Land Use and Land Cover Changes: A Case Study of Bandarban District

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DEDICATION

I would like to express my heartfelt gratitude and dedication to my beloved parents who have been a constant source of support and encouragement throughout my academic journey and life. Their unwavering love and guidance have played an integral role in shaping me into the person I am today.

I would also like to extend my sincere appreciation to my respected teachers, whose compassionate and consistent cooperation and guidance have been invaluable to me. Their dedication to teaching and commitment to my academic success have been instrumental in helping me achieve my goals.

I am truly grateful for the unwavering support and guidance of my parents and teachers, and I will always cherish their contributions to my life and education.

DECLARATION

The paper entitled "Land Use and Land Cover Changes: A Case Study of Bandarban District" has been prepared by me to submit to the Department of Environmental Science and Disaster Management, Daffodil International University as a requirement for the partial fulfillment of the degree B.Sc. in ESDM. This paper has neither been submitted nor been accepted elsewhere for any purposes. To my best knowledge and conviction, it contains no material beforehand distributed or composed by someone else, aside from when due references are made in the content of this paper.

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CERTIFICATION

This is to be certified that, ID No:191-30-004, Batch: 26 has prepared this paper entitled "Land Use and Land Cover Changes: A Case Study of Bandarban District" under my supervision. I do hereby approve the style and content of this paper. This is for the partial fulfilment of the degree of B.Sc. in ESDM, Daffodil International University.

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Abbreviations and Acronyms

LULC: Land Use and Land Cover Change

GIS: Geography Information System

RS: Remote Sensing

USGS: United States Geological Survey

TM: Thematic Mapper

ETM+: Enhanced Thermic Mapper

OLI: Operational Land Imager

TIRS: Thermal Infrared Sensor

WGS: World geodetic System

NASA: National Aeronautics and Space Administration

ABSTRACT

In the Bandarban district of Bangladesh, optical satellite imagery has been analyzed for the purpose of determining the spatial distribution of land use and land cover (LULC) categories, as well as the temporal changes that have occurred, and making predictions about those categories. This is the primary study area work in which multi-temporal Landsat imagery has been utilized to generate LULC maps for the years 1992, 2002, 2012, and 2022. The first part of the process consisted of deriving a total of six LULC categories through the integration of NDVI and supervise classification techniques. These categories also were evaluated through the use of the error matrix table and kappa statistics. Overall accuracy and Kappa statistic for all four years were both above 90%, according to the results of the accuracy assessment process. An exhaustive change analysis was performed with the help of the Land Change Modeler (LCM), and the results showed that significant shifts had occurred in the hilly forest, shrub land, and crop land categories between the years 1992 and 2022. From 1992 to 2022, hill forest decreased 74.41% to 46.66%, or 121504 hectares, while shrub land and cropland increased 16.48% to 43.61% and 5.26% to 7.39%, respectively. During the second stage of the process, Markov chain-cellular automata was utilized to model and make predictions regarding LULC in the study area. The Markov chain was used first to generate transition probability matrices between LULC categories, and then cellular automata was used to predict the LULC map for 2022 to validation. Afterwards, following the successful validation of the observed and predicted LULC maps for 2022 (approximately similar), the combined procedure was used to simulate land use and land-cover for 2052. The results of the simulation for the years 2022-2052 showed a significant rise in the amount of shrub land, crop land, and settlement area while there was a dramatic decrease in the amount of hilly forest, which dropped from 46.66% to 32.59%. All of these findings from the research could offer the opportunity for more skilled management and policy making in the study region regarding biodiversity, forests, land, and other environmental resources.

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CHAPTER 1. INTRODUCTION

1.1 Background

The importance of land as a vital natural resource for human survival and prosperity, and for the balanced functioning of terrestrial ecosystems cannot be overstated [1]. Changes in land cover are easily observable and serve as significant indicators of alterations to the Earth's surface [1]. In modern times, information on land cover is vital across various aspects of life, including the scientific, economic, and political realms [1]. Detecting changes in land use and land cover is crucial in determining the impact of human activities on the planet [2]. Anthropogenic influences, especially changes in land cover, are widely regarded as one of the primary factors contributing to environmental degradation [3]. Therefore, estimating temporal changes in land cover enables the evaluation of the rate at which changes advance, links them with issues or impacts, and improves predictions of future trends and impacts in environmentally degraded areas [4]. The causes of land cover changes are multifaceted, including factors such as tropical deforestation, conversion of forested land to agricultural land, urbanization, encroachment, and other human interventions [5, 6]. Land cover changes are also influenced by socioeconomic and biophysical factors [7].

The degradation of soil caused by LULCC is a silent disaster for terrestrial ecosystems. The erosion of the most nutrient-rich topsoil, breaking of the food chain, and damage to wildlife habitats leads to a loss of biodiversity and ecosystem services [46, 47, 48, 49, 51]. Additionally, LULCC contributes to pollution in the atmosphere, hydrosphere, and biosphere from various point and non-point sources [52], increased concentration of CO_2 and other greenhouse gases in the atmosphere [50], and disrupted hydrological cycles.

LULCC is a dynamic process that is occurring globally [4]. Bangladesh, being primarily an agricultural nation with a greater proportion of rural than urban areas, has experienced significant levels of LULCC due to heavy population pressure and the urbanization process [8]. Only 10.96% of Bangladesh was covered by vegetation in 2016, and the majority of that land was covered by evergreen and semi-evergreen tropical rain forests, most of which are located in the Chittagong hill tracts region [10]. Bandarban, one of the three hill districts of Bangladesh and a part of the Chittagong Hill Tracts, is an area with pristine natural resources and rich flora and fauna diversity

[11]. However, the natural resources in the Bandarban region have been deteriorating due to shifting land use and land cover patterns. Therefore, proper environmental conservation and ecological engineering design are essential to protect forest quality and the entire ecosystem in the region [8].

LULCC is a significant issue with global implications. The causes and consequences of LULCC are multifaceted, affecting environmental, economic, and social aspects of life. Estimating temporal changes in land cover is essential for evaluating the rate at which changes advance, linking them with issues or impacts, and improving predictions of future trends and impacts in environmentally degraded areas. In Bangladesh, LULCC is primarily driven by population pressure and the urbanization process, leading to the deterioration of natural resources in areas such as Bandarban. Therefore, proper environmental conservation and ecological engineering design are critical to protect forest quality and the entire ecosystem in the region.

1.2 Justification

Geographic Information System (GIS) and Remote Sensing (RS) are powerful tools for analyzing and modeling Land Use and Land Cover (LULC) changes. These techniques have been used extensively for monitoring natural resources through sustainable resource management [8]. Traditional ground-based methods of monitoring vegetation cover are labor-intensive, time-consuming, and produce maps that quickly become obsolete, particularly in rapidly changing environments [12]. Remote sensing data have become the primary data source for change detection applications due to their higher temporal resolution, wider synoptic perspective, and digital format. Satellite data sources provide more precise estimates than traditional inventory techniques, and their low cost or free availability makes them a useful tool for forest managers and scientists in developing countries like Bangladesh.

Geographic Information System and Remote Sensing allow for critical analysis and decision support for changes in the Earth's surface in an appropriate time frame. Remote sensing data from multi-temporal and multispectral satellite images with multiple spatial resolutions provide great potential for LULC monitoring [38], including historical patterns and future simulations, which are required for sustainable land use, planning, and policy development at the governmental and non-governmental levels. GIS is used to model and simulate LULC using information obtained from remotely sensed data [39, 40]. There are two main categories of LULC models: spatial and aspatial. Spatial models are used to predict LULC in a particular region and associated factors [44]. Empirical-statistical models and rule-based models are included in the spatial category and are primarily used to analyze the changing pattern and spatial location of existing and potential future LULC changes. The Markov chain model integrated with Cellular Automata is a popular spatial model used for spatio-temporal modeling of LULC.

