LAND-USE AND LAND-COVER MONITORING IN THE HAOR REGION OVER THE LAST 40 YEARS USING HISTORICAL LANDSAT SATELLITE IMAGERY

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CERTIFICATE

*This is to certify that the thesis entitled "**LAND-USE AND LAND-COVER MONITORING IN THE HAOR REGION OVER THE LAST 40 YEARS USING HISTORICAL LANDSAT SATELLITE IMAGERY**" submitted to the Faculty of Agriculture, Sher-e-Bangla Agricultural University, Dhaka, in partial fulfillment of the requirements for the degree of **Master of Science in Agroforestry and Environmental Science**, embodies the result of a piece of bona fide research work carried out by **MD. RAYHAN ISLAM**, Registration number: **18- 09174** under my supervision and guidance. No part of the thesis has been submitted for any other degree or diploma.*

I further certify that any help or source of information, received during the course of this investigation has duly been acknowledged.

Dated: DECEMBER, 2020
Dhaka, Bangladesh

Tania Sultana
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DEDICATED TO

MY BELOVED
PARENTS

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ABSTRACT

Land-use and land-cover change is a common and prominent feature in the haor region such as Sunamganj district. The Sunamganj district harbors a large number of wetlands and haors. The aim of this research was to prepare time-laps land-use and land-cover map for every 10 years since 1978 and to analyze and understand the long-term dynamics of land-use/land-cover changes from 1978 to 2018 period of Sunamganj haor region using historical Landsat satellite imagery. 1978, 1988, 1998, 2009 and 2018 images were obtained from http://earthexplorer.usgs.gov. Ground truth data were created using historical Google Earth images, which were primarily utilized to improve supervised classification and accuracy assessments. Maximum likelihood supervised classifications were undertaken in ArcGIS (Version 10.5) for classification. Each image was classified into four land-use classes: Water Body, Tree cover, Agricultural Land and Other. The accuracy assessment showed that the classification was relatively acceptable and effective in detecting the long-term land-use changes in Sunamganj haor region. It was found that around 245 Km^2 water body had lost and 870.5 Km^2 agricultural land had increased from 1978 to 2018. Tree cover class showed increasing and decreasing trend and around 818 Km^2 other land class had lost from 1978 to 2018. Higher levels of deforestation, combined with population growth and cropland expansion have impacted on Sunamganj haor region. These findings clearly show that the ecosystems of the haor are being harmed as a result of a scarcity of adequate monitoring and management.

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LIST OF ABBREVIATIONS

AL	Agricultural Land
BBS	Bureau of Statistics
EIE	Environmental Influence Evaluation
et al.	et alibi (and others)
etc.	et cetera (and so on)
ETM+	Enhanced Thematic Mapper Plus
FCC	False color Composite
GIS	Geographic Information System
ISODATA	Iterative Self-Organizing Data Analysis Technique
Km^2	Square Kilometer
KML	Key hole Markup Language
LUCC	Land-Use and Cover Change
LULC	Land-Use and Land-Cover
MSS	Multi Spectral Scanner
NASA	National Aeronautics and Space Administration
NIR	Near-Infrared
OLI	Operational Land Imager
OT	Other
%	Percentage
RS	Remote Sensing
SAU	Sher-e-Bangla Agricultural University
TC	Tree Cover
TM	Thematic Mapper
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
WB	Water Body
WGS 84	World Geodetic System 1984

CHAPTER 1

INTRODUCTION

1.1 Background

The popular element for human life and social growth are land. The use and coverage of land resources can have an effect not only on the sustainable growth of the social economy but also indirectly on the transition in the global climate. The most land-use and land-cover change has occurred by urbanization, industrialization, large-scale farming operations. At the same time, the trend of the ecosystem is the development on various scales of the variety of ecological processes in the long-term consequences (Sheeja *et al.*, 2011). The world has been in a state of non-stop transition for a long time. Since the downfall of humanity, the modification of the earth's surface by man's intervention has taken place either to create a better living condition or to manage the need for materials sufficient for the fulfillment of survival. By jeopardizing the equilibrium state of nature, these human activities produce an effect on the atmosphere that induces variation. The environmental change may be defined as modification and complete conversion. Since agriculture was introduced, environmental degradation is the most dominant phenomenon in the world (Asubonteng, 2007). A variation in land-cover, as also suggested in Tegene (2002), can adversely affect the future usage of an environment and can eventually lead to erosion and loss of production. The surface changes of the Planet may be related to the natural dynamics of human activities that occur both rapidly and slowly (Turner *et al.*, 2007). Since human beings first initiated to attain their environment, the land has been changing (Martinez *et al.*, 2009). Land -use and land-cover variations are caused by natural and human activities. Land-use change caused by human actions accelerates the rate of deforestation, soil erosion, loss of biodiversity. Land-use and land cover change have an unlimited impact on global warming, loss of biodiversity, and impact on human life (Anwar, 2002). The natural habitats are depreciated by aggregated human operations. Forest cover heterogeneity triggers the loss of neighboring organisms and the reduction of natural environments and ecosystem services, thus disrupting biodiversity and ecosystem service delivery (Steffan-Dewenter and Westphal, 2008; Sapkota *et al.*, 2010). Loss of trees and land depletion have risen considerably in tropical nations with biodiversity ramifications (Wright, 2005) and human wellbeing (Alfonso *et al*., 2017).

By now, agricultural expansion is the most popular land-use transition associated with the cover of forest damage, along with the construction of infrastructure and wood extraction (Geist and Lambin, 2002).

Wetlands include sites of world heritage with major geological, cultural, zoological, hydrological qualities, including phenomena such as thermal characteristics and underwater rivers (Blasco and Aizpuru, 1997). Bangladesh is a wetland area and can be classified as a wetland by more than two-thirds of the country. Wetland provides financial and environmental benefits to the people living in the haor region. Wetland ecosystems are rich in biodiversity and excessive significance to Bangladesh (Kabir and Amin, 2006).

The word “haor” is the unified term for Bangladesh as a floodplain-controlled country of marshes, swamps, bogs, related areas. In the north-eastern portion of Bangladesh, in particular Sunamganj, Habiganj, Moulvibazar, Sylhet, Netrokona, Kishoreganj districts, it is used for traditional terms of wetlands (Bevanger *et al*., 2001). Bangladesh has large wetland areas such as rivers, streams, haors, baors, beels, jheels, lakes, etc. The haors, baors, beels, and jheels are of river descent and are commonly referred to as wetlands of freshwater. The wetland basin takes up the better part of the northeast area (Uddin *et al*., 2013). Overall, the haor region covers 1.99 million ha, which is around 13.5% of the total surface area of the land (Khan, 2010).

Saneer haor, Hail haor, Hakaluki haor, Dekar haor, Builder haor, Chayer haor, Tanguar haor, and Kawadighi haor are the most popular haors in big Sylhet (Shopan *et al*., 2013). The district of Sunamganj covers a significant number of wetlands and haors. Haor basin is a low-lying bowl-shaped basin covering around 3747 km^2 which located Sunamganj district. One of the major wetland systems in the northeast region of Bangladesh is Tanguar haor. It is also claimed to be a component of the largest geosynclines in the world. Tanguar haor is located in Tahirpur and Dharmapasha Thana of Sunamganj (Sobhan *et al*., 2012).

1.2 Need for monitoring the haor region

Haor are widely known as freshwater wetlands, offering social, economic, environmental benefits that provide income and jobs as a basis of their livelihoods. It is the habitat of indigenous birds and sweet water trout. It is of considerable significance in the processing of food, protecting biodiversity, satisfying local and regional demand, acting as a good source of seafood. To live and raise their quality of living, humans are dependent on the working of ecosystems (Khan, 1993). Haor includes certain dynamic roles responsible for preserving the region's and the whole country's natural ecosystem including groundwater recharge, groundwater discharge, flood management, shoreline stabilization, erosion control, sediment or toxicant retention, nutrient retention, biomass export, storm protection/windbreak, micro-climate stabilization, water and transportation, recreation or toxicant retention, nutrient retention, biomass export, storm protection or windbreak (Haque and Basak, 2017).

Due to natural resource loss, soil loss, forest destruction, habitat degradation, water scarcity, unbalanced human interference, and illegal poaching, haor faces immense threats. A common and most serious factor in Bangladesh is rapid population growth, which also greatly affects this part of the country. In the haor sector, extensive agricultural activities have been expanded over the last few decades, pushing the haor to be a vast farm space ecosystem. More and more settlements are established around the haor region to cope with population pressure, which directly and indirectly disturbs wildlife, particularly waterfowl and fish ecosystems. The overwhelming use of agrochemicals, such as insecticides, rendered the problem worse for fertilizers (Sobhan *et al*., 2012).

The monitoring of changes in land-cover using remotely sensed multi-temporal data provides an accurate and detailed measure of the human effect on the environment (Abdullah *et al*., 2015).

Land-use change has been highlighted as a crucial human-induced effect on habitats among the many features of climate change (Turner *et al*., 2007; Lambin *et al*., 2001). To implement environmental conservation and preservation of wetlands and ecologically vulnerable areas, Bangladesh needs effective interdisciplinary policy recommendations and political will (Haque and Basak, 2017).

1.3 Satellite remote sensing for haor monitoring

Land-use/land-cover mapping using the application of RS and GIS technology will classify regions at possible risk of change in land-use and extensive degraded areas of land (Moore and Wilson, 1992). Change detection may be characterized by analyzing it at various times as the method of detecting changes in the state of an entity or phenomena. The system is commonly applied to the surface of the planet since the surface of the earth is constant change in many aspects. To measure changes in forests, haor regions or urbanization, it is very important to know how the land-cover has evolved over time. It provides a detailed overview of the geographical distribution of the community of interest. Comparison of datasets is collected at various times. Decision-makers on land resources and the environment require quantitative knowledge on the geographical distribution and conditions of forms of land-use as well as temporal adjustments. Undoubtedly, the technology of RS and GIS has helped ecologists and managers of natural resources to obtain timely data and observe periodic changes (Bedru, 2006). Remote sensing is a method for data collection that offers a specific insight from which broad areas can be monitored and global surveillance is possible from every place on Earth (Richards and Jia, 2006). A timely and accurate discovery of variance of the surface of the Planet will offer a deeper understanding of the relations between human and natural phenomena to better accomplish and exercise resources (Lu *et al*., 2004; Zhao *et al*., 2006). The remote sensing picture is relevant evidence for the study of land-use/land-cover change (LUCC) (Cihlar, 2000; Kurnar, 2011). A significant resource for tracking LUCC is the Landsat satellite data (Wulder *et al*., 2008; Abdullah *et al.*,2015). Accessibility of Landsat data in the Geo-Cover dataset and the United States Geological Survey (USGS) offers free entry for ground cover classifications of all Landsat imagery (Knorn *et al*., 2009). Exact and up-to-date LUCC evidence is essential for planning and monitoring of forest to realize the influence on the terrestrial ecosystem as well as to attain sustainable development (Ahphan, 2003; Muttitanon *et al*., 2005; Zhen *et al*., 2014).

Moreover, timely and reliable data on LUCC may enable the development of haor region resource monitoring and management policies. According to its continuous data collection, a multimedia format appropriate for computer analysis, and detailed geo-referencing techniques, satellite remote sensing is the most common data source for identifying, quantifying, mapping LUCC trends and adjustments (Yuan *et al*., 2005; Abd El-Kawy *et al*., 2011).

Using multi-temporal remote sensing techniques, tracking land cover changes around haor can provide an efficient and accurate assessment of the human impact on Sunamganj haor region. Significant data for sustainable haor management and LUCC analysis to determine the variations at different spatiotemporal scales in the remote sensing image. For ground cover mapping, the United States Geological Survey (USGS) gives free access to all archived Landsat imagery. For the planning and monitoring of haor and detecting of LUCC, correct and up-to-date LUCC knowledge is important to understand the history and present state of this haor ecosystem as well as to achieve sustainable growth. Also, timely and accurate data on LUCC can encourage the formulation of integrated monitoring and management policies for haor resources. Remote sensing technologies have also been used in this research to investigate haor cover change and its effects on the environment for the development and evaluation of appropriate land use management in the Sunamganj haor region.

1.4 Research objectives

Considering the above facts, the present research work was designed with the following objectives:

- To prepare time-laps land use cover map for every 10 years since 1978 in the Sunamganj haor region from satellite imagery.
- To analyze and understand the long-term dynamics of land-use/land-cover changes from 1978 to 2018 in Sunamganj haor region.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Definition of wetland

According to BHWDB (2012), apart from any channel, a wetland is a region of variable size filled with water situated in a basin that is surrounded by land. It is possible to contrast wetlands with rivers or streams which normally flow. Rivers and lakes feed and drain most of the wetlands.

Wetlands have been identified by the Ramsar Convention as areas of marsh, fen, peatland, or water, whether natural or artificial, permanent or temporary, with stagnant or flowing water, dry, brackish, or salt, including areas of marine water not exceeding six meters in depth at low tide. The term wetland community thus incorporates a wide variety of freshwater, coastal and marine environments that share several similar characteristics (Dugan, 1990).

Haors which are bowl-shaped depressions every year between the natural levees of a river prone to monsoon floods, are mostly located in the country's eastern region, collectively known as the Haor basin covering an area of around 24,500 km². There are 411 haors altogether (Chakraborty *et al*., 2005).

Baors are created by dead river arms, are located in the western part of the country in the moribund delta of the Ganges. The role is also known locally as beel and jheel. During the monsoon, baors are usually heavily flooded, either by local rains and drainage water or by river floods. It functions as local water reserves during the monsoon season and helps to monitor the level of local flooding. This serve as an important source of irrigation during the dry season in some regions (Nishat, 1993).

Beels are large surface water bodies that via internal drainage channels absorb surface runoff water; these depressions are mainly erosion-generated topographic lows. In winter, much of the beels dry up but grow into large and shallow sheets of water during the rains. There are many large and small beels in the active floodplains of the Surma-Meghna, the Brahmaputra-Jamuna, and the Ganges-Padma River systems. There are thousands of beels of varying sizes in Bangladesh. Chalan beel, Chand Beel and Arial beel are some of the most prevalent names. Beels typically stay heavily inundated for much of the wet season (IUCN, 2004).

2.2 Importance of wetland

Bangladesh's lives and livelihoods rely on the wetlands. Wetlands are the source of fishing, aquatic vegetation and biodiversity, irrigation, flood control and navigation etc. In the country's environment, economy and livelihoods, the haors, baors, beels, and lakes play an important role.

Flood water reservoir

A reservoir is a storage space for water. A reservoir usually means an enlarged natural or artificial lake, storage pond, or impoundment created using a dam or lock to store water. Reservoirs can be created by controlling a stream that drains an existing body of water. They can also be constructed in river valleys using a dam. Alternately, a reservoir can be built by excavating the flat ground and/or constructing retaining walls and levees (Ahmed *et al*., 2004).

Irrigation

Irrigation includes freshwater supplied from surface supplies of fresh eaters. More than half of the world's wetlands, which contain almost 90% of all surface liquid freshwater, pose immense ecological challenges that challenge the global ecosystem as a whole, according to a panel of experts at the 3rd World Water Forum. Any wetlands are quickly dying (Reservoir, 2018). The volume of water contained in the freshwater wetland of the planet is about 35 times that found in rivers and many of these lakes are significant human water supplies. Shallow wetlands are the most vulnerable in developed countries, especially those situated in areas of intensive agriculture that send tons of agricultural chemical runoff into lakes or have been drained for drinking water and industrial uses (Ahmed, 2009).

Source of potable water

Wetland water can be a perfect source of water for drinking. Yet raw surface water is not safe to drink in rivers, streams, lakes, and wetlands until it is screened to kill 9 bacteria, viruses, and parasites. Chemical pollutants such as diesel, petroleum, pesticides, and heavy metals can come from drainage pipes, chemical storage areas, petrol tanks, oil drums, or anywhere else open water chemicals have been used (Galib *et al*., 2009).

Fisheries

Around 260 freshwater fish species are present in Bangladesh's inland bodies of water. Inland fisheries alone occupy an area of 4.3 million hectares, 94% of which are open-sea fisheries and only 6% of which are adjacent to the water supply. By implementing a culture-based fishery enhancement strategy, the haors, beels, and baors offer enormous scope and ability to improve fish yield. The principal origins and stocks of the broodstock of fish are the haors, beels, and baors. Tanguar is one of the country's famed breeding grounds for wild crabs and flatfish (Chital) (Chakraborty *et al.*, 2005).

Transport route

A perfect way of contact is wetlands. There are a variety of wetlands that are used internationally as a medium of connectivity (Alam and Chowdhury, 2003).

Recreation

Wetlands can be a perfect leisure resource. There are a variety of wetlands around the world that are considered the best areas for recreation. Kaptai Lake, Ramsagar Lake, Lake of the Ozarks, Big Bear Lake, West Okoboji Lake, Lake Cumberland, Lake Tahoe, Lake Havasu, Lake Michigan, Lake Coeur d'Alene, Flathead Lake, and Lake Powell Lake are some of the best recreational wetlands (Haque, 2006).

2.3 Historical development of application of RS and GIS in land-use and land-cover monitoring

To plan at the local and regional levels, remote sensing has been used. The most reliable and cost-effective means of spatial and temporal classification of land-use and land-cover studies are provided by remote sensing. Remote sensing (RS) and geographic information systems (GIS) are powerful instruments for advanced environmental and economic and social management systems (Lillesand *et al.*, 2015; Zhang *et al.*, 2015). The most important tracking mechanism for conservation authorities, municipal administrations, non-government organizations is land-use cover change identification using satellite imagery (Panigrahy,2010). Remote sensing is developed as a state-of-the-art instrument for forest surveillance systems capable of increasing understanding of patterns of deforestation and tropical forest distribution (Mayaux *et al.*, 2005). The improvement in the land-cover map resulting from remote sensing data helps recognize hotspots for deforestation. Satellite imagery-based temporal assessment of land-use and land-cover change is becoming a powerful collection of tools for determining the degree of vulnerability to forests. Remotely sensed data digital archiving offers an outstanding opportunity to research historical changes in land-use/land-cover and link to spatiotemporal trends of those changes to other environmental and human causes (Dewan *et al*., 2012). Forest resources are the most important material base for sustainable growth and periodic tracking of forest condition and change with the aid of remote sensing (RS) and the Geographic Information System (GIS) that underpins sustainable exploitation and regeneration of forests (Boyd and Danson, 2005; Desclee *et al*.,2006).

2.3.1 History of Remote Sensing

The current use of the word 'Remote Sensing' has much to do with the scientific methods of obtaining airborne and space-borne data. Planet observation from airborne platforms has a tradition of one hundred and fifty years, but in the last thirty years, the bulk of innovation and growth has taken place. In the development of remote sensing, the first observation of Earth using a balloon in the 1860s is considered a significant benchmark. Remote sensing is commonly characterized as the art and science of extracting information about an object without being in direct physical contact with an object (Lillesand *et al*., 2015).

