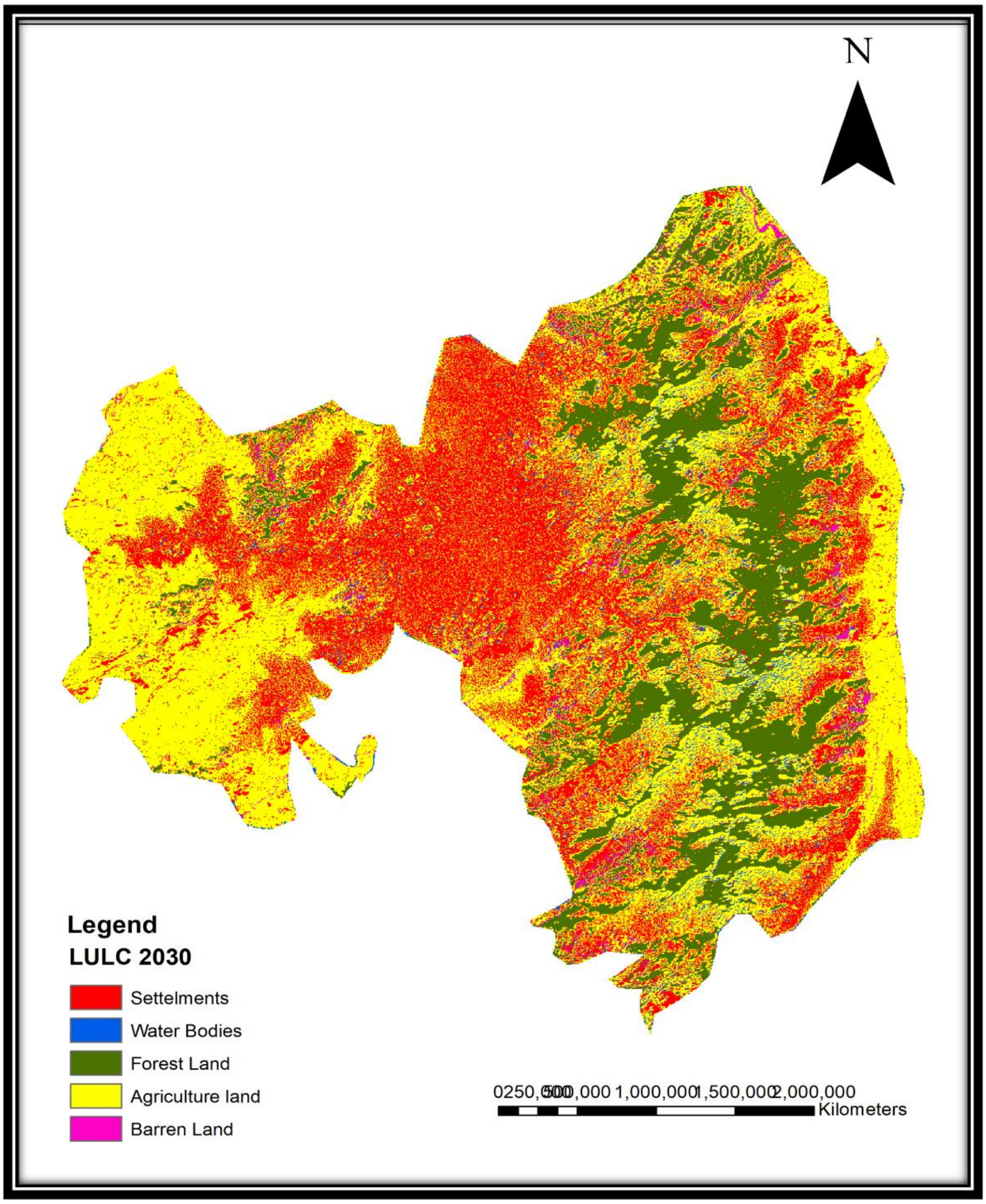

Figure 3.10. Predicted map for year 2030

Table 3.4. Explaining Area covered by each LULC in 2020 and 2030

	Class Name	**Area 2020 sqkm**	**Area 2030 sqkm**	Δ Change
1	Agriculture	609.7	653.9	44.2
2	Barren	160	112	-48
3	Forest	450	257.2	-192.8
4	Water	14.2	12.8	-1.4
5	Urban	117	315	198

Chapter 4

4.1 CONCLUSION AND RECOMMENDATIONS

This study examines the effects of different types of lulc on forest land Abbottabad District during previous two decades (2010-2020). Time-series LULC classes have been retrieved via supervised classification. The Landsat-5 image collection was utilized for 2010, while the Landsat-8 picture collection was employed for 2020. The LULC classification was obtained by utilizing the greatest likelihood approach, using the spectral bands of Landsat-5 and Landsat-8. The time-series LULC categorization maps illustrate changes in various classifications within the district over time. The analysis of several factors indicated that the primary cause for the decrease in Forest land was the significant expansion of Agriculture Land and the rise in Urbanization, which led to an increase in population.

In 2010 Forest from 48.6% declined to 33.3% till 2020 with net change of 15.27%. Moreover, almost an area of 207sqkm of Forest Land was affected. A significant increase (22.27%) in agricultural land was noticed between 2010-2020. Area change was from 302.2sqkm to 609.7sqkm. The built-up area was increased from 7.03% to 8.66% during 2010-2020 with net change of 1.63%. From 2010 to 2020, the 48% change in LULC resulted in Conversion of Forest Land into other Land types. The major drivers that significantly contributed to Deforestation were Population, Urbanization and agriculture. While Fuelwood consumption & Livestock did not significantly contribute to deforestation in the study area. Prediction of LULC indicates that in 2030 major Land use of Abbottabad will be Built-up area & and Agriculture Land.

4.2 Recommendations

The government must Plant More Trees. Engage in tree-planting initiatives in a community or through global organizations.

Forest Department makes strong connections with local farmers who practice sustainable agriculture, helping to reduce the demand for deforested land.

Government departments must Raise awareness about Deforestation in social circles and communities. The more people know, the more they can help.

Abbottabad Forest Department must take strict action against those disturbing Forest Land by any means.

Galliyat Development Authority must initiate a program that voluntarily donates time or money to organizations that work to prevent Deforestation.

The government should provide funding to allocate specific land for Urbanization.

Relations between Infrastructure Developers & and the Forest Department must be strong to prevent loss of Forest Land.

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