Although Bangladesh has started to use satellite images and GIS applications, currently there has no land cover change detection studies in the Bandarban district. This region has a significant tourism industry, but it is facing environmental challenges due to the depletion of its forest cover and natural resources [14]. Therefore, this study aims to analyze the land use and land cover changes of the Bandarban district using Landsat time-series imagery from 1992 to 2022 (30-year time range) and simulate future scenarios using spatial simulation (Markov chain and Cellular Automata) if the current trend of conversion continues. This district has been selected because to its significant tourism concentration and flourishment of settlement.

1.3 Objectives of the Study

- To develop and monitor the land use and land cover maps of Bandarban using ArcGIS for the year 1992 to 2022 (time range of 30 years) with 10 years interval.

- To simulate the future scenario, if the current trend of conversion is continued by using spatial modeling (Markov chain and cellular automata).

- To analysis how the land cover of the study area is changing over the period of time.

CHAPTER 2. LITERATURE REVIEW

2.1 Land Use and Land Cover Change

Land cover refers to the biophysical features, such as the physical, chemical, or biological categorization of the Earth's surface, such as grassland, forest, or concrete, while land use refers to the human purpose or intent applied to these attributes, such as cattle, recreation, or urban living [14]. Land use and land cover changes are related, but they are not the same. Land cover change can occur as a result of land conversion, land modification, or various land management practices. Land use change is also referred to as the modification or alternation of land use types and the conversion of one type of land use to another. Land cover may change as a consequence of biophysical factors, although this is typically the result of human-induced land use change [15].

2.2 Geographical Information System (GIS)

Geographic Information System (GIS) is a computer system made up of hardware and software for collecting, storing, retrieving, processing, and displaying geospatial data. This system makes it easier to store, manipulate, analyse, model, depict, and display geo-referenced data in order to address resource-related complicated problems [16]. Some of the primary functions of GIS include data entry, management, data display, information sorting, and data analysis. GIS can be used in the study of hydrology, urban planning, engineering, environmental and natural resource management, history, networking, facility management, crime, etc. since it can be used to find distances, quantities, densities, locations, map locations, and monitor changes [17, 18].

2.3 Remote sensing (RS)

Remote sensing is the study of acquiring information about particular properties of phenomena, objects, or materials via measurements taken at a distance from the object. Remote sensing can be described as a method of gathering data on the Earth's land and water bodies by capturing images from a high-altitude perspective, utilizing electromagnetic radiation within different parts of the electromagnetic spectrum, which are either reflected or emitted by the Earth's surface.[15]. Various objects reflect different types of radiation in different electromagnetic spectrum bands, depending on the material's characteristics, roughness, intensity, angle, and wavelength. All natural and man-made things reflect or emit electromagnetic radiation, which includes both visible light and unseen thermal infrared energy. Remote sensing is used to measure and gather this energy. Active and passive devices are indeed used in the process of remote sensing. Active devices, such as radar, beam, and the like, intentionally produce energy to deliver to a certain object and collect its reflection. Passive devices automatically detect the object's natural emission of energy [19].

2.4 ArcGIS

ArcGIS is a geographical information system (GIS) software that enables the management and analysis of geographic data through the visualization of geographical statistics on layer-building maps, such as climate data and trade flow. The system is a general-purpose GIS software programme developed by ESRI. It is a comprehensive and integrated software platform technology that is used for the development of operational GIS. The software system ArcGIS consists of four key components, which together provide a wide range of functionalities related to geographic information. These components include a geographic information model for simulating aspects of the real world, tools for storing and managing geographic information in files and databases, a suite of pre-built applications for creating, editing, analyzing, mapping, and sharing geographic information, and a set of web services that offer data and functions to networked software clients.

One of the significant advantages of ArcGIS is its versatility, as it can be deployed on various devices, including mobile devices, laptops, desktops, and servers. By using this system, users can access a range of advanced capabilities, including the ability to create detailed maps and visualizations, analyze spatial data, and share information with others through various platforms and formats.

In more detail, the geographic information model included in ArcGIS allows users to simulate real-world environments, providing a powerful tool for planning, analysis, and decision-making in many different contexts. This model can be used to represent a range of geographic features and phenomena, including terrain, land use, and natural resources.

Meanwhile, ArcGIS also includes various tools for storing and managing geographic information, which can be saved in files or databases. These tools enable users to keep track of various types of data, including maps, imagery, and tabular data, and to organize and retrieve this information as needed.

In addition to these capabilities, ArcGIS includes a suite of pre-built applications that provide a wide range of functionalities for creating, editing, analyzing, mapping, and sharing geographic information. These applications are designed to be user-friendly and intuitive, making it easy for users to work with complex spatial data and perform a range of tasks related to geographic information.

Finally, ArcGIS also includes a set of web services that offer data and functions to networked software clients, providing users with access to a wealth of additional resources. These services can be used to access real-time data, perform spatial analysis, and share information with others through web-based platforms and applications.

Overall, ArcGIS provides a comprehensive set of tools and capabilities for working with geographic information, making it an essential resource for a wide range of professionals and organizations. Whether used for urban planning, environmental analysis, or emergency response, this system offers a powerful suite of features that can help users to visualize, understand, and manage the complex world around us.

2.5 Landsat Satellite Image

For several decades, the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA) have been actively involved in monitoring the Earth's surface through the use of remote sensing technology. In this study, utilized satellite imagery obtained from Landsat-5 TM, Landsat-7 ETM+, and Landsat-8 OLI-TIRS platforms. These highly advanced and sophisticated satellites capture high-resolution images of the Earth's land and water surfaces by sensing electromagnetic radiation across various wavelengths. By analyzing the spectral signatures present in the collected data, scientists can gain insights into a wide range of phenomena, including land use and land cover changes, vegetation health, and water quality.

Table 1: Landsat 5 TM, Details of Landsat 5 bands [20].

Landsat 5	Wavelenth (micrometers)	Resolution (meters)
Band 1 - Blue	0.45-0.52	30
Band 2 - Green	0.52-0.60	30
Band 3 - Red	0.63-0.69	30
Band 4 - Near Infrared (NIR)	0.76-0.90	30
Band 5 - Near Infrared (NIR)	1.55-1.75	30
Band 6 - Thermal	10.40-12.50	30
Band 7 - Shortwave Infrared (SWIR)	2.08-2.35	30

Table 2: Landsat 7 ETM+, Details of Landsat 7 bands [20].

Landsat 7	Wavelength (micrometers)	Resolution (meters)
Band 1 - Blue	0.45-0.52	30
Band 2 - Green	0.52-0.60	30
Band 3 - Red	0.63-0.69	30
Band 4 - Near Infrared (NIR)	0.77-0.90	30
Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
Band 6 - Thermal	10.40-12.50	60 (30)
Band 7 - Shortwave Infrared (SWIR) 2	2.09-2.35	30

Band 8 - Panchromatic	.52-.90	15

Table 3: Landsat 8 OLI, Details of Landsat 8 bands [20].

Landsat 8	Wavelength (micrometers)	Resolution (meters)
Band 1 - Coastal 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 - Shortwave Infrared (SWIR) 1	1.57-1.65	30
Band 7 - Shortwave Infrared (SWIR) 2	2.11-2.29	30
Band 8 - Panchromatic	0.50-0.68	15
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

2.6 Supervised Image Classification

Supervised classification is a quantitative technique commonly employed for analyzing remotely sensed image data. It operates on the principle that a user can select sample pixels within an image that are representative of specific classes and then utilize these training sites as references for the classification of all other pixels. Essentially, the technique involves dividing the spectral domain of the image into areas that correspond to different types of ground cover, and then using the known samples to classify the unknown pixels. The accuracy of the classification depends on the quality and representativeness of the chosen training sites, and successful implementation of this technique requires significant knowledge and experience [21].