Multispectral data provided by on-board sensors have contributed to an increased understanding of crops, trees, soils, population development, land depletion, many other features and processes of the earth. Landsat's photographs that were made available shortly after its launch showed the disturbing reality of Amazonian deforestation. The so-called 'fish-bone' pattern observed by remote sensors has exposed the role of modern roads in promoting deforestation. All navigable waterways in the Amazon that may have been used for uncontrolled extraction were also found (Peres and Terborgh, 1995). This occurrence not only sparked a global deforestation alert but also opened the door to wide-ranging remote sensing of natural resources and preservation of energy.

In the 1980s, there was a sharp rise in the use of remote sensing for natural resource management (Tucker, 1980). The availability of powerful desktop computers and developments in object-oriented GIS have encouraged several industries to explore the use of remotely sensed items. Precision agriculture, health care, catastrophe early warning systems, a wide range of other sectors have rapidly adapted to the possibilities that remote sensing has provided. Since the early 1990s, the use of remotely sensed information for land management, marine ecology, habitat studies, wildlife ecology, greenhouse impact tracking, related activities have expanded logarithmically. Applied geospatial analysis that connects natural resource sciences to the remote sensing sector has begun to take off (Csaplovics, 1992).

The rise in these applications has created opportunities for input to enhance radiometric sensitivity, spatial, temporal-spectral resolution. A new generation of platforms and scanning technologies such as RADAR, LIDAR, SONAR is now evolving. While optical remote sensing provides digital images of the amount of electromagnetic energy reflected or emitted from Earth's surface at different wavelengths, active remote sensing of long-wave microwaves (RADAR), short-wave laser light (LIDAR), sound waves (SONAR) tests the amount of electromagnetic energy reflected or emitted from Earth's surface. Backscatter from electromagnetic radiation generated by the sensor itself (Bergen and Dobson, 1999).

2.3.1.1 Landsat overviews

Landsat is a program that offers a series of platforms and products for remote sensing that are jointly operated by the Geological Survey of the United States (USGS) and the National Aeronautics and Space Administration (NASA). In 1972, this initiative began. Landsat has continually gathered remote sensing imagery around the globe for over 40 years as one of the longest space-based record networks and provides useful knowledge for geoscience researchers. NASA launched the 8th Landsat satellite, called Landsat-8, on February 11, 2013. The previous satellites were called Landsat-1, Landsat-2, Landsat-3, Landsat-4, Landsat-5, Landsat-6 (failed), Landsat-7. There are two Landsat satellites currently active, the Landsat ETM+-7 and Landsat OLI-8.

Table 1. General band information of Landsat 1-5 Multispectral Scanner (MSS)

Landsat 1-3	Landsat 4-5	Wavelength (micrometers)	Resolution (meters)
Band 4	Band 1	0.5-0.6	60
Band 5	Band 2	0.6-0.7	60
Band 6	Band 3	0.7-0.8	60
Band 7	Band 4	0.8-1.1	60

(Source: https://landsat.usgs.gov)

Table 2. General band information of Landsat 4-5 Thematic Mapper (TM)

Landsat 4-5	Wavelength (micrometers)	Resolution (meters)
Band 1	0.45-0.52	30
Band 2	0.52-0.60	30
Band 3	0.63-0.69	30
Band 4	0.76-0.90	30
Band 5	1.55-1.75	30
Band 6	10.40-12.50	120(30)
Band 7	2.08-2.35	30

(Source: https://landsat.usgs.gov)

Table 3. General band information of Landsat 7 Enhanced Thematic Mapper Plus (ETM+)

Landsat 7	Wavelength (micrometers)	Resolution (meters)
Band 1	0.45-0.52	30
Band 2	0.52-0.60	30
Band 3	0.63-0.69	30
Band 4	0.77-0.90	30
Band 5	1.55-1.75	30
Band 6	10.40-12.50	60(30)
Band 7	2.09-2.35	30
Band 8	0.52-0.90	15

(Source: https://landsat.usgs.gov)

Table 4. General band information of Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Landsat 8	Wavelength (micrometers)	Resolution (meters)
Band 1-Costal aerosol	0.43-0.45	30
Band 2- Blue	0.45-0.51	30
Band 3- Green	0.53-0.59	30
Band 4- Red	0.64-0.67	30
Band 5- Near Infrared (NIR)	0.85-0.88	30
Band 6- SWIR 1	1.57-1.65	30
Band 7- SWIR 2	2.11- 2.29	30
Band 8- Panchromatic	0.50-0.68	30
Band 9- Cirrus	1.36-1.38	30
Band 10- Thermal Infrared (TIRS) 1	10.6-11.19	100
Band 11- Thermal Infrared (TIRS) 2	11.50-12.51	100

(Source: https://landsat.usgs.gov)

2.3.2 History of GIS

While its history dates back hundreds of years in the fields of cartography and geography, the standardized GIS as such began to appear in the 1960s (Goodchild, 1992). It was a tradition long before computerized GIS to represent various levels of data on a set of base maps, and to relate details geographically. Also during the mid19th century, the practice of superimposing many cartographic maps on each other was painstakingly used. The blending of computing technology and cartography in the 1960s paved the way for the use of the technique of overlaying and superimposing maps in fields other than cartography. An effective multiplication resulting from the incorporation of climate, land, environmental, agronomic, economic, social, institutional management data makes a modern and efficient tracking and modeling method accessible to scientists and managers alike. However, these early GIS packages were mostly written for particular purposes and demanded a degree of computing power commonly seen in government or university settings. During the 1970s, private sellers started offering off-the-shelf GIS bundles. Intergraph and Environmental Systems Research Institute (ESRI) arose as the main sellers of GIS programming (Foresman, 1998). As registering power expanded and equipment costs plunged during the 1980s, GIS turned into a suitable innovation for common assets administrators (Jensen 1996). As Allan (1990) noticed the way toward receiving GIS was anyway a long way from smooth. The Vector or Raster map legislative issues along the expert line was the significant obstacle. These two gatherings supported unrelated systems that were an issue for information coordination during the 1970s and 1980s. The customary planning network was sure that the vector arrangement of spatial information the executives would tackle all issues and those that it would not unravel were not worth considering. This contention was especially appealing to the vector bunch as their methodology implied that they need to roll out no improvement in the extent of their planning exercises since the vector approach was completely viable with their ordinary arrangement of composed geographic control and introduction of detail. They were keen on straight and point information and not in any manner worried about giving information on the spaces between lines.

2.4 RS and GIS in environmental impact assessment

This particular integrated approach, linked to the technique as well as the interdisciplinary follow-up, is highlighted by situation research of the EIE (Environmental Influence Evaluation). The EIE may have been outlined because of the accurate identification and examination of the future impacts of the proposed EIE. Tasks, proposals, projects, legal proceedings related to physicochemical, biochemical, cultural, socio-economic aspects of the whole of the environment. GIS can include not only the tools needed for the EIA but also the field or atmosphere in which this form of research can be carried out. These specific papers demonstrate the real utility of GIS to the actual ingredients of GIS. The ecological claim is that this is an essential component of the real EIA procedure. The case used is an EIA technique relating to the planned modification of land-use within the area to the north-east of Cambridge, through farmland to the international daily rowing lake. The major environmental issues dealt with the problems of archaeology, land-use, geology, sound, ecology (Hamud *et al*., 2019).

2.4.1 Use of GIS

Within the Community region, just fifty-eight (4.25%) incorporated GIS of the thirteen hundred and sixty EIA references referenced in the GEOBASE bibliographical databases between January 1990 and February 2003. The same mixture of remotely sensed visuals right addicted to the GIS is now well recognized for the illustration and identification of the regional city. The unique mix of GIS knowledge also informs the map-like characteristics of satellite imagery, making the perception even more similar as well as personnel not properly trained in imagery examination, as well as an instance inside the Disaster Administration (Kerle and Oppenheimer, 2002). While remotely sensed visuals may 'capture' the transient geographic region of lens ads before the GIS is a discreet example of the short-term field, the problems most of the information saved are exacerbated. Within the GIS, there is a minimum of compromised individuals afflicted with errors (Openshaw, 1989). Mistakes have been identified in the estimation, spatial and temporal versions as well as information usability problems. Mistakes have been published over the digitizing period. A major downside to GIS is that concerns are typically repeated, allowing the propagation of error. For example, while an airborne image would indicate a gradual transition from urban to rural landscaping and GIS would define an area similar to a polygon-based more on previous knowledge. Mistakes in GIS can also be caused by repetition, transformation, generalization, limitation in polygon illustration (Goodchild *et al*., 1992). Multiplicative errors using overlays weaken the consistency and self-confidence of results. These constraints must have been taken into consideration in the analysis of the findings of the GIS.

2.4.2 Use of Remote Sensing

Remote sensing technologies have gradually been recognized as a valuable method for emergency prevention and environmental control assistance (Bessis *et al*., 2004; Ito, 2005). However, as a result, from the dimension as well as the elevated dimension of Earth observation (EO) Powerful and automated imaging procedures are necessary for the rapid extraction of info images (Inglada and Giros, 2004). Few elements of the geospatial info-technologies probably the most crucial applications of satellite technologies may have found inside the situation of all-natural disasters. Correctly precisely where satellite pictures might be used to supply a warning for the particular occasion dangerous s to movement up (Gens and VAN GENDEREN, 1996). To track the domain of the problem, or to get a brief review of the damage done, to assist the decision-making process within the functions. Simply because of the pervasive applicability of remotely sensed knowledge within the context of the establishment of various environmental duties, innovations may have been seen as a valuable aid in the investigation of all-natural dangers, as well as in the case of environmental duties. Satellite and airborne imagery alone will provide a valuable contribution to all-natural source management. However, the most promising field tends to be the remote sensing appliance and geographic information systems (GIS). Satellite remote sensing uses natural properties and facilitates the acquisition of scene information situated at a significant distance from the sensor (Vorovencii, 2011). Inventory and monitoring studies will likely be the most commonly used applications of remote sensing in environmental impact assessment. Satellite imagery is also a valuable source of knowledge on landscape topography, land use/land cover, regional and regional quantification. Remote sensing records play a key role in the classification, mapping, and identification of ecosystem changes, thereby achieving identical maps with predictable characteristics (Roudgarmi *et al*., 2008).

2.5 Land-use/land-cover

Some persons use land-use and land-use terms interchangeably but they are distinct. Land-cover refers to the physical characteristics of the earth's surface which are captured in the distribution of soil, water, desert, ice, other physical features of the land including those produced entirely by human activities such as mine exposure and settlement (Billah and Rahman, 2004). The same author describes land usage as the planned jobs management of plan on the landform by human agents or land managers. The need for land-use and land-cover data may increase as we attempt to assess and maintain areas of significant importance for environmental control, such as the increasingly vulnerable eco-system, wildlife habitat, areas such as agricultural production sites. Land-cover is probably the most significant feature of the land floor, both from an agricultural point of view and the viewpoint of society. Most ecosystem processes rely heavily on land-cover, which in turn affects the ground cover attributes. Similarly, land-use is greatly influenced by land-cover. Knowledge of current patterns of land-use and shifts in land-use over time is a crucial precursor for improved land-use (Anderson, 1976).

Advanced satellite image classification is a reliable and cost-effective alternative to standard land-cover mapping techniques. Since land-cover varies in time and space, mapping techniques have been used in the past to collect information on land-cover distribution and spatial variation. Satellite data with synoptic vision, repeated coverage, multispectral viewing, etc. have brought in significant improvements in land-use/land-cover mapping and tracking (Chaudhary *et al*., 2008).

Continuous tracking of land-use in remote sensing has created an important means for land-use planning to prepare land-use maps and to track changes regularly. Remotely sensed data can be translated into a land map using a standardized method in a shorter period compared to the time spent in manual land surveys. The use of remotely sensed images and GIS has proven to be a very effective strategy for land-use mapping where time limitations and data synchronization are taken into account. According to Giri and Jenkins (2005), the special focus in land-use/land-cover mapping is to help understand and manage to change environmental challenges on a local to the global scale. Land-use and land-cover mapping is the main task to be carried out due to a transition in detection study.

2.5.1 Land-use and land-cover changes

Land-use refers to the function of land for humans, which usually emphasizes the importance of land in economic activity. To gain social, cultural, economic advantages, requires all plans, practices, inputs performed in a certain form of land-cover, while the land-cover is the actual presence of land surface that offers clear evidence of land-use (Sannier *et al*., 2002; Meyer and Turner, 1992). In essence, land-cover is more apparent in the field than land-use which is typically derived by the cover. These two terms are closely related in such a way that they are viewed together in mapping to prevent misunderstanding (Lillesand *et al*., 2015). Nagendra *et al.* (2004) demonstrated the difficulty in distinguishing the two concepts due to the dynamic feedback loop that occurs between them, finding it impossible to differentiate between the result and the source. According to Meyer and Turner (1992), land-use and land-cover share a common source of change in the form of human activities that directly alter the physical environment. Over the years, human beings have attempted to derive higher value from the land by transforming or changing the forms of natural cover through varied uses. To reap the benefits of land, a series of transfers are triggered in land-use, typically culminating in the shift of the cover to another state.

Transfers are used as a synonym for the transition. Land usage has evolved after people started to control their climate (Metzger *et al*., 2006). Braissoulis (2019), describes land-use and land-cover transition as a spatial change in the area of a given form of land-use or land-cover respectively. Land-cover transition is a dynamic mechanism and requires careful analysis. Land-use transition is extensive and spatially heterogeneous; its national importance is largely due to the convergence of many local changes in many local ecosystems (Vitousek, 1994; Lambin *et al*., 2001). Changes occur as a complex of subtle alteration and complete transfer as seen in changes in forest density and from forest to agricultural land (Meyer and Turner, 1992; Lambin, 2001; Veldkamp and Lambin, 2001).

2.5.2 Nature and effects

Land-use/ land-cover changes have been introduced in time for reasons of significance due to their effect on the world and its inhabitants (Meyer and Turner, 1992; Verburg *et al*., 2006). Overall, these developments have important short-and long-term effects on the physical, chemical, biological processes of the earth (Lambin *et al*., 2003).

Changes in land-cover and land-use and effects can be positive or detrimental both spatially and temporally. However, the equilibrium is usually tipped to negative in tropical forest areas (Ingram and Dawson, 2005). These harmful long-term shifts decrease the continuous ability of the planet to generate products and services for human survival (Dale *et al*., 2000). Most land-cover changes involve a net removal of vegetation from the land and disrupt the underlying soil resulting in a net release of carbon contained in vegetation and soil to the atmosphere, adding up to atmospheric concentrations and eventually contributing to global warming.

For example, Wright (2005) argues that approximately half of the potential tropical canopy forests have already been cleared and the land converted to other uses, a minimum loss of about 28% of biodiversity has been reported in Singapore as a result of habitat conversion (Brook *et al*., 2003). Lambin *et al.* (2003) warn that not all of the impacts are harmful since certain aspects of land-use/land-cover transition are correlated with a steady rise in food and fiber production that leads to human survival.

The diverse impacts of land-use/land-cover change can be permanent or reversible depending on the form and cause of change. The study by Rudel *et al*. (2005) found that 38% of the world enjoyed forest cover after a time of decline in the 1990s. Turner *et al.* (2003) observed woodland regeneration following the abandonment of small-scale farms in the Southern Appalachian Mountains in the 1900s. The results of the changes are not limited to the place of the transition and combine actively and indirectly in an unpredictable way. Land-cover shifts in upstream slopes, such as those caused by clear-cutting, can result in short-term increases in downstream discharge and sedimentation (Baron *et al*., 1998).

2.5.3 Driving forces of land-use/land-cover changes

A natural and/or anthropogenic occurrence is the change in land-cover. Thus it emerges more frequently from individual actions than happens spontaneously. Studies by Turner (1989) showed that natural rather than anthropogenic disturbances-influenced landscapes can react differently, with natural disturbances raising the complexity of the landscape. Storms, landslides, and diseases, pests of established plants are the natural causes as well as burning, which is the most common in most regions. The reaction of the increased use of nature to address the many complex human survival and developmental needs is land use/land-cover transition. The major driving force of land- cover transition was classified by Meyer and Turner (1992) into technological capabilities, socioeconomic organization, level of growth, culture. Furthermore, Heilig (1994) cited exponential population growth, increasing prosperity in Europe, North America, and parts of Asia and Latin America, shifts in lifestyles worldwide, partially explained by increasing per capita income and the increasing impact of diplomatic, fiscal, and military systems and policies most of which are typically neglected in debates, as significant drivers. Most land-use/land-cover transition literature has acknowledged the negative contribution of rapid human population development to the great demand for land resources (Lambin and Ehrlich, 1997; Meyer and Turner, 1992; Verburg *et al*., 2006; Verburg *et al*., 1999; Wright, 2005). Contrarily to Turner *et al* (2003), land-use can increase without the associated change in land-cover if construction takes place under natural conditions. e.g. within the cover of the trees. The driving forces are typically distant from the observed shifts in space and time and frequently include macro-economic changes, technical impacts, socio-political variables, political changes that are impossible to expect (Lambin, 2001; Serneels and Lambin, 2001). This is true for deforestation in most countries, which stands out in the phase of land cover change due to the strong difference in the transition from woodland to cleared land.

2.5.4 RS and GIS for land-use/land-cover

The remote existence of remote sensing technologies allows one to make observations, to take measurements (i.e.to calculate reflected and/or transmitted electromagnetic radiation from earth features), to create photographs of objects outside the boundaries of our senses and skills. This was the arrival of the first commercial remote sensing satellite. At the end of July 1972, this opened the way for current remote sensing applications in many areas, including natural resource management (Lillesand *et al*., 2015).

Satellite remote sensing offers a vast amount of data at varying geographical, spectral, temporal resolutions, using the required mix of bands to collect the natural and man-made characteristics that are most important to a particular change detection mission. Data from satellite imagery used for a wide variety of transition-based application fields such as landscape and habitat dynamics, hazard control, hydrology, land usage, land-use and land-cover change, and so on. Satellite image data allows direct observation of the land surface at repeated intervals and thus allows mapping of the scope and tracking and evaluation. Remote sensing at different scales plays a crucial role in the tracking of space-temporal earth surfaces. Remote sensing can identify features that are not visible on the surface, map them precisely, and provide explanations depending on their shape, distribution, meaning. The techniques are especially suited to provide accurate, up-to-date, detailed land use/land cover data. (Burka, 2008).

The most useful aspect of Remote Sensing in land-use and land-cover shift identification is the multi-spectral and time resolution of the images. That is, the images are generated in various portions of the electromagnetic spectrum and the same region is seen with a specified periodic time interval. The benefit of using remote sensing land-use/land-cover is that information from the same location may be conveniently accessed at various times, and this is important for change detection applications. Furthermore, remote sensing can provide the necessary evidence with fair precision in a limited (Billah and Rahman, 2004) and has a significant contribution to make in recording the real shift in land-use/land-cover on a regional and global scale since the mid-1970s (Lambin *et al*., 2003). At present remote sensing in conjunction with GIS has resulted in more reliable and geographically referenced data on land-use and land- cover has provided opportunities for better evaluation and interpretation of problems relating to land-use/land-cover dynamics (Codjoe, 2007).

2.5.5 Monitoring land-use/land-cover changes

The first step in decision-making to combat the negative impact of the process is understanding the patterns and developments of land-use and land-cover transition. Frequent monitoring, in the context of the search for knowledge, becomes a method for achieving such understanding. According to Lambin (1994), deforestation monitoring calls for the use of remote sensing and GIS in data collection, analysis, analysis in determining the extent, magnitude, rate of shift. Earlier reviews are aimed at providing accurate information on the phase of on-going transition in response to forest product shortages. Identifying regions of actual and prospective deforested areas, quantifying areas (Lambin and Ehrlich, 1997; Van Laake and Sanchez-Azofeifa, 2004), and where necessary, create a connection with the driving forces at play. Lambin and Ehrlich (1997) argued, however, that wide-scale examination offers fewer details on the social interactions of sophistication, modifications to particular ecological environments, and the local socioeconomic context.

2.5.6 Accuracy assessment for LULC related to environmental research using GIS and RS

Land-use differentiation is important directly as it provides knowledge that could have been used as feedback for modeling, especially those using the environment, such as designs for local weather adjustments and recommendations for improvement (Disperati and Virdis, 2015). Thus the mixed land-use/land-cover (LULC) offers an extensive example of understanding the interchange between geo-biophysical, socio-economic behavioral approaches and interactions. Remote Sensing is also combined with the Geographic Information System (GIS) technique to provide even more accurate knowledge on land cover (Rwanga and Ndambuki, 2017). Remote sensing will be the top supply for certain kinds of thematic information important to GIS research, such as information on land-use and land-cover consistency. Aerial and Landsat satellite images can be used to determine the distribution of land-cover and often to update the current geospatial characteristics. Using remote sensing approaches as well as computer tools for image processing, the importance of remote sensing in the Geospatial Info Method GIS has greatly increased. Accelerated use of remote sensing info as well as of techniques generated a geospatial technique that was faster and more durable, even though high complexity often creates high error choices (Murty and Tiwari, 2015).

2.5.7 Integration spatial analysis for environmental research using GIS and RS

There are so many land map techniques that cover changes using remotely sensed information, standard optimum probability category, post-classification image difference and even substantial elements change-detection techniques for vegetative index differentiation, post-classification alter differentiation, multi-date without supervision category. Numerous forms of spatial knowledge are required to review and understand the reasoning method, as well as to increase the accuracy of the environmental simulator models needed for experimental assessment of environmental issues and the effects of human experiences. Multidisciplinary info sets of soil/subsurface quality are the main inputs to this form of research. Multi-objective projects require knowledge on the multi-temporal behavior of land surface quality, in addition to the parametrization of spatially heterogeneous and dynamic landscape quality. This type of spatial dataset was required for a variety of optional support methods. Besides, the expanded use of integrated/coupled system approaches for modeling procedure over several cycles, spare scales, allows to find appropriate locations for various projects (Madhu *et al.*, 2017).

The land-cover may have been created by analyzing satellite and aerial images. Land-use may not have been decided from a satellite image. Land-cover maps provide information to help experts better understand modern landscaping. To figure out how to change more drastically than time, land maps have been needed for a few decades. Remote sensing and GIS have covered a wide variety of projects in the areas of agriculture, environment, advanced eco-climate assessment. Some scientists have targeted the LU/LC analysis simply because of their adverse environmental and vegetation results (Prathap and Reddy, 2015; Sridhar *et al*., 2016; Hamud *et al.*, 2019). Land-use and land-cover change have been the key aspect in modern strategies for controlling all-natural supplies as well as tracking environmental changes. The real creation within the concept of mapping vegetation provides a substantially elevated analysis of land use. Land-cover change, providing the reliable study of the growth and well-being of the world's forests, grasslands, agricultural services have become an urgent priority (Wardell *et al*., 2003; Vibhute and Gawali, 2013). Viewing the planet Earth from the field is now more than time-consuming in the direction of true knowledge from the impact of human activity on their all-natural basis base. In the event of sudden and frequently unrecorded land-use alterations, measurements on the field by area provide real details on the rational use of the landscape (Anil *et al.*, 2011; Hejazi *et al.*, 2017).

2.6 Image processing

2.6.1 Image pre-processing

In addressing sensor and platform geometric and radiometric distortions present in image data, image pre-processing is important to ensure that information obtained from the images is an accurate reflection of the situation in the real world. In remotely sensed images, geometric distortions are naturally present. Geometric adjustment compensates for distortions due to different causes such as sensor optics perspective, scanning device movement, platform movement, platform altitude, altitude and velocity, terrain relief, earth's curvature, rotation. However, a detailed simulation of sensor and platform movement and geometric relationship between platform and earth should resolve structural or predetermined variations in nature. Instead of geometric registration to the known field coordinate scheme using ground control points, random errors cannot be modeled (Asubonteng, 2007; Lillesand *et al.*, 2015).

Radiometric correction is a technique used to eliminate undesired effects on image brightness values from system noise and environmental interference. Due to differences in scene lighting and viewing geometry, ambient conditions, response sensor noise the procedure is required. The variants are sensor, platform, day-specific. In remote sensing and GIS research, digital image processing is the most significant role. The retrieval of useful information from raw data, mainly satellite imagery, is carried out. To retrieve valuable information, all remotely sensed data must undergo a certain degree of preprocessing before analysis and interpretation. This method is called image processing which is part of science and art (Lillesand *et al.*, 2015).

Many pre-processing procedures must be done on the satellite data before the study to make the pixel brightness values equivalent between dates. For example, if images of different years are compared, precise co-registration is imperative. With a computing lab, optical image processing is carried out and multiple methods are implemented. To improve the contrast between features in a well-defined spectral range or to improve resolution and information from a collection of raw image data, some of these techniques include changing an image. Raw satellite information also includes a significant volume of data that is not immediately visible to the observer. The techniques of image enhancement are also used to emphasize characteristics of significance and to reveal subtle variations in the spectral signature of the target materials. For example, Histogram equalization is one of the most well-known methods for contrast improvement (Starck *et al.*, 2003). The research such as land use and land cover classification and change identification could be done after the required preprocessing is applied to the raw data.

2.6.2 Satellite image classification

Classification is the process by which several characteristics are grouped into classes based on common characteristics. Satellite image data classification is based on the grouping of pixels with identical values and the recognition of common features of the objects represented by these pixels. Kokaljl and Ostir (2007) defined the key objective of satellite imagery classification as the identification of objects on the earth's surface and their display in the form of thematic maps.

Classification is one of the digital image analyses that is very valuable when comparing multispectral imagery of the same geographical area. Classification algorithms that extract the value of each pixel in the image from its brightness values in each image can be used. An observer who classifies an image must differentiate between spectral groups and knowledge classes. Spectral classes are clusters of pixels with almost uniform spectral characteristics. Information classes are the common topics or categories of analysts. It's trying to recognize in a picture. Knowledge groups can include classes such as deciduous and coniferous forests, different types of crops, etc. Each object has special and different reflective or emission properties in a different atmosphere as a result of which the object can be detected using the reflected/emitted electromagnetic radiation from that object (Billah *et al.*, 2004).

One band classification is typically very difficult to identify when more than one surface form shows the same digital number. As a consequence, for classification, two or more bands are used and their digital numbers together are used to classify the spectral signatures of the spectral groups present in the image. As a result, remotely sensed datasets offer valuable thematic information and derive thematic information from data collected by image classification. A variety of techniques exist to extract thematic details from an image. Unsupervised and supervised image classifications are the most widely used classification methods for remote sensing. The pixels in an image are analyzed by the computer in unsupervised classification and grouped into spectral groups. The classification is based entirely on the numerical details in the data and the analyst later compares the spectral groups to the information classes. The analyst usually calculates the number of spectral groups to classify to construct an unsupervised classification and a computer algorithm can search pixels with similar spectral properties and correspondingly group them. To evaluate the statistical groupings in the data for the achievement of the unsupervised classification, clustering algorithms like ISODATA are used.

When any previous or gained knowledge of the groups in a scene is used to classify representative examples of various cover types, a supervised classification is conducted. This previous experience is used within the picture to select homogeneous areas that have the thematic material to be collected. To create a numerical definition of the spectral attribute for each land cover type of interest, the first step in the supervised classification is to define representative areas (Yuksel *et al*., 2008).

These areas are generally referred to as training sites and must be chosen for each image class to be classified. The determination of training sites is based on the awareness of the geographical area by the observer and the types of surface cover present in the picture. The classifier algorithm explores the spectral features after all training sites have been chosen and training sites to classify mathematical parameters correlated with each class. Next, all the pixels are spectrally measured and allocated to a class, including the training locations, depending on the greatest chance of becoming a part of that class. The final result is a classification in which one of the predefined groups has been allocated to all pixels within the image. The maximum likelihood classifier is the commonly used algorithm in supervised classification which is based on the calculation of probability distributions in the training data for the forms of land cover (Lillsand *et al.,* 2015).

2.6.3 Land-cover mapping

The purpose of land-cover mapping is to approximate the surface of the earth as much as possible by delineating the various characteristics as they appear in nature. Remote sensing has continued to play a key role in delivering satellite imagery and/or aerial photography information to characterize spatial variation in land-cover and to track temporal shifts inland properties at different scales by classification procedures. Aerial photography was the primary source of information on land cover and use, but its high cost of collection, processing, analysis limited its cost usage. For purposes of cost savings, wide-area coverage, multimedia format availability, specialists in the field have resorted to the use of multispectral satellite imaging (Yuan *et al*., 2005).

The procedure used to automatically categorize all pixels in an image into land-cover groups or themes based on the spectral patterns in the image data is multispectral image classification. The type of classification mentioned above is defined as the identification of spectral patterns (Lillesand *et al*., 2015).

2.6.4 Accuracy assessment

The accuracy of the land-cover is generally defined as the degree to which the derived classification agrees with fact, and the accuracy of the map largely decides the utility of the map (Ge, 2007). An accuracy evaluation includes clear comparisons between the final description and data obtained from independent ground-truth and ground truth data is decisive in distinguishing and/or recognizing the surface characteristics contained in the satellite imaging (Kazadi, 2003).

The classification scheme must allow all areas of the region under study to be included and should also include a reference unit for each form of land-use and land-cover. In classification accuracy measurement, the error matrix and related figures are valuable methods (Hammond *et al*., 1996).

To verify the digitally labeled images, accuracy assessment is essential. The approach for matching the results of the classification with geographical reference data is assumed to be valid (Lillesand *et al*., 2015). Due to the study of the area, its accuracy was determined by both the visual perception of the ground and the initial satellite images were used (Cushman and Wallin, 2000) and the ground reference data that were collected from Google Earth. The accuracy of classification greatly impacts the detection of changes. To prove the experimental validity, it is necessary to perform an accuracy assessment for classification. A classification accuracy assessment was carried out based on 120 random points suggested by the use of a stratified random approach in the ERDAS program to reflect the various types of land use in the region. They checked the effects of 120 random points against high spatial resolution Google Earth maps and sample points obtained from fieldwork. The classification accuracy of the grouping achieves 88.33% and 0.835 is the kappa. Due to the assistance of supervised classification and visual analysis, the results showed high accuracy, which allowed us to correct the misclassified pixels (Zeng and Fan, 2020).

2.6.5 Detection of change

The change in land-use and land-cover has become a core component of new policies to control natural resources and track changes in the climate. Land-use/land-cover studies using remote sensing data have gained considerable attention worldwide due to their significance in the study of global change and improvements in both human-induced and natural land will affect global change due to its relationship with the terrestrial environment, biodiversity, landscape ecology (Dewan and Yamaguchi, 2009).

According to Billah *et al*. (2004), land-use and land-cover change can be grouped into two broad categories: conversion and modification. Conversion refers to the complete substitution of one cover type with another, while alteration entails more gradual modifications that influence the essence of the ground cover without altering the overall classification (Coppin, 2004). For different purposes, one land-cover may be modified to other land-use/land-cover forms (i.e. forested land to agricultural land) and a change in intent and/or management. Detection of change is the method of detecting variations in the status of an entity or phenomena by analyzing it at various times (Singh, 1989; Mas, 1998). Change identification is an important process for tracking and controlling the production of natural resources because it provides a detailed overview of the spatial distribution of the component under study.

With change identification, the rate of change can be quantified and the cause and destination of land-use and land-cover changes can be identified at a given area. Understanding land-use and land-cover modifications that have taken place at a given location allow us to infer knowledge about the state of the area. Bergen *et al.* (2002) reported that there is a range of methods available for the identification of changes in temporal land-use; and some of them need to be mentioned in the post-classification comparison, temporal picture distinction and rationing, vector shift analysis, and spectral mixture analysis. According to Fan *et al*. (2007), the post-classification change detection system was found to be the most effective for land-use/land-cover change detection. In the post-classification technique, two photographs from different dates are separately categorized and correct classification is important to ensure accurate outcomes in the identification of changes.

2.7 Previous research on land-use and land-cover monitoring by using RS and GIS

With the introduction of the first remote sensing satellite (Landsat 1), a significant number of land-use experiments were carried out in 1972. These studies have been carried out in different fields, including urban areas, rural areas, haor areas, forest areas, mining areas.

Zeng and Fan (2020) showed that the land use in the hilly region of central Sichuan had changed seriously between 1989 and 2009. This study was conducted in the Lizixi basin which was the typical area in the hilly region of central Sichuan. Supervised classification was applied to the processing procedure of TM, SPOT data in 1989, 1999, Rapidede data in 2009 and found overall classification accuracy 88.33% and the kappa was 0.8350. They also showed that overall these changes reflect the regional polices and human activities were the major and important force factors of changes in the hilly regions of central Sichuan last two decades.

The Lakshmibaur-Nalair haor is a freshwater wetland ecosystem in Bangladesh's north-eastern area. This location is the second biggest freshwater swamp forest in Bangladesh. This unique region which is rich in biodiversity is subject to severe landscape changes. Using Landsat multispectral imageries and remote sensing (RS) and geographic information system (GIS) techniques, this study investigates land-use and land-cover (LULC) changes in the Lakshmibaur-Nalair haor region between 1989 and 2019. The haor's changing condition was investigated using the normalized difference vegetation index (NDVI) and the modified normalized difference water index (MNDWI). Using NDVI and MNDWI threshold values, the unsupervised classification approach was used to categorize these images into four primary groups (vegetation, cropland, bare soil, shallow water, and deep water bodies). The post-classification comparison approach was used to examine the change detection after the accuracy evaluation. Over the previous three decades, this valuable region has lost 2208.6 ha (37.54 %) of its deepwater body and 489.6 ha (8.34 %) of its vegetation, according to this research. It has, however, gained around 1729 ha (29.39%) of cropland, 2673 ha (45.44%) of shallow water, and 1124 ha (28%) of bare soil (Bhattcharjee *et al*., 2021).

From 1980 to 2010, Haque and Basak (2017) experimented with the Tanguar Haor regions. The pre-classification and post-classification shift identification approaches were used to determine the outcome of the change from 1980 to 2010. In the pre-classification method, to analyze the transition situation, CVA, NDVI, NDWI analysis were added. To establish the signature class of the important land cover group, the maximum probability supervised classification technique was carried out (deep water, shallow water, vegetation, and settlement). A detailed post-classification shift detection analysis was conducted after ensuring a satisfactory precision value for each categorized image. To determine statistics of historical change compared to current, image distinction, predictive change detection strategies (transition likelihood matrix), change dynamics analysis were also conducted. This research found that about 40% of the land-cover of the overall study area was converted over for 30 years. The forested and high land vegetation quickly disappeared, deep water sources made up of large lakes became the unusual characteristic of the region of study. The natural wetland was turned into permanent low-lying agricultural land by extensive settlement growth and dominant shallow water features.

An experiment was performed in the Modhupur Sal (*Shorea robusta*) forest from 1972-2015 by Abdullah *et al*. (2015). Using Landsat satellite data from 1972, 1989, 2010, 2015, the current research has examined and quantified the degradation in the field of natural Sal forests. A technique for hybrid image classification was applied. The system of study of post-classification transition was used to measure the natural Sal forest covering to explain forest cover depletion. As a result, the size of the original natural salt forest was decreased by 75%,64%, 31% in 2015, 2010, 1989, respectively, relative to 1972. Land use/coverage of the research area was also discussed, indicating that human activities such as settlement, commercial cultivation, cultivation, agroforestry methods were the key drivers of natural forest depletion.

Solly *et al*. (2020) experimented in West-African coastal during 1987 and 2018. They acquired Landsat images in 1987 and 2018 using a method of multistage unsupervised classification. On a thematic level, the results showed that between 1987 and 2018, forest areas decreased by 377,118.7 ha (or 27.4%), while wooded areas and agricultural and soil surfaces increased by 263,172.4 ha (or 19.1%) and 156075.5 ha (11.3%). In terms of change, deforestation by growing agriculture and soil surfaces along the Gambia border was noted with the central part and stabilization of forest surfaces accompanied by a small rise in savannah and agricultural and soil surfaces in the south.

An additional research feature investigates land-use/land-cover shifts in urban development between 1975 and 2005 in Higher Dhaka, Bangladesh, using satellite imagery and socio-economic details. Spatial and temporal patterns of land use/land-cover modifications. Using 3 Landsat images, a controlled category algorithm criterion, as well as the post-classification method of changing detectors in GIS, were quantified. The assessment showed that major growth of built-up locations with Higher Dhaka even more than the study era contributed to a drastic decrease in water sources, cultivated land, vegetation, and swamplands within the real area. Urban land production is mainly motivated by elevation, demographic growth, financial enhancement. A broad range of environmental impacts, such as top-quality habitat, culminated in rapid urban development by infilling low-lying areas and even cleaning up vegetation (Dewan and Yamaguchi, 2012).

Hasan *et al*. (2020) were carried out an experiment in Sundarbans Reserve Forest (SRF) between 1989 and 2019 which shares the largest mangrove territory in the world, into a great degradation status. They used satellite earth observation Historical Landsat imagery as current evidence and main data from 1989 and 2019. Also, the geographic information system model was considered to forecast the transition in land cover (LC) and the spatial health condition of the SRF from 1989 to 2029 based on the categories of large and small trees. The Maximum Likelihood Classifier (MLC) methodology was used to identify historical images with five distinct LC forms that were further considered for future prediction (2029) including patterns focused on the 1989 and 2019 LC simulation maps using the Markov cell automation model. The total accuracy was achieved 82.30%-90.49% with a kappa value of 0.75-0.87. The historical finding showed a forest loss in the past (1989-2019) of 4773.02 ha yr^{-1}, perceived to be a significant forest degradation (GFD) and a decreasing position after proceeding with a prediction (2019-2029) of 1508.53 ha yr^{-1} and a cumulative decrease of 3956.90 ha yr^{-1} in 1989-2029. Besides, they had found that the dense forest was steadily degraded (good to bad) but, conversely, the light forest was improved, and would occur until 2029 in the future if no successful maintenance is carried out.