2.7 Accuracy assessment

Accuracy assessment is an important step in the processing of remotely sensed data. It implies that the classified image was verified using the reference image. Accuracy assessment allows for the evaluation of errors that may have been carried on by the preprocessing phase, the imaging systems, or by both manual and automated interpretative methods. While evaluating the accuracy of the classified image, a comparison is made between the ways in which pixels are classified and the definitive land cover conditions obtained from their corresponding locations in the real world [22].

CHAPTER 3. METHODOLOGY

3.1 Study Area

Bandarban District, located in the southeastern Chittagong Division of Bangladesh, is known for being the country's most remote and sparsely populated district. It is situated within the Chittagong Hill Tracts, which comprises three districts, including Rangamati and Khagrachhari. With its stunning natural landscapes, Bandarban is considered to be one of the most alluring tourist destinations in Bangladesh. The study area, which was used to classify land use and land cover, covers a total land area of 437,824 hectares, ranging between 21°11' and 22°22' north latitudes and 92°04' and 92°41' east longitudes. The district shares its borders with Rangamati District to the north, Arakan (Myanmar) to the south, Chin Province (Myanmar) and Rangamati District to the east, and Chittagong and Cox's Bazar District to the west. Bandarban is a district situated in the southeastern Chittagong Division of Bangladesh, and is considered the most remote and sparsely populated area of the country. It is part of the Chittagong Hill Tracts, along with Rangamati District and Khagrachhari District.

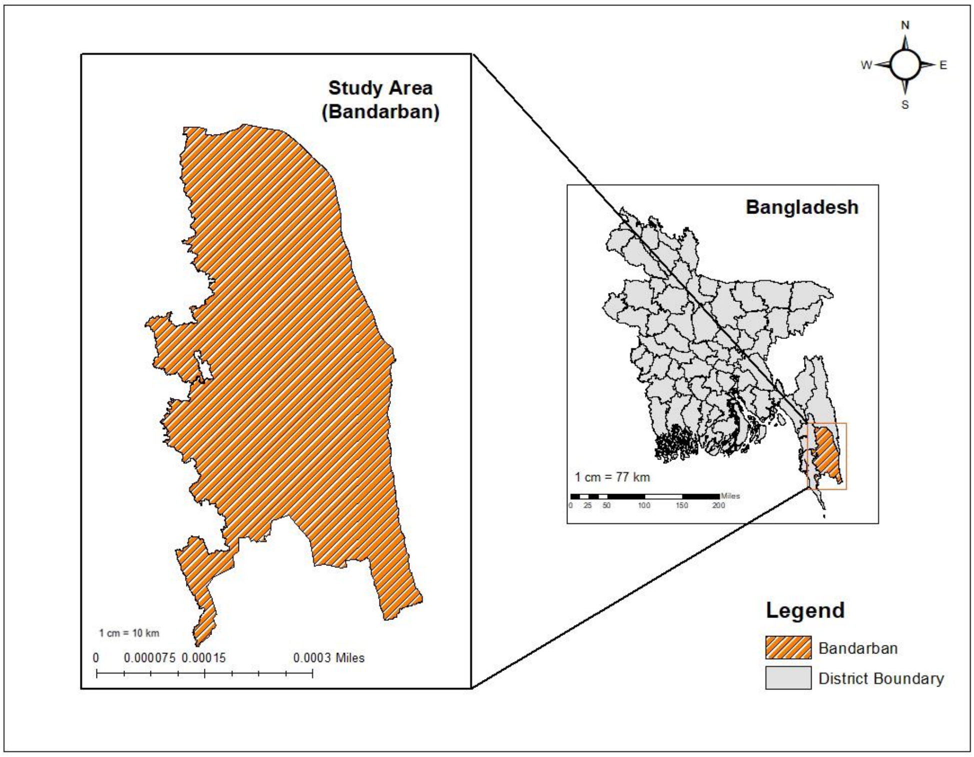

Figure 1: Location map of Bandarban District, Bangladesh

Among the notable hills in this district are Marmiana Tang, Bathil Tang, Kewkradang, Langfi Tang, Lakpang Tang, Thaingkiang Tang, Moudak Tang, Murangiang Tang, Rungrang Tang, Naprai Tang, Murifa Tang, Busi Tang, and Sara Tang. The population of the district is 298120, with 162133 males and 135987 females. The major religious groups are Muslims, Hindus, Buddhists, Christians, and others. Indigenous communities living in this upazila include Marma, Chakma, Bawm, Murong, Tripura, Khyang, Khumee, and Lushei. The economy of Bandarban is mainly based on agriculture, with 61.95% of the population engaged in agricultural activities. Non-agricultural labor accounts for 7%, while industries contribute 0.48%, commerce 9.92%, transport and communication 1.11%, construction 1.08%, religious service 0.26%, service 8.12%, rent and remittances 0.37%, and others 9.71%.

Bandarban has a tropical climate with three distinct seasons, including a dry, cool season from November to March, a hot, humid season from April to May, and a warm, cloudy, wet monsoon from June to October. The district's annual average temperature ranges from a high of 37°C to a low of 12.5°C, with an average temperature of 25.0 °C (76.9 °F), which is slightly lower than the national average. The annual precipitation is approximately 2085 mm | 82.1 inches.

Bandarban's economy is predominantly based on subsistence farming, known as Jumia, which makes it difficult to generate significant economic value. The major exports from the district include fruits such as banana, pineapple, jackfruit, and papaya, as well as masala like ginger and turmeric, and tribal textiles. The tourism industry is rapidly growing and has become an important source of revenue. However, much of the fruit trade and other commerce in the area has been taken over by Bengali settlers.

3.2 Satellite Data acquisition

The use of satellite imagery to study and analyze land use and land cover (LULC) on both a regional and a global scale has proven to have significant potential in recent years. This potential lies in the fact that satellite imagery can provide researchers with a comprehensive overview of the earth's surface over time, allowing them to track changes in land use and land cover patterns and their impacts on the environment. In this study, utilized Landsat data to investigate the changing patterns of land use and land cover in the Bandarban district of Bangladesh. To cover the entire study area, multiple paths and rows of Landsat image tiles were utilized, including path 135, 136, and row 45.

In order to ensure the accuracy of their findings, the researchers acquired two satellite scenes from each year for the dry season (December-February) from the Earth Resources Observation and Science (EROS) Center through the USGS Global Visualization Viewer. This acquisition of eight images included two Landsat5 TM images for 1992, two Landsat7 ETM+ images for 2002, two Landsat7 ETM+ images for 2012, and two Landsat8 OLI-TIRS images for 2022. By acquiring satellite images from the dry season, the researchers aimed to minimize seasonal influences that could potentially skew their results.

Furthermore, the imagery acquired for 1992, 2002, 2012, and 2022 from Google Earth Pro Map were utilized for the accuracy assessment of the classification. In this study, conducted this accuracy assessment to verify the validity of their results and ensure that their classification accurately reflects the LULC patterns of the Bandarban district. Overall, the use of satellite imagery and Landsat data in this study provides a valuable insight into the changing patterns of land use and land cover in Bandarban, which can inform future land management decisions and aid in the conservation of the region's natural resources.

Table 4: Detailed information of Landsat Images used in this study.