Tadese *et al*. (2020) experimented in the Awash River Basin (ARB) using the Remote Sensing and Geographic Information System (GIS) between 1988 and 2018 to examine and consider the long-term dynamics of land-use/land-cover transition and population development in the Awash River basin (ARB). Landsat images for 1988, 2002, 2018 were used for collection, classification, analysis. The accuracy review found that the definition was relatively acceptable and successful in identifying long-term land-use changes in ARB. Cropland increased by 12% between 1988 and 2002 and increased by 15% by 2018. Similarly, the built-up area increased by 52 km² (184%) between 1988 and 2002 and reached 225% by 2018. The research found that cropland and built-up areas grew at the detriment of forests and shrub lands, with shrub lands and forests decreased by 4% and 25% respectively, over the 30-year study period. Higher levels of deforestation, coupled with population growth, urbanization, cropland extension, have had an impact on the water supply and drainage available in the region.

As a Ramsar site, Tanguar Haor is recognized around the world as a repository of marine biodiversity. It has reached biodiversity relative to other haors in Bangladesh due to the abundance of water flow during the year. In the arrival of thousands of migratory and resident birds, this haor becomes sonorous in each season. There are several marine plants floating and others underwater. Over the middle of the last century, human habitat around the haor has also expanded. Over the last 60 years, nearly 12,870 ha of water was lost from 23,230 ha. From 1955 to 2015, 1.17% of the water body in Tanguar Haor was lost annually. As a result, owing to the destruction of the ecological balance of the wetland ecosystem, and the number of birds and animals is declining alarmingly (Hussain and Hasibul, 2017).

In the Abuja City region of Nigeria between 1987-2017, Enoguanbhor *et al*. (2019) conducted a research focused on the identification of urban land cover change using geographic information systems and techniques of remote sensing to collect baseline information in support of land use planning. They applied LANDSAT data from 1987, 2002, and 2017 to the supervised classification of land cover. From 1987 to 2017, they plotted land-cover changes and calculated the net shift in land cover over this period. Finally, the mismatches between the former and existing urban land-cover and land-use plans were examined and the non-urban growth area lost to urban/built-up was quantified. They found that the findings revealed a rise in forms of urban/built-up and barren ground cover, while the land-cover of vegetation decreased. Mismatches between past/current ground cover and the existing land-use plan were also found.

Siraj *et al*. (2018) performed a research to examine the dynamics of land-use cover change (LUCC) and to investigate their drivers for the study period (1973-2015) in the central highlands of the Dry Afromontane Chilimo-Gaji forest. The outcome of the study showed that over the past 43 years, landscape patterns had occurred in the Chilimo-Gaji forest and five LUCC groups had been identified, namely shrubland, rural settlement, bare land and roads, forest land, and agricultural land. The Landsat satellite images with route 169 and row 54 (169/54) for 1973, 1984, 1998, 2008, and 2015 were downloaded and used to examine temporal shifts. Supervised classification was also used for classification. The study showed that 922.14 hectares (26.96%) were lost in the forest ground cover category and were converted into other land-cover categories such as cultivation and settlement for the study duration under consideration at an annual rate of 21.45 ha. Deforestation rates showed decreasing patterns between the 2008-2015 ages.

From 2005 to 2015, Islam *et al*. (2018) conducted a study at the Chunati Wildlife Sanctuary (CWS). In this study, CWS land-use improvements were analyzed by using Landsat TM and Landsat 8 OLI/TIRS images from 2005 to 2015. ArcGIS 10.1 and ERDAS Imagine 14 were used to process satellite imagery and to test quantitative data for the evaluation of land-use transition in this region of the study. The algorithm for maximum likelihood classification was used to extract the classification of supervised land-use. It was found that within 10 years (2005-2015) about 256 ha of degraded land had been raised and the average rate of change was 25.56%. Another 159 ha of permanently forested land with an average rate of change of 15.88% had been converted to other land uses. The overall supervised classification accuracy was found to be 92.16% for 2015, 86.15% for 2010, and 83.96% for 2005 respectively with Kappa values of 0.89, 0.82, and 0.81 for 2015, 2010, and 2005, and these were reasonably satisfactory. To protect the rich biodiversity of the Chunati wildlife sanctuary, the findings of this analysis will be useful in preparing and enforcing critical management decisions.

A study was done by Del *et al*. (2015) from 1987 to 2010 in the forest cover in Moncayo National Park (Spain) using remote sensing methods, geographical information systems (GIS), and landscape ecology quantitative indices. In this preserved region in both years, four Landsat photos were used to map nine representative ground cover groups. In 1987 and 2010, the average accuracy of classification of ground cover maps was 87.65% and 84.56% respectively. Landscape metrics collected at the level of the landscape indicate an increase in fragmentation and an increase in spatial variability in the landscape.

Yuan *et al*. (2005) developed a technique for mapping and tracking land-cover change in the seven-county Twin Cities Metropolitan Region of Minnesota in 1986, 1991, 1998, and 2002 using multi-temporal Landsat Thematic Mapper (TM) data. Over the four years, the cumulative seven-class grouping accuracy averaged 94%. The overall accuracy of land-cover change maps developed from methods of detection of post-classification change and evaluated using several approaches, ranging from 80% to 90%. The maps found that the amount of urban or built land rose from 23.7% to 32.8% of the total area between 1986 and 2002, while rural farmland, woodland, and wetland cover types declined from 69.6% to 60.5%. The findings quantified the dynamics of land-cover change in the metropolitan region and showed the ability of multi-temporal Landsat data to provide a reliable, economic way of mapping and assessing land-cover changes over time that can be used as inputs to land management and policy decisions.

CHAPTER 3

MATERIALS AND METHODS

3.1. Study area

This research was conducted in the Sunamganj district which lies between latitudes north of 24º34' and 25º12' and longitudes east of 90º 56' and 91º 49'. The district's entire area is 3747 km² of which 71.28 km² are under forest (District statistics Sunamgani, BBS, 2011).

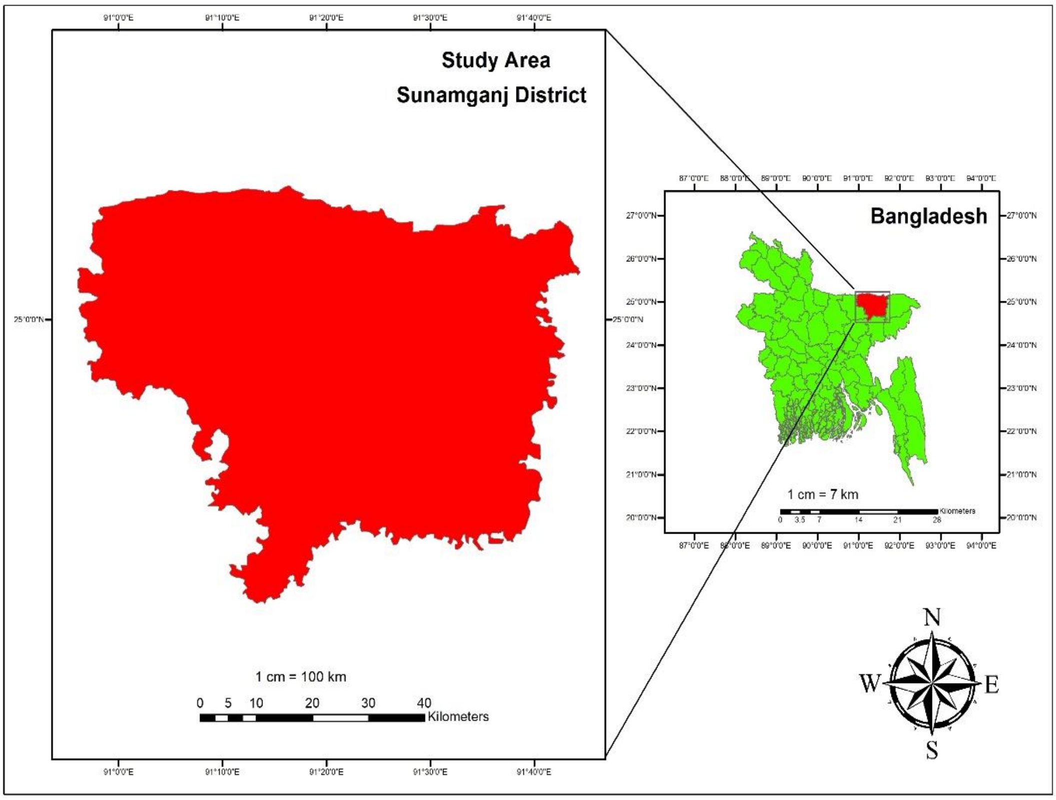

Figure 1. Location of the study area.

3.1.1 Climate

The district is renowned for a decent number of haors within it, not deep, those are like large natural lakes. Over the winter season, most of them become dry. A haor appears like a vast, almost endless strip of green soil during the winter and a vast sea of swirling water during the rainy season. There are large depressions of land where water accumulates after the rains and persists for around 8 months, and some of them during the year. Most of the broad haors are located in the Sunamganj areas of the

Sylhet division. In the summer, the temperature of the district is warmer and in winter it is colder. The annual temperature in 2011 was a high of 32.7 ° C and a low of 8.6 ° C and 73.7% average monthly relative humidity (District statistics Sunamganj, BBS, 2011). During the monsoon, strong rainfall occurs. Annual precipitation as recorded in the year 2018 was 3292 millimeters and in the year 2017 was 5413 millimeters in diameter (BWDB, 2019).

3.1.2 Soil

The district is situated in the country's northern hilly regions that have young plain piedmonts. In the northern part of the district, the piedmont plain is a gently sloping terrain composed largely of loamy sediments prone to shallow flooding. Blush silty clay from the Surma, Kushiara old flood plain Basin, is found in the central portion of the district (District statistics Sunamgani, BBS, 2011).

3.2 Materials

3.2.1 Data Collection

Two types of data were used to conduct research. Data types along with their sources are mentioned below

1. Landsat Satellite image: USGS
2. Historic Google Earth Images as Reference Data: Google Earth

Satellite Remote Sensing plays a key role in determining, improving, and monitoring global spatial and temporal landscape change. For the study of patterns in LUCC dynamics, a total of 5 Landsat satellite images for the past 40 years were downloaded from http://earthexplorer.usgs.gov, which were freely available (Table 5) to determine land use and land cover changes over the study period (Abdullah *et al*., 2015; Haque and Basak, 2017; Bhattcharjee *et al*., 2021). All Landsat images were processed and corrected in the same coordinate system and for various years these were downloaded for the same month and season to minimize seasonal variations in land use and land cover. The images were downloaded during the dry season of the year so these were more likely to be cloud-free and their spectral properties were less influenced by the availability of moisture (Siraj et al., 2018; Bhattcharjee *et al*., 2021). Winter season is the main season for cultivating rice specially Boro (local variety) rice (Alam *et al*., 2010). The month of February has been selected for the study area because December to January is the sowing time of Boro rice (Uddin *et al*., 2013). In this study, 10 year intervals Landsat satellite images were downloaded from http://earthexplorer.usgs.gov. Unfortunately, February 2008 cloud-free Landsat satellite image was not found. So, February 2009 cloud-free Landsat satellite image was used for conducting research. Historical Google Earth Images was used for creating ground truth data which was mainly used for improving supervised classification and accuracy assessments (Zeng and Fan, 2020). Based on visual analysis, 200 ground-truth points were digitized for each land cover category to enhance the classification of the land cover. The accuracy assessments were performed for classified images of 1978, 1988, 1998, 2009 and 2018.

Table 5. Description of remote sensing data

Satellite	Sensor	Image acquisition date	Path	Row	Cloud Coverage %	Source
Landsat 8	OLI	2018/02/21	137	42	0.52	USGS
Landsat 5	TM	2009/02/28	137	43	2.00	USGS
Landsat 5	TM	1998/02/14	137	43	0.00	USGS
Landsat 5	TM	1988/02/19	137	43	2.00	USGS
Landsat 2	MSS	1978/02/03	147	43	0.00	USGS

3.2.2 Software

ArcGIS 10.5 software was used in this study for image preparation, mapping and data analysis.

3.3 Methods

The flow chart of the methodology is given below

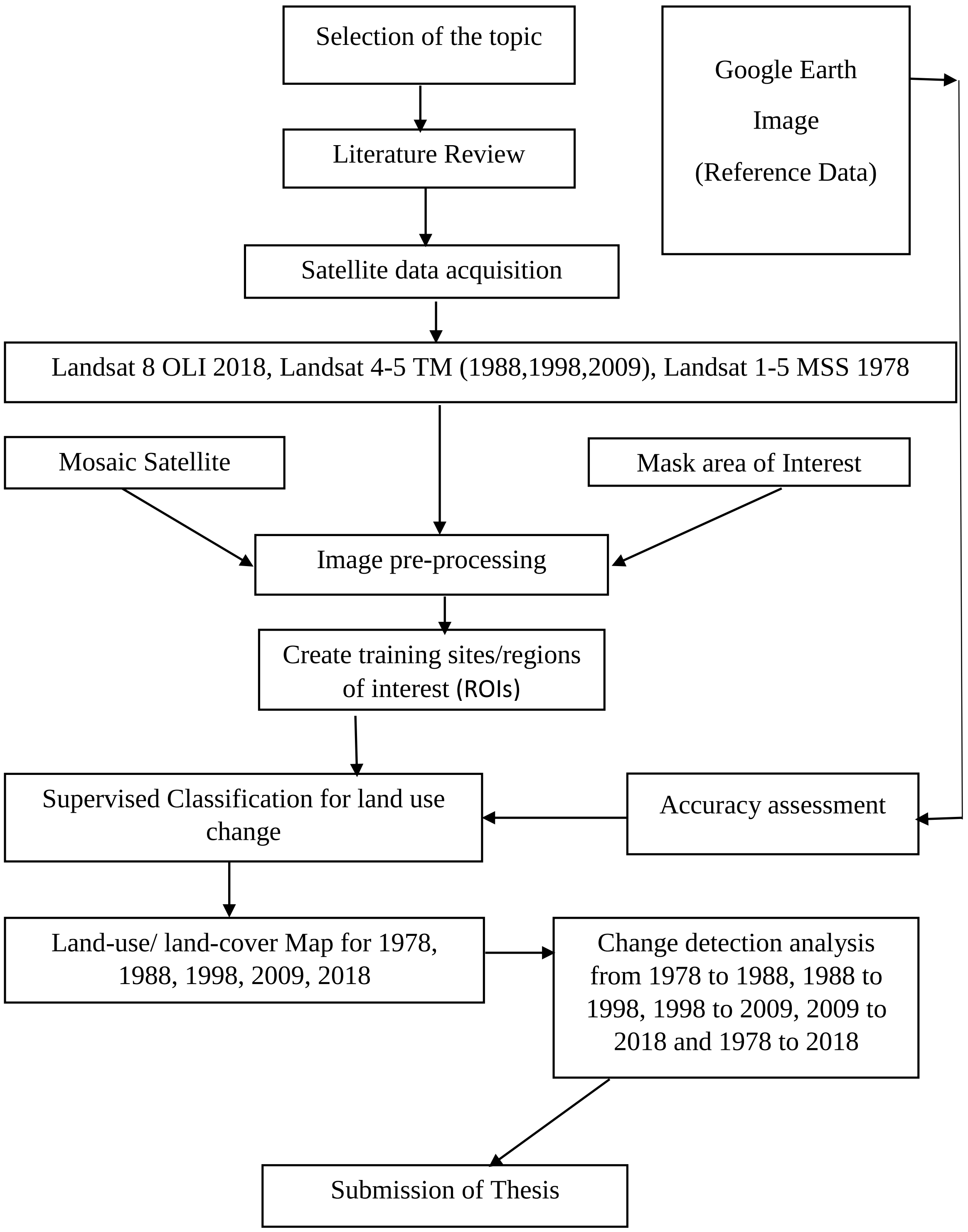

Figure 2. Flow chart of methodological approach

3.3.1. Data pre-processing

Systematic and spontaneous errors have affected raw satellite images and will not be used directly for classification of features and any applications. Some correction is needed and the errors need to be eliminated. Standard image processing techniques for extraction, layer stacking, radiometric correction, geometric correction/ geo-referencing, and detection of changes were then carried out on the 5 Landsat images downloaded and acquired on various dry season dates and years in the study area (Siraj *et al*., 2018). Using WGS (World Geodetic System) 1984 zone 46N, the satellite images were coordinated to a Universal Transverse Mercator (UTM) projection. Landsat thermal bands were not included to detect land use/cover changes. Landsat MSS 1978, TM 1988,1998,2009 and OLI 2018 imagery were enhanced using enhancement techniques to improve the interpretability of the image. As accurate image classification, band selection is also crucial since one feature which is not discriminated apparently may be differentiated on another band. Red Green Blue (RGB) False Color Composite (FCC) image was prepared by stacking the spectral bands 654 (MSS data), 432 (TM data), and 543 (OLI data) (Abdullah *et al*., 2015). The MSS image has four bands with a spatial resolution of 60m. 654 band combination had been used for LULC mapping of the year 1978. The TM image has seven bands with a spatial resolution of 30m. 432 band combination had been used for LULC mapping of the year 1988,1998 and 2009 respectively. The OLI 2018 image has 11 bands. Among them, the OLI 2018 image has 9 bands with a spatial resolution of 30m and 2 bands with a spatial resolution of 100m. 543 band combinations had been used for LULC mapping of the year 2018.