Year	Date of acquisition	WRS Path	WRS Row	Cloud Cover	Image quality	Sensor	Spatial Resolution
1992	31st January	135	45	2.00	7	Landsat5 TM	30
	07th December	136	45	3.00	7	Landsat5 TM	30
2002	7th March	135	45	0.00	9	Landsat7 ETM+	30
	26th February	136	45	0.00	9	Landsat7 ETM+	30
2012	30th January	135	45	0.00	9	Landsat7 ETM+	30
	06th February	136	45	0.00	9	Landsat7 ETM+	30
2022	9th February	136	45	0.00	9	Landsat8 OLI-TIRS	30
	18th February	135	45	0.00	9	Landsat8 OLI-TIRS	30

3.3 Geometric Correction

Geometric distortion is a common issue that arises in remotely sensed images, making it difficult to use them directly in a GIS with base map products. Geometric correction is a process that involves rectifying errors that are inherent in remotely sensed data, such as those caused by satellites or aircraft that do not maintain a consistent altitude or sensors that deviate from the primary focus plane. The goal of this process is to determine the exact locations and correct pixel values of the images by comparing them to ground control points on accurate base maps and resampling them. The satellite imagery obtained from the EROS data center was already geometrically corrected and projected onto the global geographic coordinate system (WGS 1984). The BTM projection system, which was developed specifically for Bangladesh by the WRPO (Bangladesh Water Resource and Planning Organization), was utilized for the projection system.

3.4 Image Processing

The images used in this study were collected from different months of the year to ensure that they were free from clouds. However, the images may have been affected by changes in seasonal weather patterns and atmospheric factors such as aerosols, dust particles, and sun angles, among others. Moreover, the data may contain noise due to the limitations of the sensor, signal digitization, and data recording process, making the radiometric information in the image less useful [36].

To mitigate the impact of clouds, the atmosphere, and the angle of the sun, rigorous atmospheric and radiometric correction was carried out on the images. Various atmospheric correction techniques, including the Empirical Dark Object Subtraction (DOS) technique [27], the Modified DOS method [32], the Cosine Estimation of Atmospheric Transmittance (COST) [26], the Moderate Resolution Atmospheric Transmission (MODTRAN) model developed by the United States Air Force, the Spectral Science, Atmospheric Correction (ATCOR) developed by German Aerospace Center (DLR), and the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) incorporated in ENVI software, have been developed.

In this study, the Semi-Automatic Classification Plugin in QGIS was used, and the dark object subtraction (DOS) technique was applied. Once the images were atmospherically corrected, each image set, which contained two images for each year, was mosaicked using the mosaic to new raster method to prepare a single scene of each study year. As a result, four single scenes were produced, which were subsequently clipped to the boundary of the study area derived from the vector file (ESRI shapefile) of the study area in ArcGIS.

3.5 Image Classification

To achieve the desired land use and land cover (LULC) categories from satellite imagery, this study used the Modified Anderson Level I classification scheme [23], which is a widely accepted and commonly used scheme worldwide. This classification scheme identified five major classes, namely vegetation, crop land, settlement area, bare land, and water body. To conduct a more detailed analysis, the vegetation class was further subdivided into hilly forest and shrub land, as shown in Table 5.

Table 5: Classification scheme of LULC used in this study.

LULC Category	Description
Hill forest	The areas of land covered by evergreen and semi-evergreen forests, as well as commercially planted forests that have extensive canopy coverage.
Shrub land	The shrublands are comprised of vegetation consisting of shrubs or short trees. This type of vegetation is often referred to as bushes, scrub, or other similar terms.
Crop land	Agricultural fields refer to land that is used for growing crops or raising livestock, while hill slope cultivated lands are agricultural lands that are cultivated on sloping terrain.
Bare Land	The study area includes open fields, exposed lands, and sand fill areas.
Settlement area	The land use and land cover (LULC) in the study area includes urban settlements, rural settlements, transportation networks, and areas used for commercial and industrial purposes.
Water BODY	The types of water bodies present in an area can include flowing water confined within a channel, as well as perennial bodies of water such as lakes, ponds, and other water reservoirs.

In order to obtain the desired categories and make decisions based on Landsat images, various methods were utilized such as NDVI and different band compositions. NDVI, which is a common and widely used method for retrieving vegetation information, uses the red and infrared bands of satellite imagery [42]. Ultimately, the Maximum Likelihood Supervised classification method was employed to generate the desired categories and facilitate decision making.

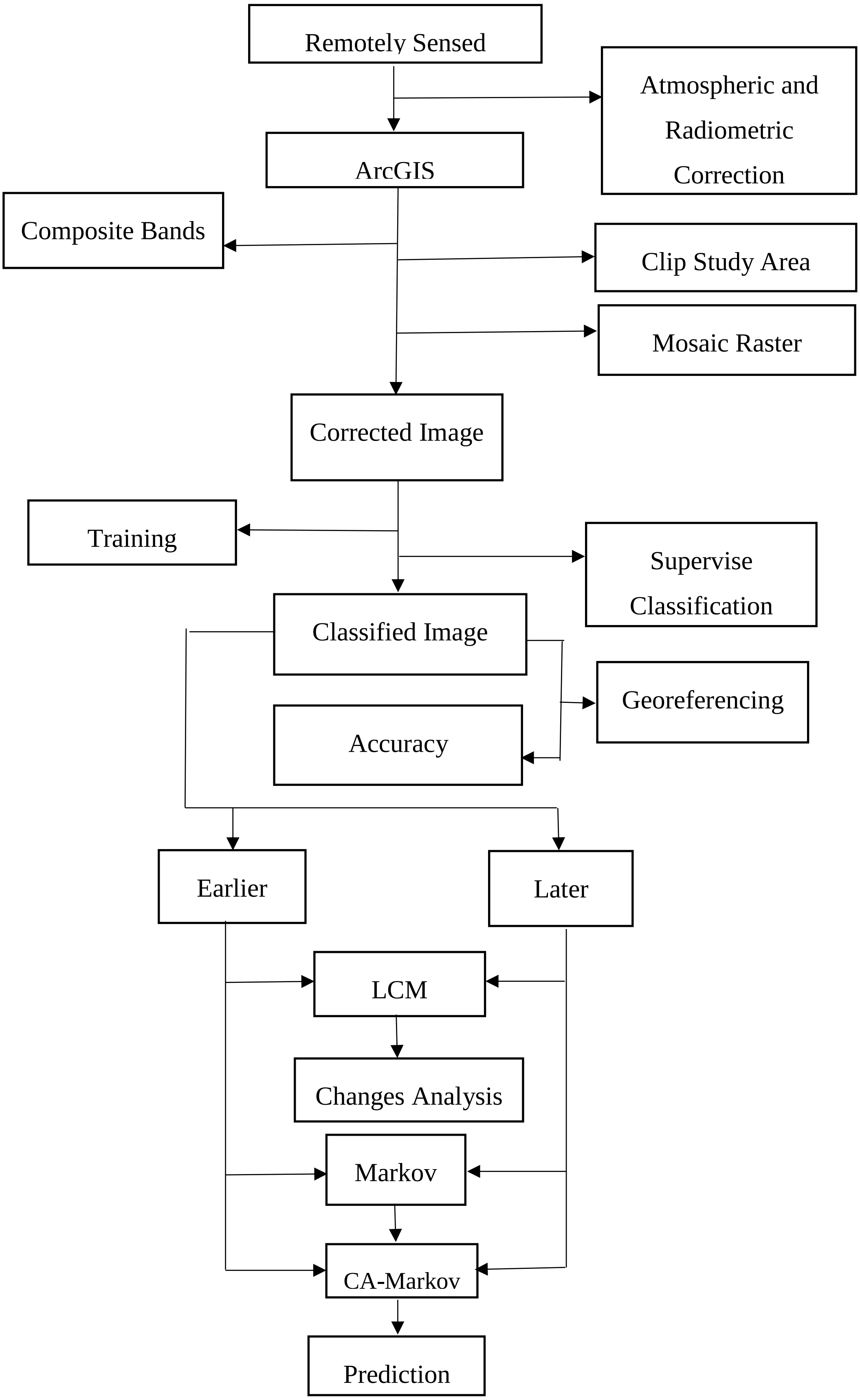

Figure 2: Work Flow Chart of the research.