The Figure 3 show the different raw satellite imagery color composite used in different band combinations for LULC classification

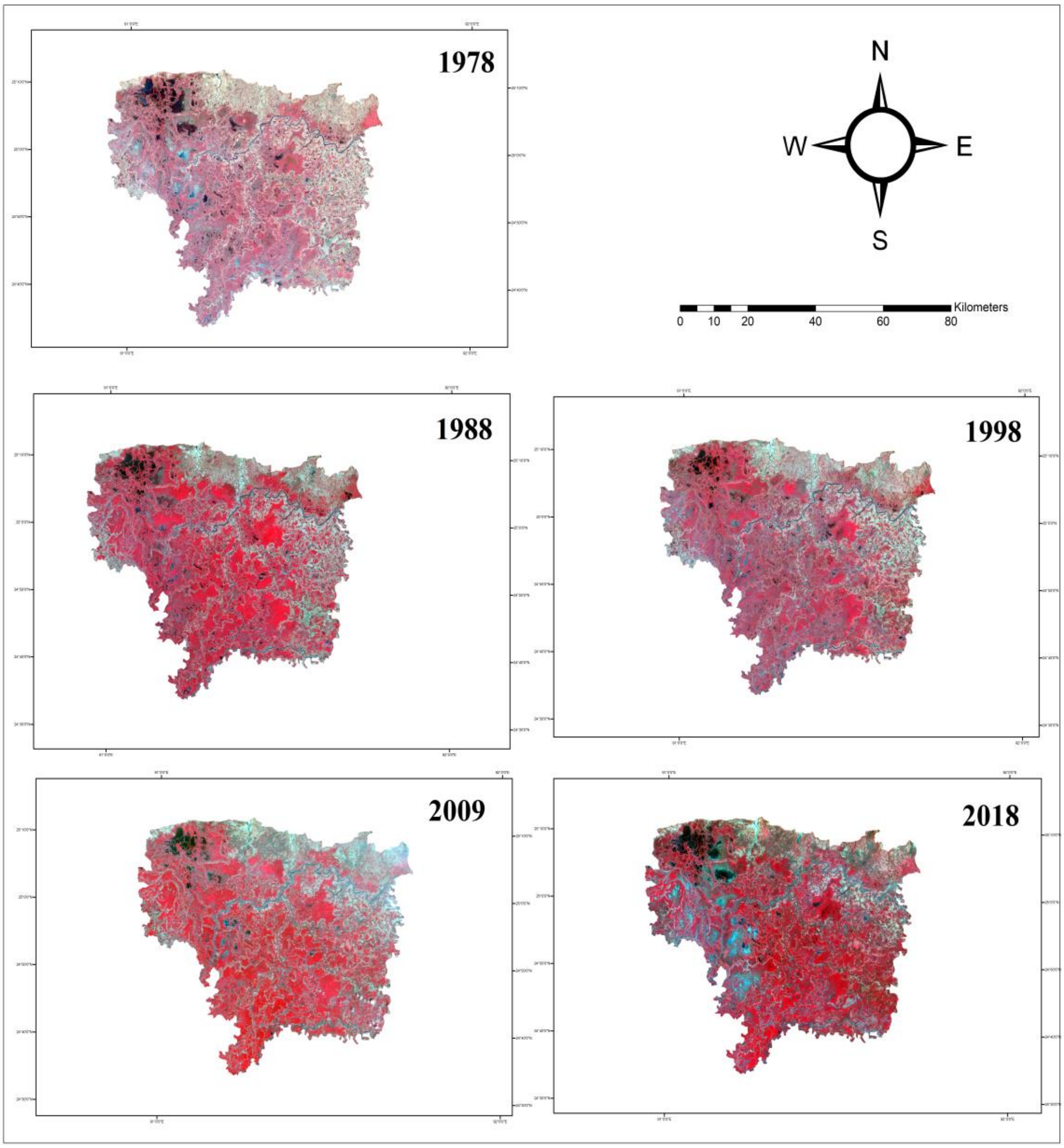

Figure 3. False Color Composite (RGB: NIR, Red, Green) maps of 1978, 1988, 1998, 2009 and 2018

3.3.2 Image classification

In this research, spatial analyses were conducted using ArcGIS (Version 10.5) including land cover classification, accuracy assessments, transition mapping, and change detection. The image classification process is to convert image data to thematic data. For remote sensing, two basic image classification approaches are used: supervised and unsupervised. Supervised classification is a method in which samples of pixels from a satellite image are specifically chosen at positions where the true ground cover form of each pixel is identified (e.g., following google earth reference data). The spectral signatures of these identified pixels are then analyzed for estimation and assigning of information classes to unknown pixels. This technique allows the analyst to have control over the assignment of various pixel groups based on known knowledge of the study area (Campbell and Wynne, 2011). In the case of supervised classification, one wants to know the terrain of the involved area. To derive types of land-cover, a supervised classification method was applied. The supervised classification algorithm used in this study was the maximum likelihood classifier, which focused on the possibility that different pixels belong to different classes and assign pixels to the class with the highest probability. The maximum likelihood algorithm was used, as demonstrated in the literature to achieve high accuracy results for land-cover classification (Ganasri and Dwarakish, 2015; Islam *et al*., 2018; Siraj *et al*., 2018; Hasan *et al*., 2020). The spectral signature was drawn on these types of LULC on a Landsat image. To identify the pattern of each land-use class, signatures class were drawn separately for each category. Five LULC temporal maps were prepared and based on the signature files for generating random points using ArcGIS (Version 10.5) software. Maximum likelihood supervised classifications were undertaken in ArcGIS (Version 10.5) on 1978, 1988, 1998, 2009 and 2018 Landsat images. With the classified model, a total of 200 random points were generated and validated for each image. Again, these points were converted into a KML file and export to google earth and validate the classification. The same approach was applied to the other images.

Each Landsat image was classified into four land use classes: Water Body, Tree cover, Agricultural Land, and Other. In this, research the satellite images had been classified into four land classes as shown in Table 6 below-

Table 6. Details of the land-use/land-cover classes

Class. No.	Land-use/land cover classes	Abbr.	Description
1	Water Body	WB	River, permanent open water, haors, baors, lakes, ponds, canals, and reservoirs.
2	Agricultural Land	AL	Agricultural field, vegetable lands, fallow lands.
3	Tree Cover	TC	The study area has a tree cover which is mainly homestead. This class includes all the rural houses that are accompanied by tree cover mostly fruit and wood trees, dense trees, evergreen forest land, plantation forests, orchards, palms and swamp forest.
4	Other	OT	Exposed stone, sand and soil or non-vegetated area dominated by rocks, roads, eroded and degraded land.

3.3.3 Classification accuracy assessment

One of the post-processing measures performed in this research was the accuracy assessment of the classified image to identify the degree of agreement of the classified image with the reference data (Jianya *et al.*, 2008; Congalton and Green, 2019). The accuracy of classification greatly influences the identification of change. It is necessary to conduct a classification accuracy assessment to show experimental validity. The accuracy assessment tests how many ground truth pixels were accurately identified. Accurate land-use knowledge is important for the creation and management of sound environmental policies (Minale, 2013). Accuracy assessment is very important to consider the results of the classification and to use these results for decision-making (Lu *et al.*, 2004). Classification accuracy assessment was done by many researchers in their experiment (Abdullah *et al.*,2015; Del *et al.*,2015; Haque and Basak, 2017; Islan *et al*., 2018; Zeng and Fan, 2020; Bhattcharjee *et al*, 2021). This was carried out using 200 ground truth random points for 1978, 1988, 1998, 2009 and 2018 respectively. The validation random points used for the images of 1978, 1988 and1998 were collected through visual analysis based on local knowledge of the research area. Random points were collected from historical images of Google Earth for 2009 and 2018 image correction. Using error matrices, statistical comparisons were carried out between the reference data and the classified image.

Table 7-11 shows the accuracy assessment of land use in 1978, 1988, 1998, 2009 and 2018, respectively. It indicates that the overall classification accuracy of land-use maps was 82.50% for 1978, 81.00% for 1988, 84.00% for 1998, 84.00% for 2009 and 90.00% for 2018. The Kappa coefficient for the maps of 1978, 1988, 1998, 2009 and of 2018 were 76.38%, 73.00%, 77.00%, 77.28% and 86.00%, respectively.

Table 7. Accuracy assessment of land-use map in 1978

1978	Reference Data						User's Accuracy (%)	Kappa Coefficient (%)
Classified Data		WB	AL	TC	OT	Total		
	WB	28	2	0	0	30	93.33	76.38
	AL	0	45	4	0	49	91.84	
	TC	0	19	42	0	61	68.85	
	OT	0	10	0	50	60	83.33	
	Total	28	76	46	50	200		
Producer's Accuracy(%)		100	59.21	91.3	100		82.50	

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

Table 8. Accuracy assessment of land-use map in 1988

1988	Reference Data						User's Accuracy (%)	Kappa Coefficient (%)
Classified Data		WB	AL	TC	OT	Total		
	WB	21	4	0	0	25	84.0	73.0
	AL	9	64	2	0	75	85.33	
	TC	0	18	47	0	65	72.31	
	OT	0	5	0	30	35	85.71	
	Total	30	91	49	30			
Producer's Accuracy(%)		70.0	70.33	95.92	100		81.0	

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

Table 9. Accuracy assessment of land-use map in 1998

1998	Reference Data						User's Accuracy (%)	Kappa Coefficient (%)
Classified Data		WB	AL	TC	OT	Total		
	WB	27	3	0	0	30	90.0	77.0
	AL	5	71	4	0	80	88.75	
	TC	0	16	34	0	50	68.0	
	OT	0	4	0	36	40	90.0	
	Total	32	94	38	36	200		
Producer's Accuracy(%)		84.38	75.53	88.47	100		84.0	

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

Table 10. Accuracy assessment of land-use map in 2009

2009	Reference Data						User' Accuracy (%)	Kappa Coefficient (%)
Classified Data		WB	AL	TC	OT	Total		
	WB	34	0	0	1	35	97.14	77.28
	AL	10	73	1	9	93	78.49	
	TC	0	2	34	0	36	94.44	
	OT	1	7	1	27	36	75.00	
	Total	45	82	36	37	200		
Producer's Accuracy(%)		75.56	89.02	94.0	72.97		84.0	

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

Table 11. Accuracy assessment of land-use map in 2018

2018	Reference Data						User's Accuracy (%)	Kappa Coefficient (%)
Classified Data		WB	AL	TC	OT	Total		
	WB	37	3	0	0	40	92.5	86.0
	AL	1	69	0	0	70	98.57	
	TC	0	10	32	0	42	76.19	
	OT	0	6	0	42	48	87.5	
	Total	37	88	32	42	200		
Producer's Accuracy(%)		100	78.40	100	100		90.0	

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

3.3.4 Area calculation

After completing supervised classification, the area of the selected classes was calculated. This step is very crucial as it provides the area size of the study area for the particular classes (Water Body, Agricultural Land, Tree Cover, and Other). By doing calculation, this provides accurate information what was the size for selected four classes in 1978, 1988, 1998, 2009 and 2018, respectively. In this research, the area was calculated in a “square kilometer” unit. The result would show that in a year particular class increased or decreased. The Area of each class was calculated by multiplying the total pixel count by pixel resolution.

3.3.5 Detection of change

Post-classification comparison (PCC) was used to compare and evaluate land-use maps in the Sunamganj haor region resulting from the combination of visual perception and supervised classification data (Zeng and Fan, 2020). Land-use change detection was conducted using the ArcGIS 10.5 overlay technique for the 1978-1988, 1988-1998, 1998-2009, 2009-2018, and 1978-2018 images. Finally, pixel-to-pixel cross tabular statistics were used to classify the form and degree of land-use transition (Lu *et al*., 2004; Sinha and Kumar, 2013). Transition matrixes/statistics showed the region of transition from one land-use class to another class within the chosen year. It showed the particular quantity of each change of class during the original and final year of the period.

CHAPTER 4

RESULTS AND DISCUSSIONS

In this research, 5 land use classifications of Sunamganj haor region was prepared by both supervised classification and visual interpretation from Landsat images which were made accuracy verification. Similar kind of classification was used by Haque and Basak (2017), Islam *et al*. (2018), Hasan *et al*. (2020), Zeng and Fan (2020) and Bhattcharjee *et al*. (2021). The classified land use maps of Sunamganj haor region of the year 1978, 1988, 1998, 2009 and 2018 was prepared. The area of Sunamganj haor region was classified into four classes such as water body, agricultural land, tree cover and other. Other researchers were classified their study area into different classes (Haque and Basak, 2017; Seraj *et al*., 2018; Tadese *et al*., 2020 and Bhattcharjee *et al*., 2021). There was a huge change found in land cover in the Sunamganj haor region over the past 40 years, which was mainly reflected in water body, agricultural land, tree cover, and other.

4.1 Land-use pattern of 1978

The land-use map of 1978 was prepared by both supervised classification and visual interpretation from false color composite (654) map of Landsat MSS image of 1978 and this 1978 land-use map was classified into four classes i.e., water body (Blue zone), agricultural land (Yellow zone), tree cover (Green zone) and other (Red zone).

4.1.1 Area calculation of the year 1978

The following Table 12 is illustrating that in 1978 water body was 434 Km^2, agricultural land was 1556.5 Km^2, tree cover was 319.5 Km^2 and other was 1393 Km^2.

Table 12. Total study area of 1978

Total study area of 1978			
Land use/land cover classes	**Pixel count**	**Area (Km²)**	**Area (%)**
Water Body	122784	434.0	12.0
Agricultural Land	424315	1556.5	42.0
Tree Cover	97974	319.5	8.50
Other	383673	1393.0	37.5
Total		**3703.0**	**100.0**

4.2 Land-use pattern of 1988

The land-use map of 1988 was prepared by both supervised classification and visual interpretation from false color composite (432) map of Landsat TM image of 1988 and this 1988 land-use map was classified into four classes i.e., water body (Blue zone), agricultural land (Yellow zone), tree cover (Green zone) and other (Red zone).

4.2.1 Area calculation of the year 1988

The following Table 13 is illustrating that in 1988 water body was 291.5 Km², agricultural land was 1595.5 Km², tree cover was 557 Km^2 and other was 1259 Km².

Table 13. Total study area of 1988

Total study area of 1988			
Land use/land cover classes	**Pixel count**	**Area (Km²)**	**Area (%)**
Water Body	326564	291.5	8.00
Agricultural Land	1759274	1595.5	43.0
Tree Cover	638897	557.0	15.5
Other	1390131	1259.0	34.0
Total		**3703.0**	**100.0**

4.3 Land-use pattern of 1998

The land-use map of 1988 was prepared by both supervised classification and visual interpretation from false color composite (432) map of Landsat TM image of 1998 and this 1998 land-use map was classified into four classes i.e., water body (Blue zone), agricultural land (Yellow zone), tree cover (Green zone) and other (Red zone).

4.3.1. Area calculation of the year 1998

The following Table 14 is illustrating that in 1998 water body was 279.5 Km², agricultural land was 1879.5 Km², other was 907.5 Km² and tree cover was 636.5 Km².

Table 14. Total study area of 1998

Total study area of 1998			
Land-use/land cover classes	**Pixel count**	**Area (Km²)**	**Area (%)**
Water Body	316578	279.5	7.50
Agricultural Land	2063924	1879.5	51.0
Tree Cover	731859	636.5	17.0
Other	1002505	907.5	24.5
Total		**3703.0**	**100.0**

4.4 Land-use pattern of 2009

The land-use map of 2009 was prepared by both supervised classification and visual interpretation from false color composite (432) map of Landsat TM image of 2009 and this 2009 land-use map was classified into four classes i.e., water body (Blue zone), agricultural land (Yellow zone), tree cover (Green zone) and other (Red zone).

4.4.1 Area calculation of the year 2009

The following Table 15 is illustrating that in 2009 water body was 202 Km², agricultural land was 2031 Km², tree cover was 590 Km² and other was 880 Km².

Table 15. Total study area of 2009

Total study area of 2009			
Land use/land cover classes	**Pixel count**	**Area (Km^2)**	**Area (%)**
Water Body	225903	202.0	5.50
Agricultural Land	2245798	2031.0	55.0
Tree Cover	664741	590.0	16.0
Other	978298	880.0	23.5
Total		**3703.0**	**100.0**

4.5 Land-use pattern of 2018

The land-use map of 2018 was prepared by both supervised classification and visual interpretation from false color composite (543) map of Landsat OLI image of 2018 and this 2018 land-use map was classified into four classes i.e., water body (Blue zone), agricultural land (Yellow zone), tree cover (Green zone) and other (Red zone).

4.5.1 Area calculation of the year 2018

The following Table 16 is illustrating that in 2018 water body was 189.50 Km^2, agricultural land was 2427 Km^2, tree cover was 512 Km^2 and other was 575 Km^2.

Table 16. Total study area of 2018

Total study area of 2018			
Land use/land cover classes	**Pixel count**	**Area (Km^2)**	**Area (%)**
Water Body	212127	189.5	5.00
Agricultural Land	2672214	2427.0	65.5
Tree Cover	582757	512.0	14.0
Other	647768	575.0	15.5
Total		**3703.0**	**100.0**

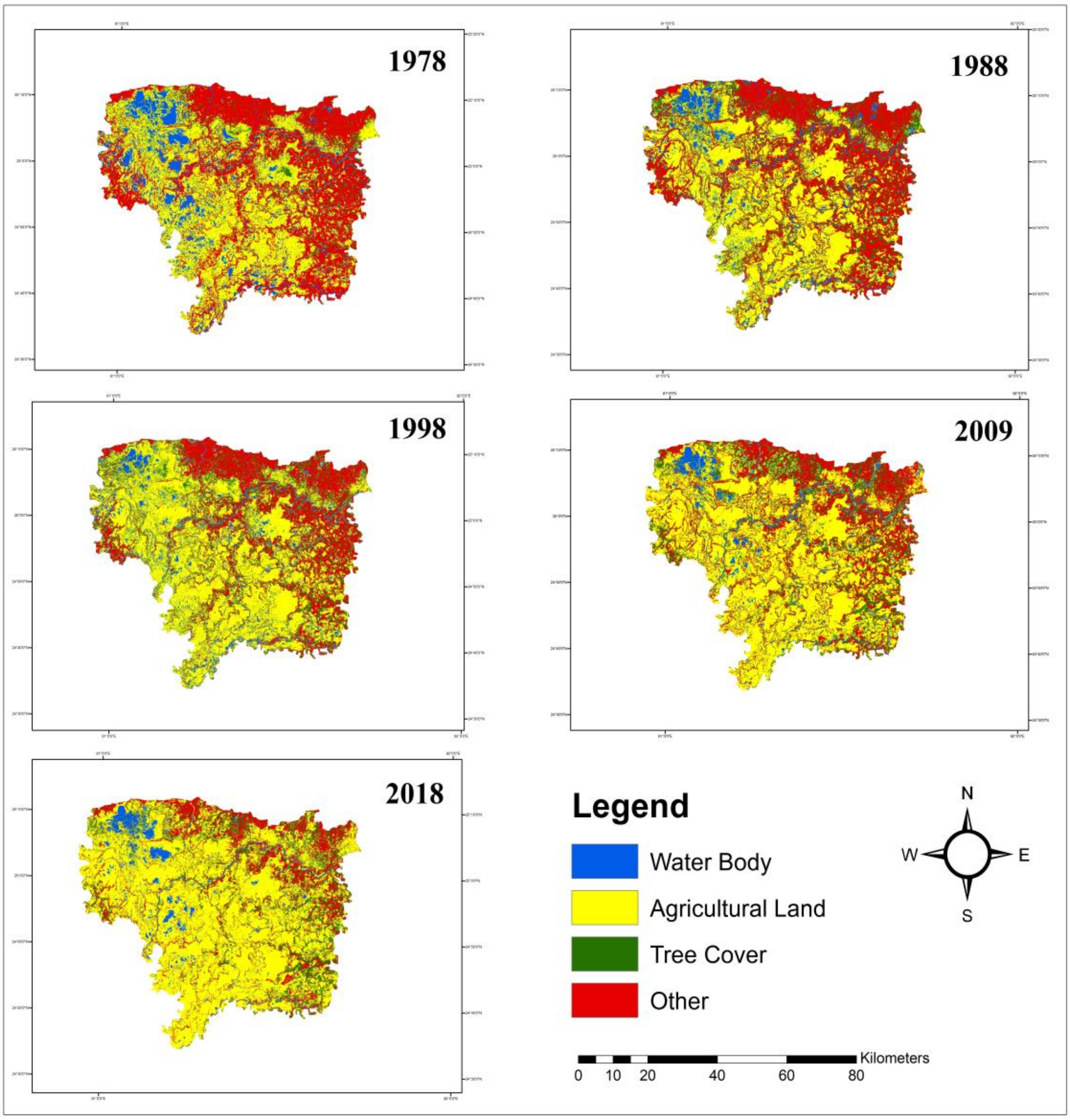

Figure 4. Land-use maps of Sunamganj haor region for 1978, 1988,1998, 2009 and 2018

4.6 Area comparison for the year 1978, 1988, 1998, 2009 and 2018

After the image analysis, classifying and processing, identification of changes in the last 40 years distinguished properly. The water bodies had distinctly changed in the last 40 years which converted mainly to agricultural land. The types of changes can be easily identified by the observation of classified image maps of study area's in 1978, 1988, 1998, 2009 and 2018 years, respectively. Table 17 showed that the tree cover areas were remarkably less and other was a vast amount, about 37.5% of the total study area in 1978. Other was decreased from 1978 to 2018. Tree cover was increased from 1978 to 1998 because of increasing homestead forest and was decreased from 1998 to 2018 because of increasing deforestation. Agricultural land was remarkably increased from 1978 to 2018 because of increasing agricultural practices.