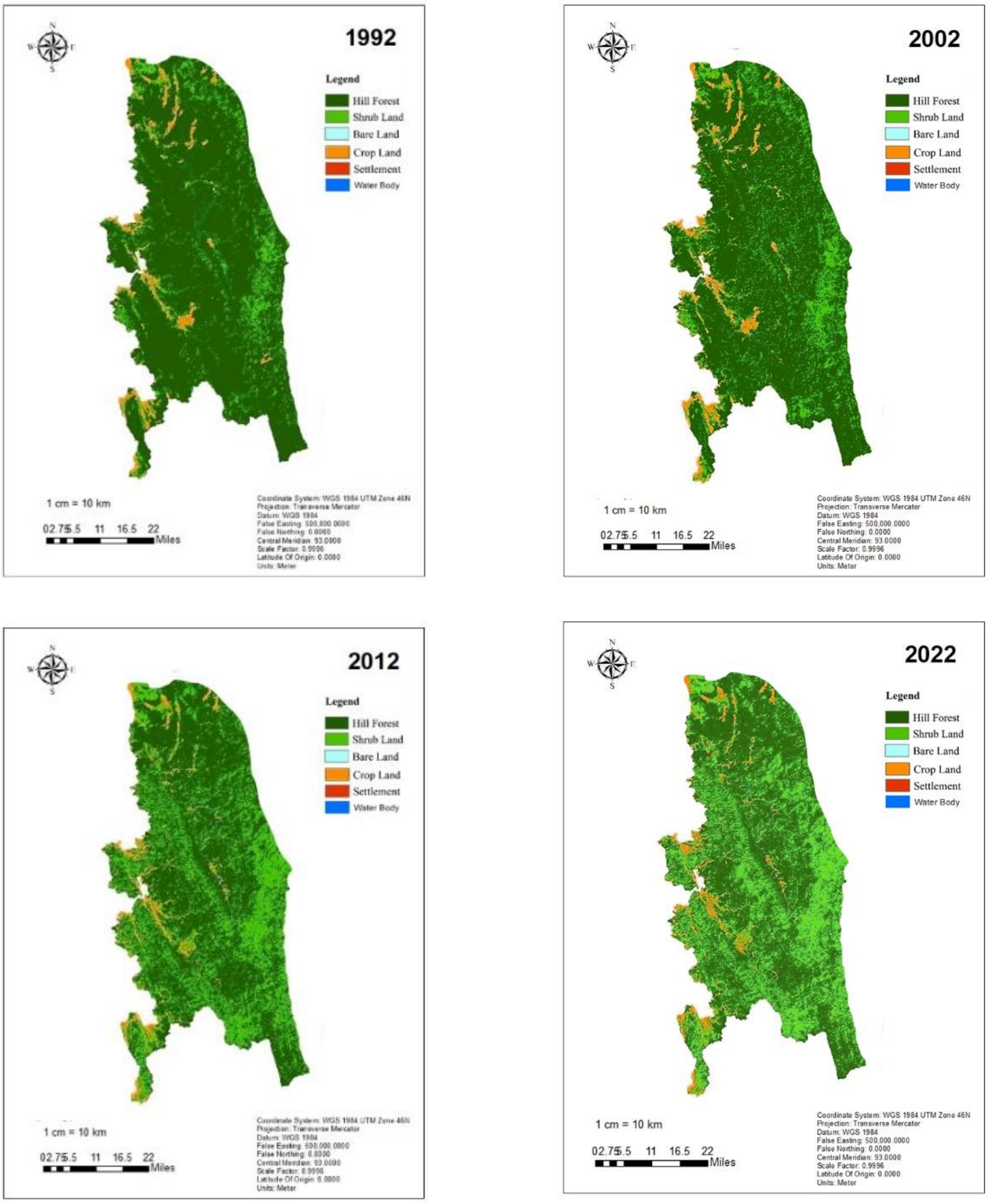

Figure 3: LULC categories obtained from image classification. 1992, 2002, 2012, 2022.

The selection of the most appropriate band composite image was done to ensure the compilation of training sites for classification in an efficient manner while minimizing the correlation among spectral bands. The selected bands were then used to generate natural color, color infrared, and false color composite images for each study year. The process involved randomly extracting 200 signatures for each LULC class, covering the entire study area through the use of ArcGIS software. A maximum likelihood supervised classification technique was then used, based on the extracted signatures, to classify the image into the desired classes such as hill forest, shrub land, crop land, bare land, settlement, and water body.

3.6 Accuracy Assessment of LULC

During the classification process, there were some misclassified or poorly classified pixels in each image, known as the salt and pepper effect [36], which occurred mainly due to the similarities in spectral characteristics between pixels in different categories. The most common mistakes were made between crop land and shrub land, as well as in rural settlements, which are mostly under a tree canopy.

To report the accuracy of classification from remotely sensed data, the error matrix (also called confusion matrix or contingency table) is the most appropriate way [29]. It provides an estimate of the accuracy of each classified category, including user accuracy, producer accuracy, errors of inclusion (commission error), errors of exclusion (omission error), and overall accuracy of the classification [30, 31]. Another way to measure accuracy is the Kappa statistics, which is a non-parametric multivariate technique developed by Cohen [28] to measure the overall agreement of a matrix.

In this study, accuracy was evaluated using the Kappa coefficient, producer accuracy, user accuracy, and overall accuracy. The overall accuracy refers to how well each pixel is categorized compared to the actual land cover condition present in the corresponding ground truth data. Producer accuracy measures how accurately different types of land cover in the real world can be classified, while user accuracy is measured by commission error, which represents the probability of a classified pixel matching the land cover types of its corresponding real-world location.

To evaluate accuracy, a total of 240 sample pixels (40 per category) for each year were randomly generated using a random sampling method over the study area for all four periods of LULC maps. The error matrix was used to calculate the kappa coefficient, which is commonly used to evaluate the accuracy of image classification [28]. The column in the error matrix represents reference data, while the row represents classification-generated remotely sensed data [29]. The rigorous Kappa statistic for the stratified random sampling method was calculated using the following equation [24].

$$K = \frac{N \sum_{i-1}^{r} X_{ii} - \sum_{i=1}^{r} (x_{i+})(x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+})(x_{+i})}$$

In a matrix with r number of rows, X_{ii} refers to the observations in the diagonal element of row-i and column-i. The values $x+i$ and $xi+$ represent the marginal totals of row-r and column-i, respectively. N refers to the total number of observations in the matrix.

Table 6: Classification accuracy and Kappa statistics.