Table 17. Land-use and land-cover change (1978-2018) in Sunamganj haor region

S.N.	LUCC	1978		1988		1998		2009		2018	
		Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
1.	WB	434	12	291.5	8	279.5	7.5	202	5.5	189	5
2.	AL	1556.5	42	1595.5	43	1879.5	51	2031	55	2427	65.5
3.	TC	319.5	8.50	557	15	636.5	17	590	16	512	14
4.	OT	1393	37.5	1259	34	907.5	24	880	23.5	575	15.5
Total		3703	100	3703	100	3703	100	3703	100	3703	100

*LUCC= Land use/land cover classes, WB= Water Body, AL= Agricultural Land, TC=Tree Cover, OT= Other

4.6.1 Water Body

The main change was observed in water body. The total water body covered 434 Km² in 1978 which also covered 291.5 Km², 279.5 Km², 202 Km² and 189 Km² at the period of 1988, 1998, 2009 and 2018 respectively (Table 17, Figure 5). The water body was dramatically changed in the last 40 years. It was 12%, 8%, 7.5%, 5.5% and 5% of the total area during 1978, 1988, 1998, 2009 and 2018 years respectively (Table 17, Figure 6). Water body showed a decreasing trend in the haor region because maximum low laying was converted into agricultural land. HYV boro rice cultivation is becoming more popular in the haor region. Similar result was found in the Lakshmibaur-Nalair haor (Bhattcharjee *et al*., 2021), Hakaluki haor, Hail haor (Uddin *et al*., 2013) and Tanguar haor (Haque and Basak, 2017; Ullah, M.S. 2017).

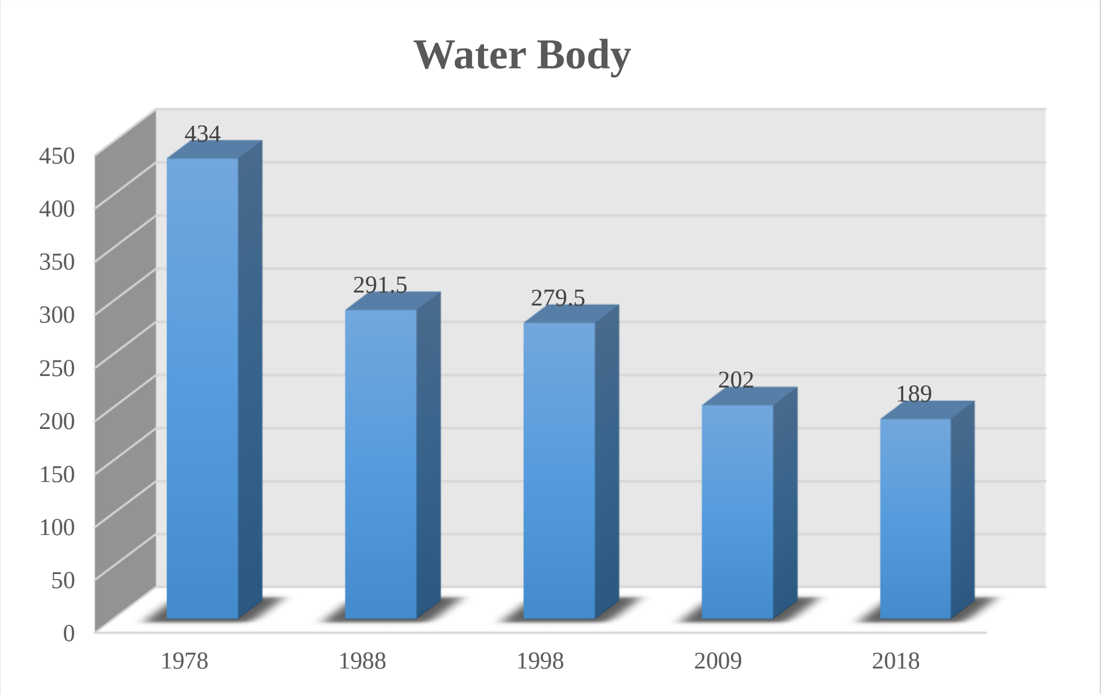

Figure 5. Water Body area (Km²) from 1978 to 2018 in Sunamganj haor region

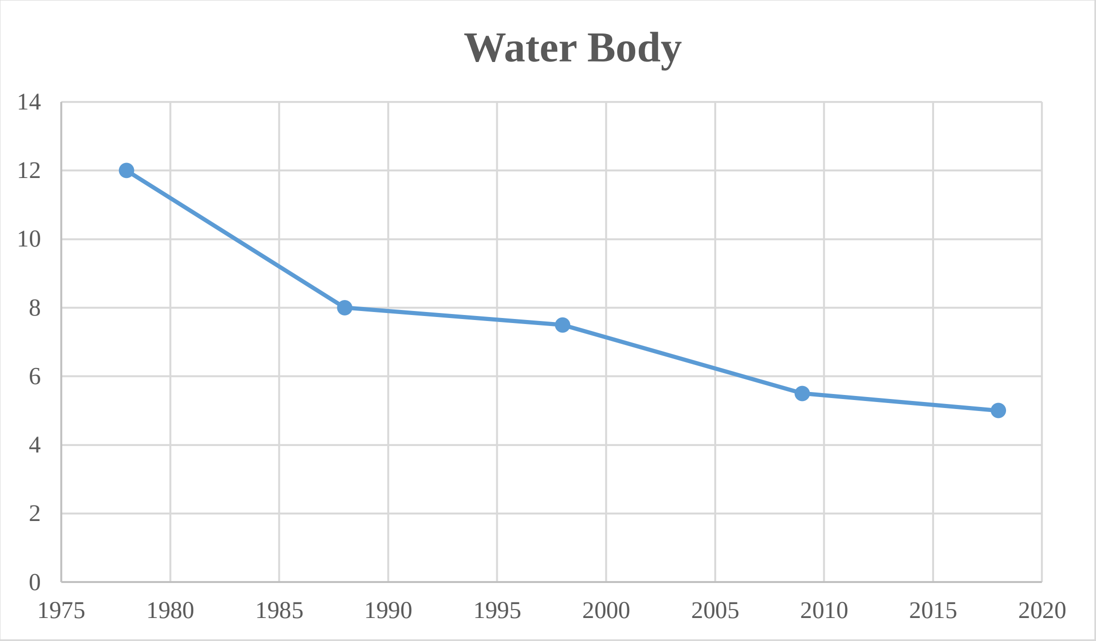

Figure 6. Water Body area (%) from 1978 to 2018 in Sunamganj haor region

4.6.2 Agricultural Land

The main change was observed in agricultural land. The agricultural land was showed increasing trend in the last 40 years. The total agricultural land coverage was 1556.5 Km² in 1978 which was 1595.5 Km², 1879.5 Km², 2031 Km² and 2427 Km² in the period of 1988, 1998, 2009 and 2018, respectively (Table 17, Figure 7). It was 42%, 43%, 51%, 55% and 65.5% of the total area during 1978, 1988, 1998, 2009 and 2018 years, respectively (Table 17, Figure 8). Agricultural land showed an increasing trend in the haor region because maximum water body and other land use cover class was converted into agricultural land. HYV boro rice cultivation is becoming more popular in the haor region. Similar result was found in the Lakshmibaur-Nalair haor (Bhattcharjee *et al*., 2021), Hakaluki haor, Hail haor (Uddin *et al*., 2013) and Tanguar haor (Haque and Basak, 2017).

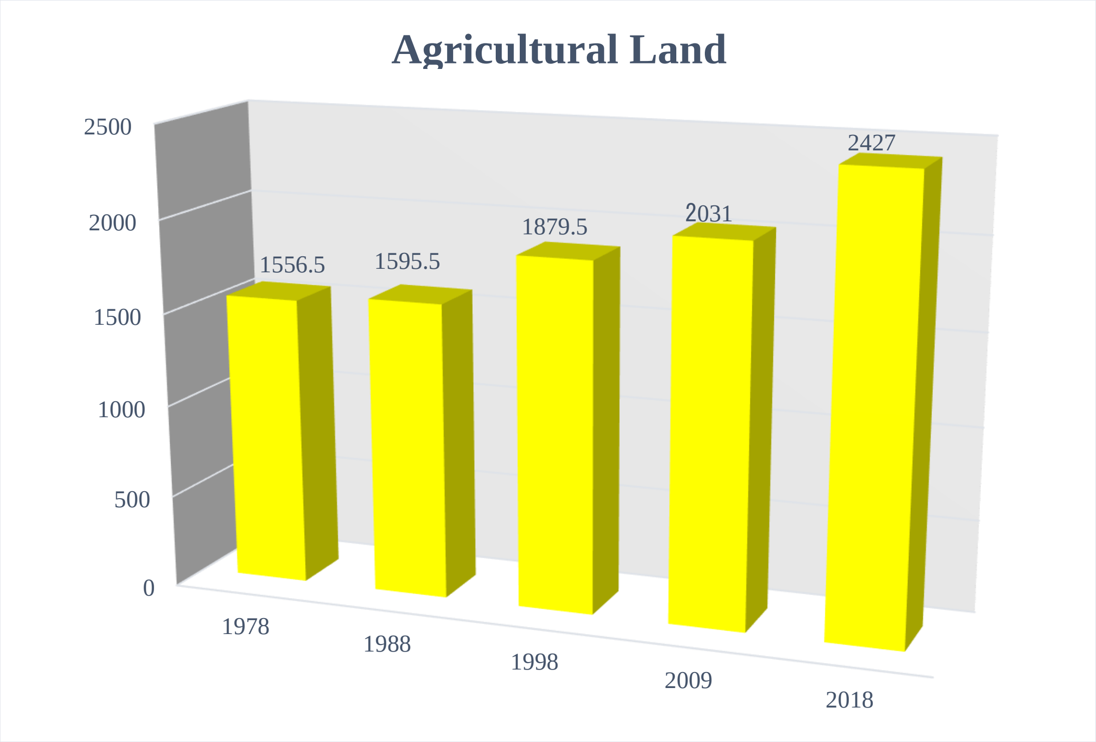

Figure 7. Agricultural Land area (Km²) from 1978 to 2018 in Sunamganj haor region

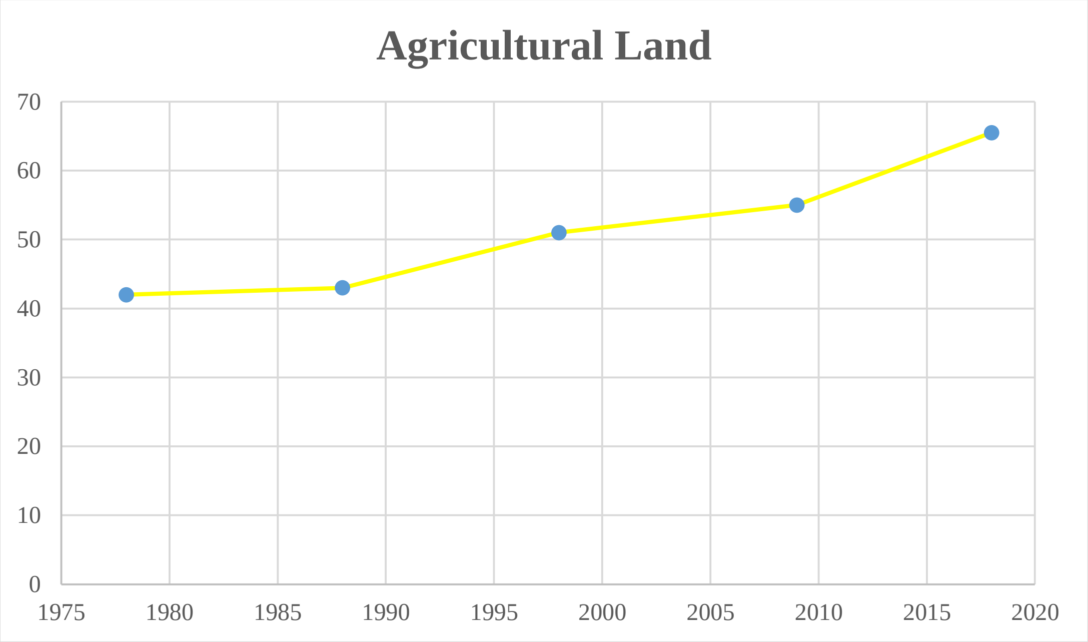

Figure 8. Agricultural Land area (%) from 1978 to 2018 in Sunamganj haor region

4.6.3 Tree Cover

Another most important change of land-cover is tree cover. The population of Bangladesh is increasing logistically day by day. So important agricultural and nonagricultural lands converted by homestead forests included tree cover. There was only 319.5 Km² area covered by tree cover during 1978. But the tree cover area was increased by about 557 Km² and 636.5 Km² in 1988 and 1998, respectively. Then tree cover decreased from 1998 to 2018 because of deforestation. It was covered 590 Km² and 512 Km² during 2009 and 2018 respectively (Table 17, Figure 9). It was 8.5%, 15%, 17%, 16% and 14% of the total area during 1978, 1988, 1998, 2009 and 2018 years respectively (Table 17, Figure 10). Tree cover showed increasing and deceasing trend. Due to increasing settlement in the haor region tree cover was decreasing year by year. Human pressure and activities were also increased the haor region. These also cause of deceasing tree cover. Vegetation was decreased in Lakshmibaur-Nalair haor (Bhattcharjee *et al*., 2021) and Tanguar haor (Haque and Basak, 2017). Vegetation class is partially similar to tree cover class.

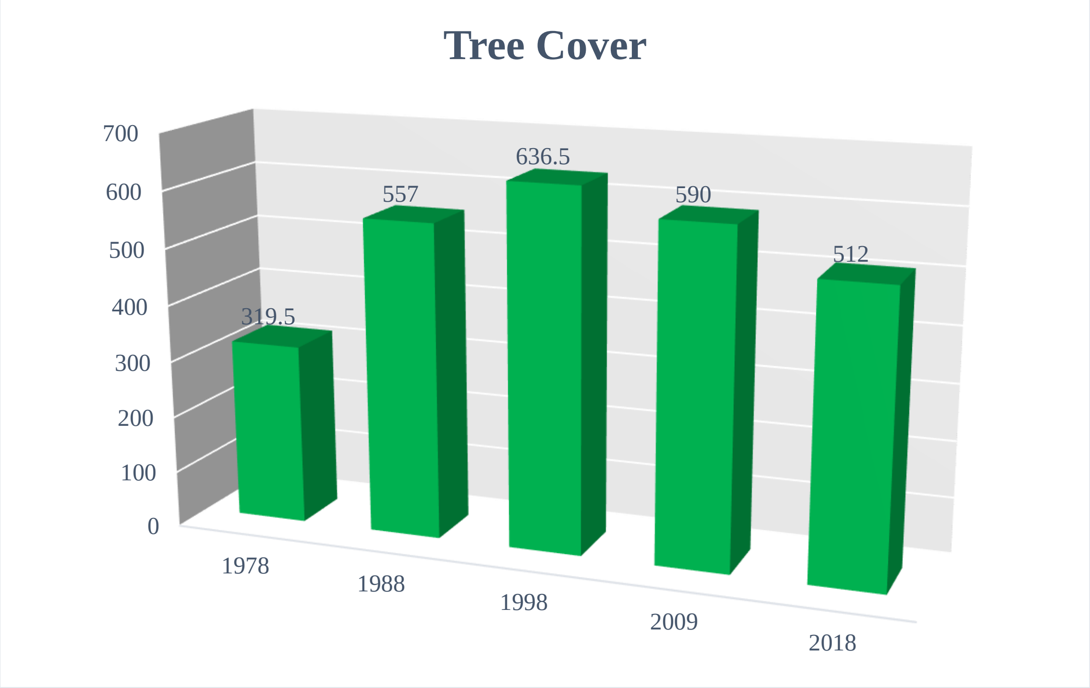

Figure 9. Tree Cover area (Km²) from 1978 to 2018 in Sunamganj haor region

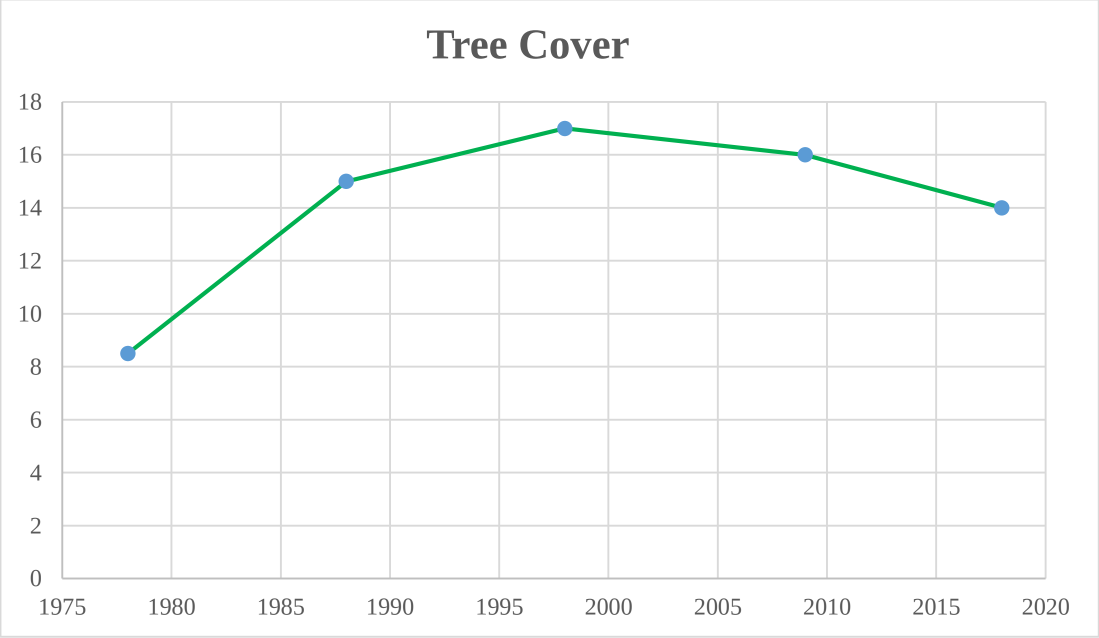

Figure 10. Tree Cover area (%) from 1978 to 2018 in Sunamganj haor region

4.6.4 Other

The most important change was observed in other class. Previously it has been reported that other land-use/land-cover class was converted to other classes, mainly to agricultural land. The total amount of other class in 2018 was 575 Km² which was decreased by a vast amount from previous years. During 1978, the total other land use cover class was 1393 Km². It was dropped during 1988 by about 1259 Km², in 1998 about 907.5 Km², in 2009 about 590 Km² and dropped again in 2018 by about 575 Km² (Table 17, Figure 11). It was 37.5%, 34%, 24.5%, 23.5% and 15.5% of the total area during 1978, 1988, 1998, 2009 and 2018 years, respectively (Table 17, Figure 12). According to the observation of last 40-year results, it was clear that other land use cover class was decreasing day by day. Other class mainly indicated soil boundaries. These soil boundaries mainly introduced by high yielding rice crops during dry season. Similar result was found in the Hakaluki and Hail haor (Uddin *et al*., 2013).

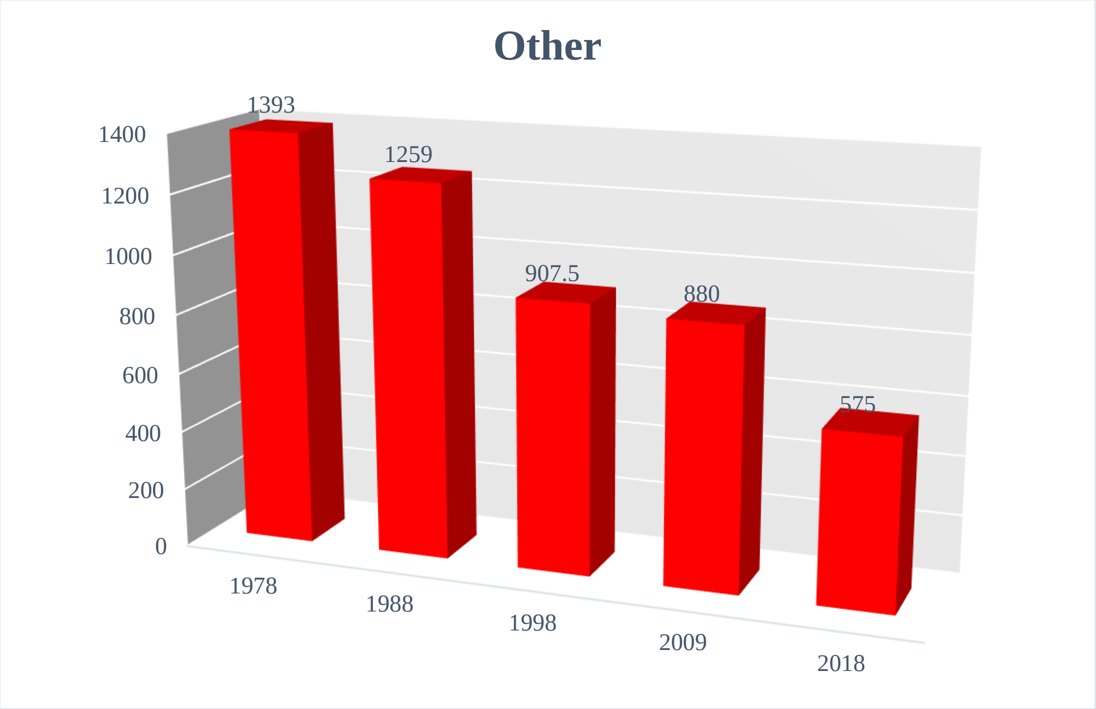

Figure 11. Other land-use/land-cover class area (Km²) from 1978 to 2018 in Sunamganj haor region

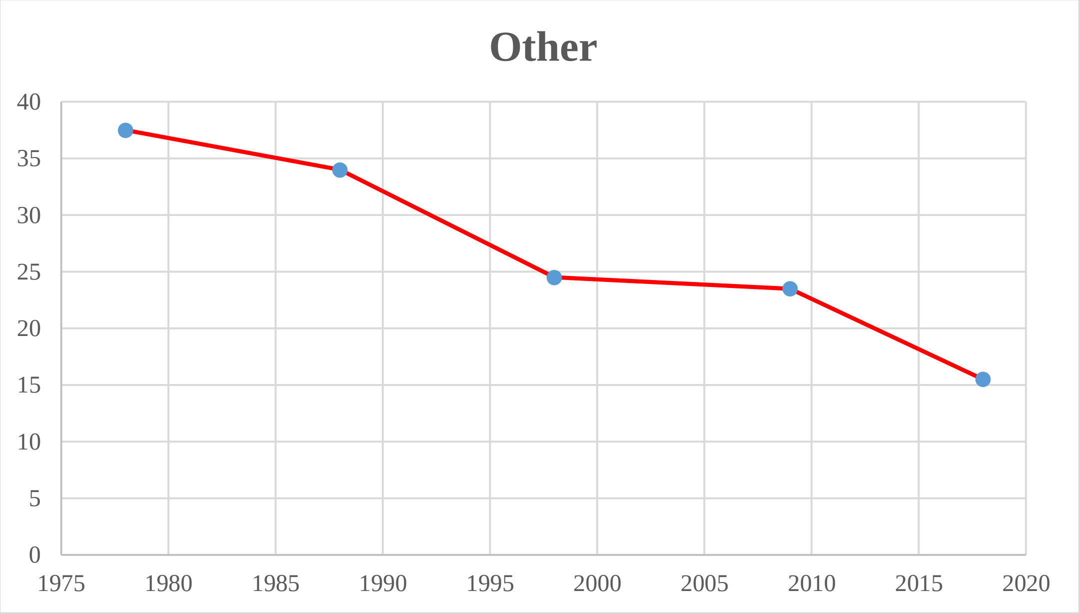

Figure 12. Other land-use/land-cover class area (%) from 1978 to 2018 in Sunamganj haor region

4.7 Lan-use/land-cover transformation

Transformation of different land-use/land-cover types for five periods was analyzed by using the spatial analysis tools in ArcGIS and the transfer matrix of land-use/land-cover was attained. The transfer matrix of LUCC in five periods and overall transfer matrix was shown in Table 18-22. Water body, Agricultural land, Tree cover and other land-use/land-cover class were showed greater changes. The transfer-in rate of other land-use/land-cover class had been rapidly decreased in five periods and agricultural area had been rapidly increased in this five periods. The finding showed that over the last five periods, other land-use/land-cover class was transferred into agricultural land and tree cover classes. Around the main water body (rivers, streams, lakes) land had shifted into agricultural land cover.

4.7.1 Land-use/land-cover change matrix from 1978 to 1988

During this period, the significant area of the water body had converted into different land-use types such as agricultural land (197.5 Km^2), tree cover (31 Km^2) and other (30.5 Km^2) and the highest portion of the water body land had transferred to agricultural land. This had resulted in the decrease of the water body land-cover area. During this period other had converted into different land-use types such as water body (60.5 Km^2), agricultural land (152.5 Km^2) and tree cover (175.5 Km^2) and the highest portion of the other had transferred to tree cover. This had also resulted in the decline of other. There had been a considerable increase in the agricultural land area which had converted into water body (52 Km^2), tree cover (211.5 Km^2) and other (163 Km^2). The highest portion of the agricultural land had converted to tree cover. There had been a considerable increase in the tree cover area (319.5 Km^2) during 1978 to (557 Km^2) 1988, mainly agricultural land and other land were converted to tree cover area as it had shown in Table 18.

Table 18. Cross-tabulation of land-use/land-cover classes from 1978 to 1988 (Area in Km^2)

1978 **1988**	WB	AL	TC	OT	**Total**
WB	175	197.5	31	30.5	434
AL	52	1130	211.5	163	1556.5
TC	4	115.5	139	61	319.5
OT	60.5	152.5	175.5	1004.5	1393
Total	291.5	1595.5	557	1259	**3703**

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

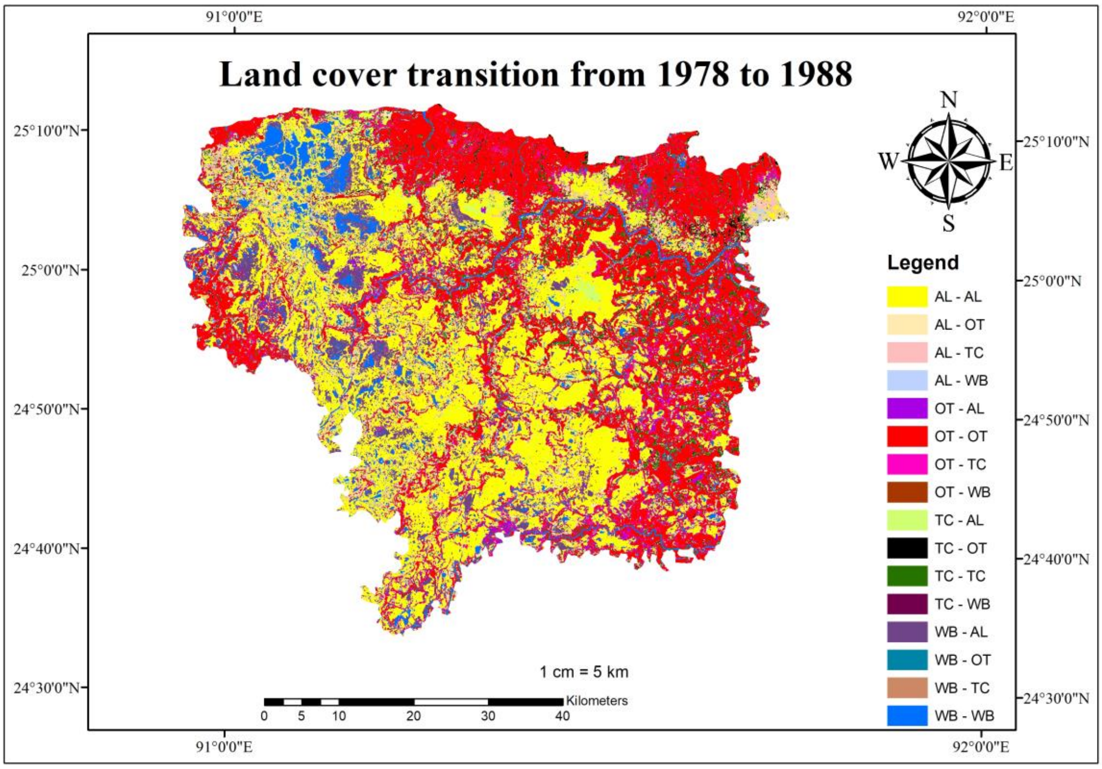

Figure 13. Sunamganj haor region land-cover transition from 1978 to 1988

4.7.2 Land-use/land-cover change matrix from 1988 to 1998

During this period, the largest portion of agricultural land area had converted into the tree cover (130.5 Km²). Agricultural land area also converted into different land-use types such as water body (72 Km²) and other (27 Km²) as evidenced in Table 19. This had resulted in the increase of agricultural land cover area. During this period, other land-cover had converted into different land-use types such as water body (36.5 Km²), agricultural land (215 Km²) and tree cover (201 Km²). The highest portion of the other land had transferred to agricultural land. This had also resulted in the decrease of other land area. During the year (1988-1998), water body had decreased considerably by 12 Km², though some portion of its cover was changed into agricultural land (90 Km²), tree cover (17.5 Km²) and other (27 Km²). During this period 72 Km² agricultural land, 14 Km² tree cover and 36.5 Km² of other had converted into waterbody. During this period tree cover had increased considerably by 79.5 Km², through some portion of its cover was changed into water body (14 Km²), agricultural land (204.5 Km²) and other (51 Km²). During this period, 17.5 Km² water body, 130.5 Km² agricultural land and 201 Km² other converted into tree cover.

Table 19. Cross-tabulation of land-use/land-cover classes from 1988 to 1998 (Area in Km²)

1988 / **1998**	WB	AL	TC	OT	**Total**
WB	157	90	17.5	27	291.5
AL	72	1370	130.5	23	1595.5
TC	14	204.5	287.5	51	557
OT	36.5	215	201	806.5	1259
Total	279.5	1879.5	636.5	907.5	**3703**

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

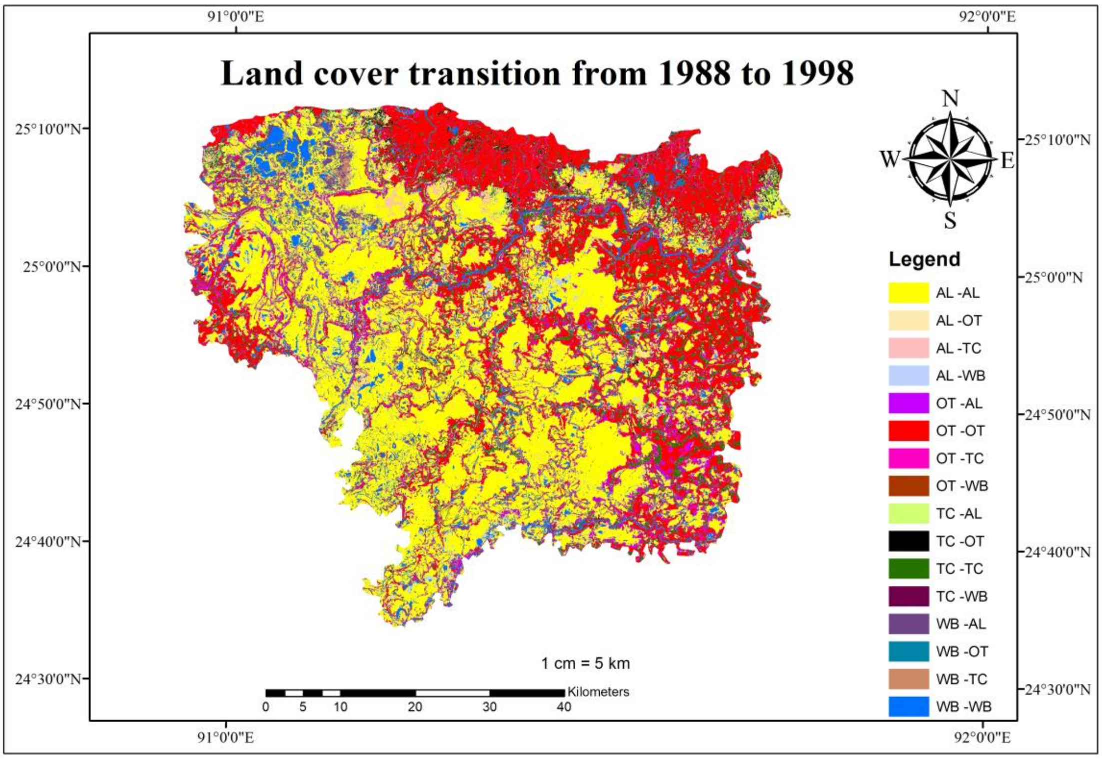

Figure 14. Sunamganj haor region land-cover transition from 1988 to 1998

4.7.3 Land-use/land-cover change matrix from 1998 to 2009

During this period, the largest portion of other had converted into the tree cover (150 Km²). Other also converted into different land-use types such as 29.5 Km² water body, 137.5 Km² agricultural land as evidenced in Table 20. This had resulted in the decrease of other. During this period tree cover had converted into different land-use types such as water body (10 Km²), agricultural land (231 Km²) and other (118.5 Km²). This had also resulted in the decrease of tree cover. During the period (1998-2009) water body had decreased considerably by 77.5 Km², though some portion of its cover was changed into agricultural land (126.5 Km²), tree cover (24.5 Km²) and other (12 Km²). During this period 46 Km² agricultural land, 10 Km² tree cover and 29.5 Km² of other had converted into water body. During the year (1998-2009) agricultural land had increased considerably by 151.5 Km², through some portion of its cover was changed into water body (46 Km²), tree cover (138.5 Km²) and other (159 Km²). During this period 126.5 Km² water body, 231 Km² tree cover and 137.5 Km² other converted into agricultural land.