Year	LULC category	Producer accuracy (%)	User accuracy (%)	Overall accuracy (%)	K_{hat} (%)
1992	Hill forest	89.34	94.20	93.72	92.49
	Shrub land	92.23	93.13		
	Crop land	94.89	90.81		
	Bare land	95.29	95.00		
	Settlement	96.01	94.14		
	Water body	95.14	93.77		
2002	Hill forest	94.59	79.54	91.04	90.00
	Shrub land	97.67	93.33		
	Crop land	100	91.11		
	Bare land	100	88.88		
	Settlement	79.62	95.55		
	Water body	81.13	97.72		
2012	Hill forest	95.66	80 .00	93.98	92.12
	Shrub land	87.81	94.74		
	Crop land	99.61	100		
	Bare land	97.38	92.38		
	Settlement	99.32	99.36		
	Water body	85.90	96.76		
	Hill forest	93.75	91.67		
	Shrub land	90.00	94.74		

2022	Crop land	90.48	95.00	93.36	91.84
	Bare land	93.19	91.12		
	Settlement	96.16	94.34		
	Water body	92.69	92.69		

The overall accuracy for 1992, 2002, 2012 and 2022 maps was 93.72%, 91.04%, 93.98% and 93.36%, respectively, whilst the Kappa statistics was 92.49%, 90.00%, 92.12% and 91.84% respectively (Table 3). The Kappa statistics (>80) for the 4 maps of four different time frames indicate a high degree of accuracy [34, 37] with minimal error propagation in classification method.

3.7 Markov Chain (MC) and CA- Markov for LULC Modeling and Prediction

Markov chain (MC) analysis has been widely used for ecological modelling [41, 25], which is a stochastic process that take into account the previous state to forecast the future changing of variables through time. Because of its enormous capacity to quantify the rates and states of conversion among and between categories, respectively, it has been equally used in the LULC change modeling. In this study, a combination of MC and a hybrid cellular-automata (CA-Markov) technique was used in order to predict LULC for the years 2022 and 2052 by taking use of the IDRISI Selva software. It is required to use two different LULC data sets of various time frames in order to obtain the probability of transition between periods. When simulating changes to LULC, the MC model often applies the following formula:

$$A_{(t+1)} = B_{ij} \times A_t;\ B_{ij} = \begin{bmatrix} B_{11} B_{12} & \dots & B_n \\ B_{21} B_{22} & \dots & B_{2n} \\ \dots \quad \dots & \dots & \dots \\ B_{n1} B_{n2} & \dots & B_{nn} \end{bmatrix} \quad (0 =< Bij < 1;\ \sum_{j=1}^{n} B_{ij} = 1;\ i = 1,2,3,\dots,n)$$

Where, $A_{(t+1)}$ and A_t are LULC at t+1 and t period, B_{ij} is the transitional probability matrix.

The MCA generates various outputs such as a transitional probability matrix, a transitional area matrix, and a set of conditional probability images (suitability images). The transitional probability matrix provides the probability of each LULC category converting to every other category, while the transitional area matrix gives an estimate of the number of pixels that will likely convert from one LULC category to another during a specific time period. In contrast, the conditional probability images represent the likelihood of each LULC class being present in each pixel over time.

In this study, a hybrid approach combining MC and a cellular-automata (CA-Markov) technique was utilized to predict LULC maps for 2022 and 2052. To generate the predictive LULC map for 2022, the MC model was operated using 1992, 2012, and 2022 LULC class maps derived from image classification. The MC generated two transition matrices by cross-tabulating two LULC maps (1992 and 2012) and a set of suitability maps. Suitability maps provide information about the appropriateness of an existing LULC class that is most likely to change to another class, and the highest suitability value indicates the maximum likelihood of change. During this process, the LULC maps for 1992 and 2022 were harmonized to have the same number of classes, allowing for more accurate predictions of LULC changes over time.

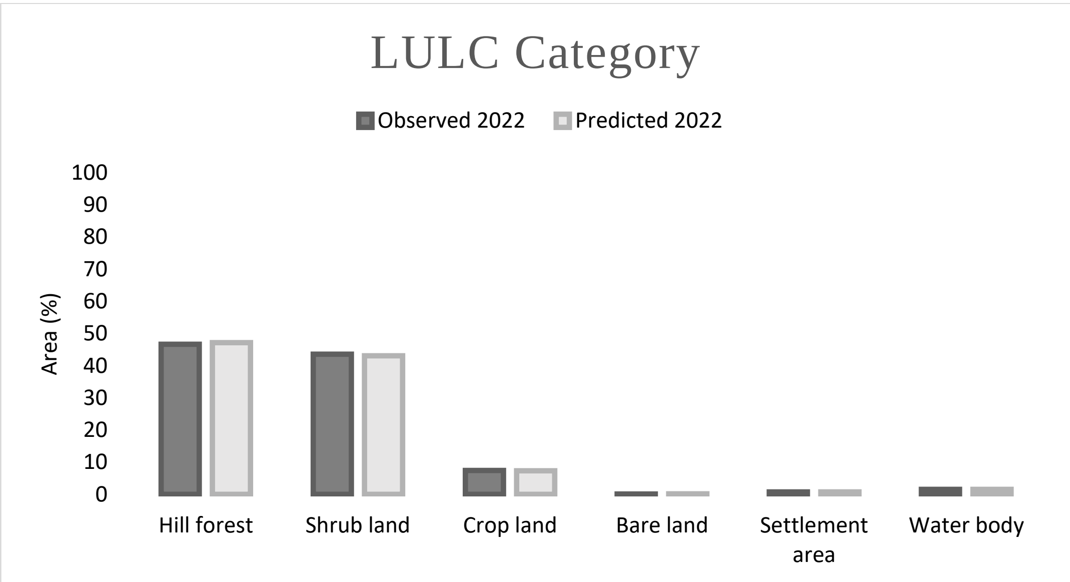

Figure 4: Area (%) of LULC category in observed and predicted maps.

To overcome the limitation of the MC model, which does not provide information about the spatial location of future LULC predictions, a hybrid CA-Markov model was employed. This model combines various techniques such as Cellular-automata, Markov chain, multi-criteria, and multi-objective land allocation to predict LULC changes [43].

The projections are based on the transition area matrix and suitability maps obtained from the MC process.

To predict the 2022 LULC map, the 2012 LULC map was used as the base land cover data, and the CA-Markov module of IDRISI Selva was employed. The number of cellular automata iterations was set to 10 to account for the ten-year gap between 2012 and 2022. The simulated result was then compared to the actual LULC data of 2022 to assess the accuracy of the model (Figure 4).

After validating the simulated data against the actual data, the model was used to predict the LULC maps for 2052. The 2022 LULC map was used as the base data, and a transitional probability area matrix, transitional suitability maps, a 5*5 kernel size contiguity filter, and 30 cellular automata iterations were used to simulate the 2052 LULC map. This approach provided information about the spatial location of future LULC predictions and allowed for an assessment of potential land use changes over time.

CHAPTER 4. RESULT AND DISCUSSION

4.1 Existing Land Use and Land Cover (LULC) scenario

Figure 6 presents the area distribution of existing LULC classes for the years 1992, 2002, 2012, and 2022. A comparative analysis of the LULC changing patterns indicates a significant divergence in the internal LULC categories, leading to substantial changes through the conversion of one LULC category to another. To facilitate better understanding, the study assessed the gain, loss, and net change for the four temporal periods: 1992-2002, 2002-2012, 2012-2022, and overall 1992-2022 for each LULC category.

To evaluate the results of land use and land cover conversion, the study generated a change area matrix for the above time spans, showing the relational changing area of one LULC category to others over the delimited periods. Hill forest and shrub land dominate the entire study area, with hill forest covering the maximum extent in all four study periods. The analysis reveals major changes in hill forest, shrub land, and crop land. A continuous decline has been observed in hill forest, while both shrub land and crop land categories show a steady increase.

Of concern is the gradual decline of inland water bodies, which are the primary sources of drinking water for the local indigenous community and act as sources of irrigation water during the dry seasons. This declining trend highlights the need for effective conservation strategies to preserve these vital resources.