Table 20. Cross-tabulation of land-use/land-cover classes from 1998 to 2009 (Area in Km^2)

1998 **2009**	WB	AL	TC	OT	**Total**
WB	116.5	126.5	24.5	12	279.5
AL	46	1536	138.5	159	1879.5
TC	10	231	277	118.5	636.5
OT	29.5	137.5	150	590.5	907.5
Total	202	2031	590	880	**3703**

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

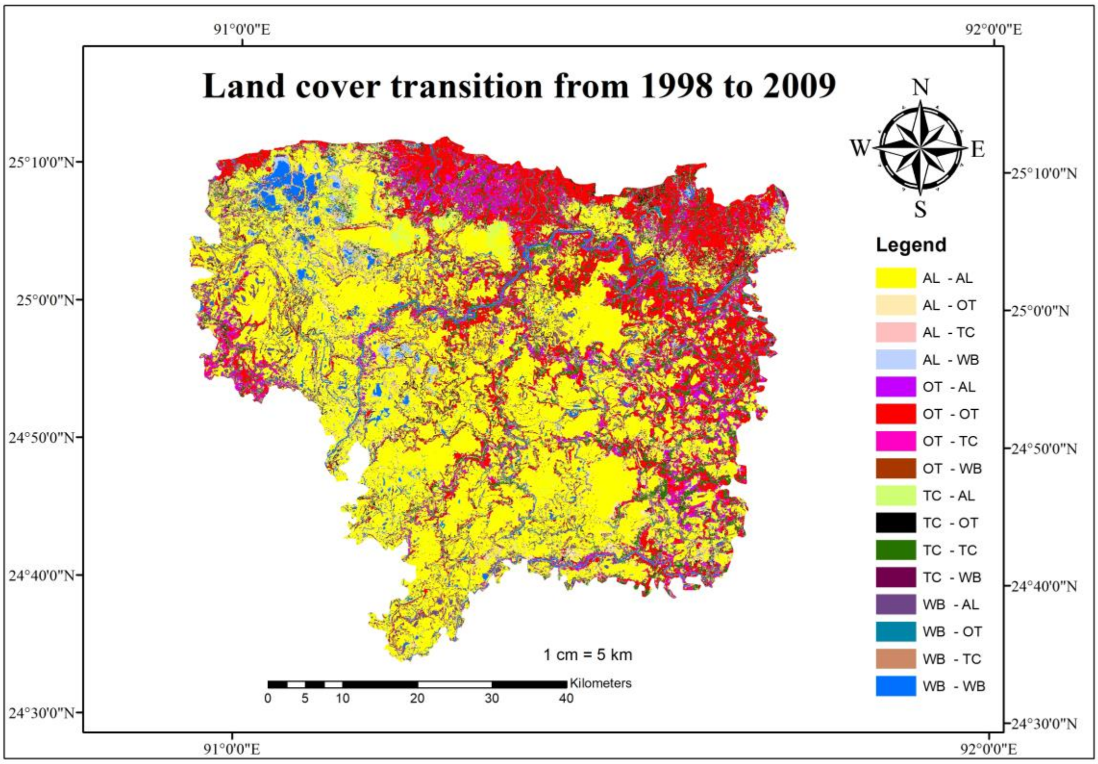

Figure 15. Sunamganj haor region land-cover transition from 1998 to 2009

4.7.4 Land-use/land-cover change matrix from 2009 to 2018

During this period, the largest portion of other had converted into the agricultural land (356 Km²). Other also converted into different land-use types such as water body (5 Km²), tree cover (92.5 Km²) as showed in Table 21. This had resulted in the decrease of other. During this period, tree cover had converted into different land use types, such as, water body (18.5 Km²), agricultural land (219 Km²) and other (74 Km²). This also had resulted in the decrease of tree cover. During this period water body had converted into different land-use types, such as, agricultural land (67.5 Km²), tree cover (4 Km²) and other (10.5 Km²). During the period, agricultural land had increased considerably by 396 Km², through some portion of its cover was changed into water body (45.5 Km²), tree cover (137 Km²) and other (64 Km²). During this period, 67.5 Km² water body (67.5 Km²), tree cover (219 Km²) and other (356 Km²) were converted into agricultural land.

Table 21. Cross-tabulation of land-use/land-cover classes from 2009 to 2018 (Area in Km²)

2009 / **2018**	WB	AL	TC	OT	**Total**
WB	120	67.5	4	10.5	202
AL	45.5	1784.5	137	64	2031
TC	18.5	219	278.5	74	590
OT	5	356	92.5	426.5	880
Total	189	2427	512	575	**3703**

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

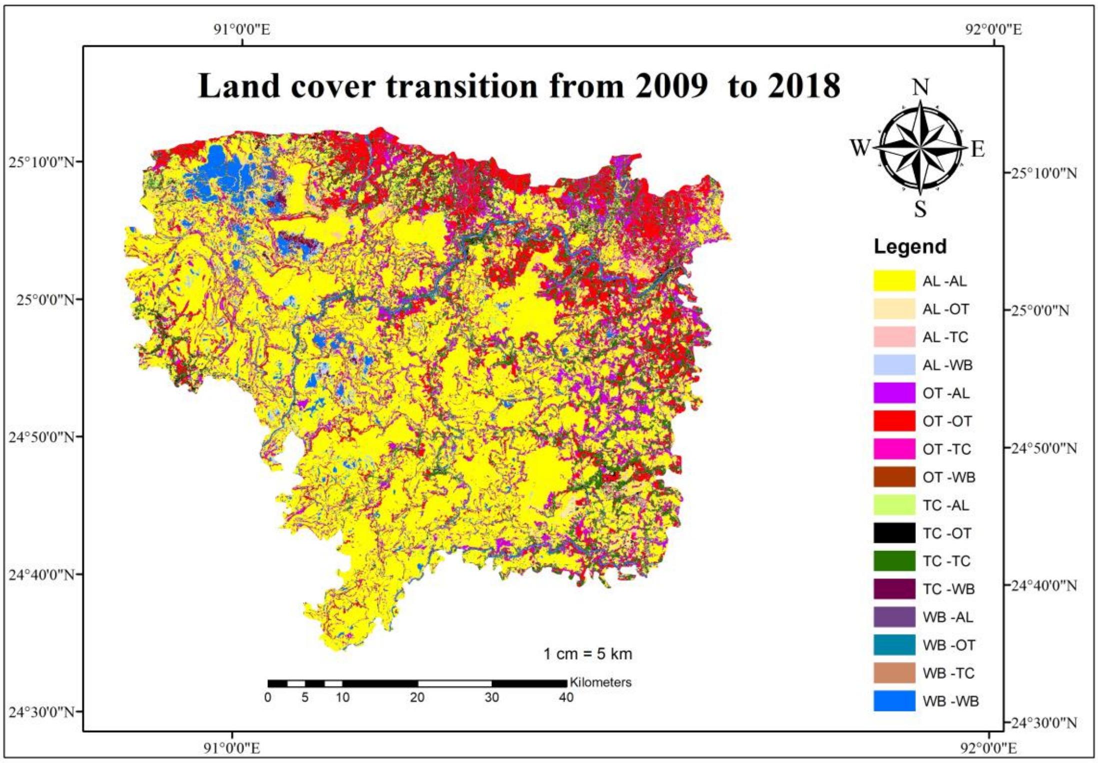

Figure 16. Sunamganj haor region land-cover transition from 2009 to 2018

4.7.5 Land-use/land-cover change matrix from 1978 to 2018

During this period the largest portion of other had converted into the agricultural land (676 Km²). Other was also converted into different land-use types, such as, water body (13.5 Km²), tree cover (258 Km²) as showed in Table 22. This had resulted in the decrease of other. During this period, water body had converted into different land-use types, such as, agricultural land (260 Km²), tree cover (12.5 Km²) and other (19 Km²). This also indicated in the decrease of water body. During this period, tree cover had increased considerably by 192.5 Km², through some portion of its cover changed into water body (2 Km²), agricultural land (161.5 Km²) and other (30.5 Km²). During the period, agricultural land has increased considerably by 870.5 Km², through some portion of its cover was changed into water body (31 Km²), tree cover (116 Km²) and other (80 Km²). During this period, water body (260 Km²), tree cover (161.5 Km²) and other (676 Km²) were converted into agricultural land.

Table 22. Cross-tabulation of land use/land-cover classes from 1978 to 2018 (Area in Km²)

1978 2018	WB	AL	TC	OT	**Total**
WB	142.5	260	12.5	19	434
AL	31	1329.5	116	80	1556.5
TC	2	161.5	125.5	30.5	319.5
OT	13.5	676	258	445.5	1393
Total	189	2427	512	575	**3703**

*WB= Water Body, AL= Agricultural Land, TC= Tree Cover, OT= Other

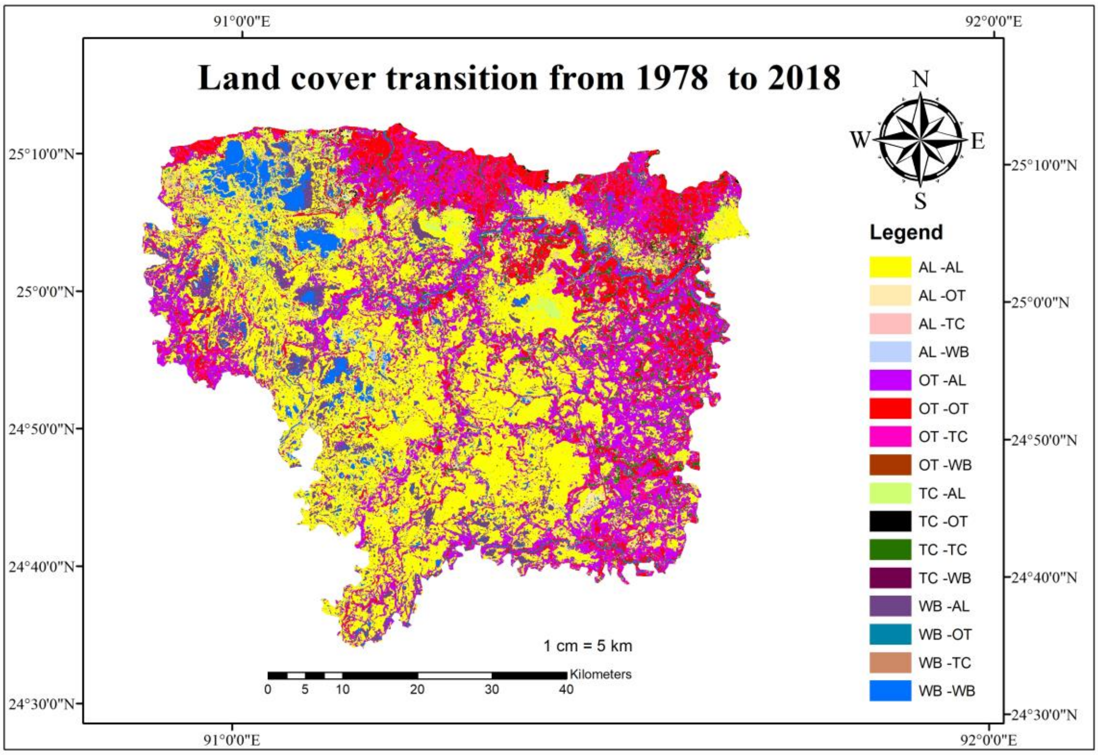

Figure 17. Sunamganj haor region land-cover transition from 1978 to 2018

In this research, the cross-tabulation of land-use/land-cover classes from 1978-1988, 1988-1998, 1998-2009, 2009-2018 and 1978-2018, respectively showed the change detection presented in Table18,19,20,21 and 22. The results of these change detections revealed that the Sunamganj haor area has seen considerable LULC changes over the previous four decades. For 1978-2018, significant changes were observed i.e. water body (260 Km^2), tree cover (161.5 Km^2) and other (676 Km^2) converted into agricultural land, while agricultural lands (13.5 Km^2), tree cover (2 Km^2) and other (13.5 Km^2) were converted into the water body. Another major conversion that occurred over the last 40 years is that about 13.5 km^2 other was converted into the water body, other (676 Km^2) into agricultural land and other (258 Km^2) into tree cover. This study results exhibited that the water surface area of Sunamganj haor has been changed during the period of examination. It was found that around 245 Km^2 water surface was lost in 2018 compared to 1978. Mainly, water body area was decreased dramatically and converted to agricultural land. The reason behind this conversion, mainly agricultural activities are popular in this haor region. Consequently, the agricultural land of the study area had increased by approximately 23.5% over the four decades due to increasing agricultural activities. It was found that around 870.5 km^2 agricultural land has increased from 1978 to 2018. Moreover, swamp forest and homestead garden in village stated as tree cover class in this study had declined gradually due to increased population and food demand. Another change was found on other land class and it showed decreasing rate. Around 818 km^2 other land class was lost in 2018 in comparison with 1978's other land cover. Fish diversity and bird habitation in the haor area were also declined for degradation of the water area. It would be worth mentioning that similar trend of LULC changes has also been found in two other haors in Bangladesh, namely Tanguar haor and Lakshmibaur-Nalair haor situated in the same haor basin. (Haque and Basak, 2017; Bhattcharjee *et al*., 2021). Over the previous four decades, the water bodies in Tanguar and Lakshmibaur-Nalair haors have diminished, tree cover has decreased, and agricultural fields have expanded (Haque and Basak 2017; Uddin et al. 2013). These findings clearly show that rising demographic pressure has affected the land-cover of haor areas substantially. The ecosystems of the Haor are being harmed as a result of a lack of adequate monitoring and management. By comparing previous and present circumstances, the current work helps to get a better understanding of such shifts. As a result, reliable and up-to-date data is critical for continuous monitoring of the haor region and more sustainable haor resource management.

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATION

Summary

The haor offers social, economic, and environmental benefits that provide income and jobs as a basis of their livelihoods. It is the habitat of indigenous birds and sweet water trout and is of considerable significance in the processing of food, protecting biodiversity, and satisfying local demand.

The research was conducted in the Sunamganj district. The Sunamganj district contains a large number of wetlands and haors. Haor basin is a low-lying bowl-shaped basin in Sunamganj district that covers 3747 Km^2. Tanguar haor is a significant wetland system in Bangladesh's northeastern area.

The use of remotely sensed multi-temporal data to monitor changes in haor land-cover gives an accurate and thorough estimate of human impact on the environment. Among the various characteristics of climate change, land-use change has been emphasized as a critical human-induced influence on ecosystems.

Hence this study was carried out to quantify Sunamganj district land-use/land-cover change from 1978 to 2018 using Landsat MSS, TM, and OLI imagery. Main objectives of this research is to develop an up-to-date land-use cover map, to prepare time-laps land-use/land-cover map for every 10 years since 1978 and to analyze dynamics of tree cover change in the Sunamganj haor region over the last 40 years from historical Landsat satellite imagery.

This research utilized ArcGIS 10.5 software for image processing, mapping, classification of image and change detection. To perform the study, two types of data were used. These were Landsat satellite images and historic Google Earth image which was used as reference data. A total of 5 Landsat satellite images for the last 40 years were obtained for the analysis of patterns in LUCC dynamics from http://earthexplorer.usgs.gov, which is freely available to estimate land use and land cover changes throughout the research period.

All Landsat images were processed and corrected in the same coordinate system and downloaded during the same month and season for varied years to reduce seasonal changes in land use and land cover. The month of February was chosen as the research period since the Boro rice sowing season runs from December to January. Landsat satellite images from 1978, 1988, 1998, 2009, and 2018 were obtained at 10-year intervals from http://earthexplorer.usgs.gov. Ground truth data was created using historical Google Earth images, which were primarily utilized to improve supervised classification and accuracy assessments.

By stacking the spectral bands 654 (MSS data), 432 (TM data), and 543 (OLI data), a Red Green Blue (RGB) False Color Composite (FCC) image was developed. Maximum likelihood supervised classifications were undertaken in ArcGIS (Version 10.5) on 1978, 1988, 1998, 2009 and 2018 Landsat images. Each Landsat image was classified into four land use classes i.e. Water Body, Tree cover, Agricultural Land, and Other.

The accuracy assessments were performed for classified images of 1978, 1988, 1998, 2009 and 2018. It indicates that the overall classification accuracy of land use maps was 82.50% for 1978, 81.00% for 1988, 84.00% for 1998, 84.00% for 2009 and 90.00% for 2018. The Kappa coefficient for the maps of 1978, 1988, 1998, 2009 and of 2018 were 76.38%, 73.00%, 77.00%, 77.28% and 86.00%, respectively.

Area calculation showed that the entire water body covered 434 km² in 1978 which also covered 291.5 Km², 279.5 Km², 202 Km² and 189 Km² in 1988, 1988, 2009 and 2018, respectively. The water body was dramatically changed during the last 40 years. It had been 12%, 8%, 7.5%, 5.5% and 5% of the entire area during 1978, 1988, 1998, 2009 and 2018 years, respectively. It showed decreasing rate of water body. The entire agricultural land covered 1556.5 Km² in 1978 which turned to 1595.5 Km², 1879.5 Km², 2031 Km² and 2427 Km² in 1988, 1998, 2009 and 2018, respectively. It had been 42%, 43%, 51%, 55% and 65.5% of the entire area during 1978, 1988, 1998, 2009 and 2018 years, respectively. There was only 319.5 Km² area covered by tree cover during 1978. But the tree cover area was increased by about 557 Km² and 636.5 Km² in 1988 and 1998, respectively. Then tree cover decreased from 1998 to 2018 due to deforestation. It had been covered 590 Km² and 512 Km² during 2009 and 2018, respectively. It was 8.5%, 15%, 17%, 16% and 14% of the entire area during 1978, 1988, 1998, 2009 and 2018 respectively. Tree cover showed increasing and decreasing trends. The entire amount of other in 2018 was 575 Km² which decreased a huge amount from previous years. During 1978, the entire other land use cover class was 1393 Km². It had been dropped in 1988 about 1259 Km², 1998 about 907.5 Km², 2009 about 590 Km² and dropped in 1988 about 1259 Km², 1998 about 907.5 Km², 2009 about 590 Km² and dropped again in 2018 about 575 Km². It was 37.5%, 34%, 24.5%, 23.5% and 15.5% of the entire area during 1978, 1988, 1998, 2009 and 2018 years, respectively. So that, consistent with the observation of last 40 years results, it had been clear that another land use cover class was decreasing day by day. The results of those change detections revealed that the Sunamganj haor area had seen considerable LULC changes over the previous four decades.

For 1978-2018, significant changes were observed in every land-use classes. Compared with 1978, the current water body area decreased by 7% of the total area. It was found that around 245 Km^2 water body losses from 1978 to 2018. Mainly, water body area had been decreased dramatically and converted to agricultural land. The rationale behind this conversion, mainly agricultural activities is popular during this hoar region. Consequently, the agricultural land of the study area has increased by approximately 23.5% over the four decades due to increasing agricultural activities. It was around 870.5 Km^2 agricultural land had increased from 1978 to 2018. Moreover, swamp forest and village homestead garden stated as tree cover class during this study showed increasing and decreasing trend. Tree cover had been declined gradually due to increased population and food demand from 1998 to 2018. Another change found on other land class and its showed decreasing rate. It was found around 818 Km^2 other land class losses from 1978 to 2018. These findings clearly show that rising demographic pressure has affected the land-cover of haor areas substantially. The ecosystems of the haor are being harmed as a result of a scarcity of adequate monitoring and management.

Conclusion

Based on the results of this research, the following conclusion can be drawn:

- This study demonstrated that the study location's water surface area declined at an alarming rate (6.15 km^2/ year) over the last 40 years. Indeed, compared with 1978, the current water body area decreased by 7% of the total area.
- Tree cover showed an increasing and downward trend between 1978 to 2018. Tree cover showed an increasing trend from 1978 to 1998 and then decreasing trend between 1998 to 2018.
- Croplands increased by 23.5% over the four decades to rising low laying area which is favorable for agricultural activities in the dry season and increased population pressure which attracts more agriculture activities.
- Other land-use class also displayed a downward trend between 1978 and 2018. It was found that around 818 Km^2 other land class losses from 1978 to 2018.
- This simple and minimal effort monitoring procedure would be useful for decision-maker, forest organizer, natural resources manager for sustainable management of Sunamganj haor region.

Recommendations

Finally, it can be recommended that-

1. Some agricultural land cover classes pixel was confused with the spectral characteristics of tree cover classes, the classification findings obtained in this study were shown to have considerable levels of agreement with the reference data. For better finding it should be considered.
2. The available satellite imagery has a limited spatial resolution. It is a key element that affects the accuracy of the outcomes. The satellite imagery used in this study has a resolution of 30m×30m. There are numerous land use classifications within 900 square meters (one pixel) in certain areas, making the categorization less precise. Imagery with a greater spatial resolution (e.g., 10m×10m) might aid in improving the categorization result as well as the overall research findings. However, the expense of such images was beyond the scope of this research.

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