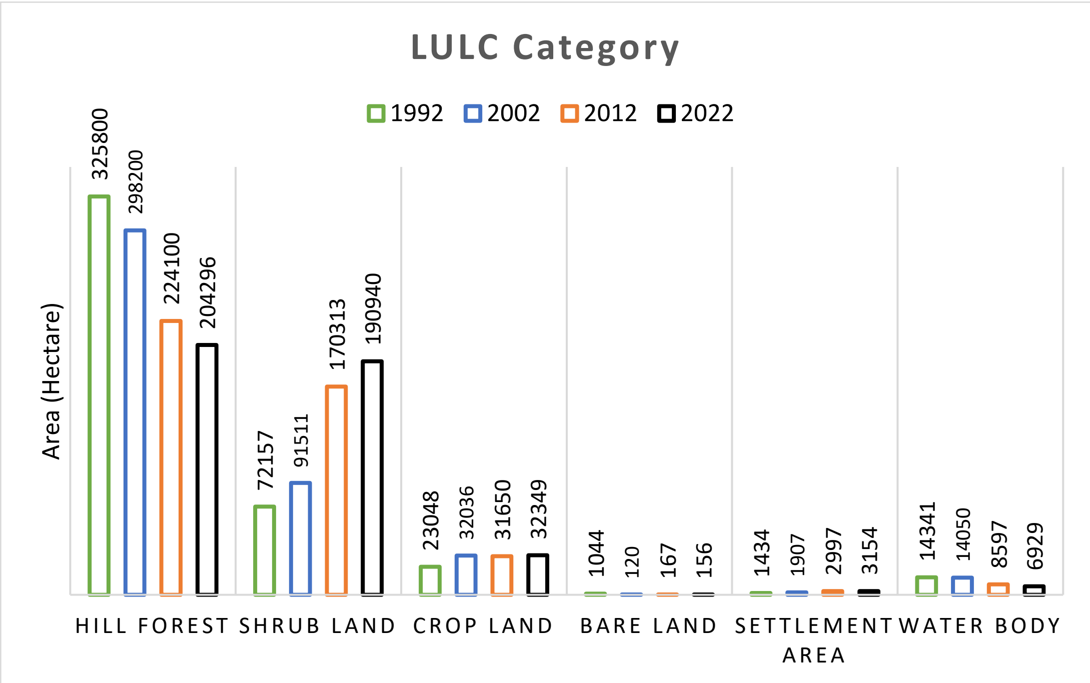

Figure 5: Existing LULC category. 1992, 2002 2012, 2022 (Area in hectare).

Table 7: Existing LULC category from 1992 to 2022 (Area in hectare and %).

Land Cover Type	1992		2002		2012		2022	
	Area	**%**	**Area**	**%**	**Area**	**%**	Area	%
Hill Forest	325800	74.41%	298200	68.11%	224100	51.18%	204296	46.66%
Shrub Land	72157	16.48%	91511	20.90%	170313	38.90%	190940	43.61%
Crop Land	23048	5.26%	32036	7.32%	31650	7.23%	32349	7.39%
Bare Land	1044	0.24%	120	0.03%	167	0.04%	156	0.04%
Settlement	1434	0.33%	1907	0.44%	2997	0.68%	3154	0.72%
Water Body	14341	3.28%	14050	3.21%	8597	1.96%	6929	1.58%
Total	**437824**	**100.00%**	**437824**	**100.00%**	**437824**	**100.00%**	**437824**	**100.00%**

4.1.1 Hill Forest

Hill forests are the most dynamic LULC class in the study area. According to Table 7, in 1992, they were the most extensive land cover in the study area, occupying 74.44% of the entire area. However, the area of hill forests underwent several significant changes over time. In the following years, a substantial decline was observed, with the coverage decreasing to 46.66% in 2022. This trend highlights the impact of human activities, such as deforestation and urbanization, on the environment and underscores the need for sustainable land use practices to preserve natural resources.

4.1.2 Shrub Land

Shrub lands are the second dominant LULC class in the study area, covering almost one-third of the total area in 2022. The coverage of shrub lands increased significantly from 72,157 hectares in 1992 to 170,313 hectares in 2012, and this upward trend continued to 190,940 hectares in 2022, representing 43.61% of the total area. At a glance, the area covered by shrub lands increased by 264.62% between 1992 and 2022, with a net increase of 118,783 hectares. This remarkable increase in the shrub land area can be attributed to various factors, including changing land use practices, climate change, and natural forest regeneration. However, it is important to note that this increase in shrub land comes at the expense of other land uses, particularly hill forests, which have declined substantially over the same period.

4.1.3 Crop Land

The category occupying the third areal position in the study area is crop lands, which increased by 8,602 hectares from 1992 to 2012, with a slight increase of 699 hectares from 2012 to 2022. Over the last 30 years, crop lands have gained 30,041 hectares from other land cover categories (as shown in Table 7). During this period, the net change in crop lands increased from 5.26% to 7.39% of the total area. This increase in crop lands can be attributed to population growth, changing food habits, and the adoption of modern agricultural practices. However, it is important to note that this increase in crop lands comes at the expense of other land uses, particularly hill forests and inland water bodies, which have been declining steadily over the same period.

4.1.4 Bare Land and Settlement Area

In the study area, settlement areas occupy a relatively small proportion of the total land cover, but their extent has been increasing over time. From 1992 to 2012, settlement areas increased slightly by 1563 hectares, and this trend continued with a more substantial increase to 3154 hectares in 2022. However, during the same time span of 1992 to 2022, bare land experienced a net decrease of 888 hectares, with a dramatic decrease from 1044 hectares to 120 hectares during the period of 1992-2002. This trend continued with a negligible increase to 167 hectares from 2002 to 2012 and a decrease to 156 hectares in 2022. Overall, the net increase in settlement areas was 1720 hectares, and the net decrease in bare land was observed during the entire study period.

4.1.5 Water Body

The water body is a crucial LULC class in any ecosystem, and its declining trend is alarming. The study area has witnessed a significant decline in water body areas over the past 30 years. Between 1992 and 2012, water body areas decreased from 3.28% to 1.96%, and from 2012 to 2022, it further slightly decreased to 1.58%. The net change of water body areas over the 30 years has shown a disturbing scenario with a dramatic decrease of 7412 hectares. This is a significant concern as water bodies are the primary sources of drinking and irrigation water for the local community. Therefore, this decline could have severe consequences on both human and wildlife populations in the study area.

4.2 Change Analysis

Total land use and land cover (LULC) transitions in the study area between 1992 and 2022 have been highly dynamic. One of the most significant findings was the decline of hill forests, which decreased by 121504 hectares over the past 30 years, at a rate of 4050.13 hectares per year. This was a concerning trend. The study revealed that hilly forests have contributed significantly to the increase in shrub land and crop land between 1992 and 2012, and then again between 2012 and 2022. However, the hilly forests have also undergone significant transitions from shrub land and crop land during the entire period between 1992 and 2022.

The results also indicated a significant increase in crop land, mainly due to the conversion of shrub land to crop land during 1992-2002, 2003-2012, and 2012-2022. The water reservoir (water body) and bare land also contributed to the increase in crop land. On the other hand, crop land has lost areas to hilly forest in 1992-2002, 2002-2012, and 2012-2022, respectively. Overall, the crop land increased by 9301 hectares in the last 30 years.

The study also found that the total loss of bare land was 888 hectares between 1992 and 2022, at a declining rate of 29.6 hectares per year. This bare land was mostly converted to crop land and to a lesser extent to shrub land. Meanwhile, the settlement category showed steady growth, with its area expanding more than double from 0.33% (1434 hectares) to 0.72% (3154 hectares) during 1992-2022, mostly at the expense of crop land. On the other hand, the water body decreased from 14341 hectares to 6929 hectares, with a net loss of 7412 hectares over the entire period.

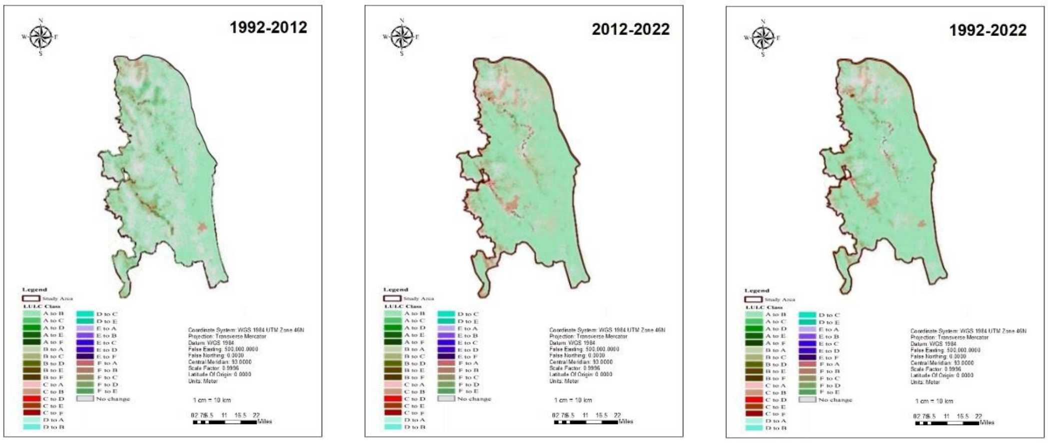

Figure 6: LULC changes in different time spans. 1992-2012, 2012-2022, 1992-2022.

4.3 Predicted Result

In order to predict future changes in LULC, a combined Markov and Cellular Automata model was employed and the results indicate a significant loss in hilly forests by the year 2052. The predicted data shows that hilly forests will decline by 61613 hectares from 2022 to 2052. On the other hand, the model predicts a significant increase in the aerial extension of shrub land and crop land categories. These two categories are projected to undergo dramatic step-ups in their areas by the year 2052. The combined Markov and Cellular Automata model provides important insights into the future changes in LULC, which can be useful in planning and decision-making for sustainable land use practices. Figure 7 presents the graphical representation of the predicted LULC changes, while Table 8 provides detailed numerical data on the projected changes in each category.

Table 8: Markov predicted results and changes analysis.

LULC Category	2052 (hectare) (Simulated)	2052 (are%)	Change (hectare) (2022-2052)
Hill forest	142683	32.59%	-61613
Shrub land	252373	57.64%	61433
Crop land	35840	8.19%	3491
Bare land	146	0.03%	-10
Settlement area	5162	1.18%	2008
Water body	1620	0.37%	-5309
Total	**437824**	**100.00%**	

The study utilized a combination of Markov and Cellular Automata modeling to predict the future changes in land use and land cover (LULC) for the year 2052. The results showed a significant loss of hilly forests, with a decrease of 61613 hectares from 2022 to 2052. In contrast, the shrub land and crop land categories showed substantial growth in their aerial extension, increasing by 61433 hectares and 3491 hectares respectively. The settlement area increased slightly, which is attributed to the gradual increase in the population in the area. However, bare land and water body categories showed negative figures, decreasing by 10 hectares and 5309 hectares, respectively, over the predicted period. The change in forest cover and shrub land denotes the exchange of area between these two categories.

The study also revealed that hilly forests have been contributing to the expansion of shrub land, while crop land has continuously been taking the place of inland water bodies, which may be happening due to the lowering of water levels. However, the accuracy of the simulation process depends on various socioeconomic, physical, and policy factors, which were not considered in this study due to a lack of data. Thus, it is highly recommended to involve relevant factors to achieve higher accuracy in the simulation process. Additionally, further research involving meteorological and land surface temperature data is needed to observe and analyze how LULC changes are shaping or altering the climate of the hilly environment.

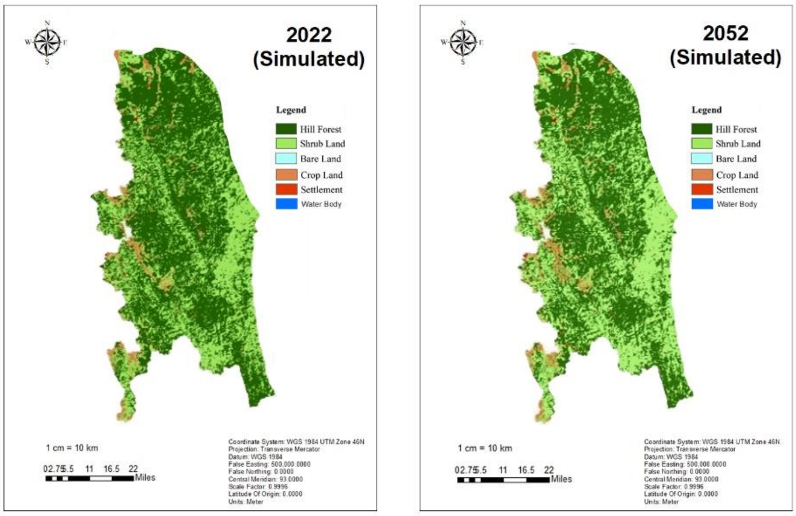

Figure 7: Simulated (Predicted LULC) maps. 2022, 2052.

4.4 Limitation of The Research

In the study area, the presence of high hills and dense forests at the extreme border made it challenging to collect accurate ground data for the research. As a result, some crucial parameters like socioeconomic, physical, and existing policy were excluded from the integrated Markov Chain and CA-Markov simulation process due to the lack of data. This limitation could potentially impact the accuracy and reliability of the study's findings.

Moreover, one of the major limitations of this research was the utilization of medium resolution satellite imagery (Landsat) due to funding constraints. While Landsat data can provide a wealth of information, it may not capture the detailed and nuanced changes in land use and land cover that high-resolution satellite imagery can offer. Therefore, the limitations of the available technology used in the study should be taken into account when interpreting the results and drawing conclusions.

In future studies, it is crucial to address the limitations mentioned above by collecting additional data and utilizing high-resolution satellite imagery to obtain more accurate and reliable results. By doing so, the findings will be more robust and can provide useful insights into land use and land cover changes, their drivers, and their potential impacts on the environment and society.

CHAPTER 5. CONCLUSION

Geospatial technologies were utilized in this study to examine the changes in land use and land cover (LULC) in the Bandarban district of Bangladesh. The study employed multi-temporal Landsat imagery from 1992, 2002, 2012, and 2022 to derive LULC maps, which were then used in the CA-Markov process to simulate future changes in LULC. The findings indicate that the rapid population growth and so-called socioeconomic development have caused constant changes in LULC, which could negatively impact the local hilly climate and environment.

The results of this study reveal a substantial decline in hilly forest, which has been replaced by an increase in shrub land. The research shows that the major conversion of hilly forest and shrub land has been taking place between each other, indicating that hilly forests have been converted into shrub lands due to commercial plantation by various development projects from both government and non-government agencies. Additionally, built-up areas have increased by 1720 hectares over the last 30 years, from 1992 to 2022. However, water bodies have dramatically decreased, which may lead to a severe water crisis for irrigation in the future.

It is generally believed that the rapid population growth, increasing demand for housing, intensive pressure from land grabbers, and unplanned urban expansion are the primary causes of land use and land cover changes in the hilly areas of the country.

This study may provide initial guidance and baseline information for efficient resource management strategies in the hilly environment through sustainable land use planning and policy guidelines. With the involvement of relevant factors such as socioeconomic, physical, existing policy, and high-resolution satellite imagery, future studies may achieve higher accuracy in the simulation process, which could lead to better land use and land cover management policies in the hilly areas of Bangladesh.

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