



Master Thesis

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Assessing the land use land cover change and urban sprawl modelling in Dhanusha District

by

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the degree of
Master of Science (Geographical Information Science & Systems) – MSc (GISc)

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Kathmandu, April 2023

Science Pledge

By my signature below, I certify that my project report is entirely the result of my own work. I have cited all sources of information and data I have used in my project report and indicated their origin.

04/04/2023

Prashant



Place and Date

Signature

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Abstract:

Globally, south Asian cities are known for rapid and haphazard urbanization and high level of pollution. In Nepal the capital city, Kathmandu is one of the most polluted and rapidly urbanizing areas of the region but like Kathmandu, cities in Terai region of the country have faced major surge in in-migration with lack of planning and the resulting haphazard urbanization. This has caused major problems in the places like Dhanusha where pollution and congestion have become very eminent. The cities like Janakpur which have great religious and cultural importance have come under the threat of haphazard urbanization. The significant point of this proposition thesis is to comprehend the endless suburbia design and urban sprawl pattern, the pattern of Land Use Land Cover (LULC) change, and the projection of a future endless urban sprawl. The change in LULC is analyzed by using temporal satellite imagery from 1993 to 2021. The analysis showed that LULC changed a lot in this time interval. Mainly the developed area increased every time span while agricultural lands decreased all along as well as there were decrease in forest areas. Urban sprawl change showed changes along major roadway intersection and mainly concentrated in Janakpur Sub-metropolitan city.

Major objective of this study has been summarized as a) Identify the change of LULC in Dhanusha district during the period from 1993 to 2021; b) Model urban sprawl trend that would follow into the years 2033 and 2043. In order to gather data and conduct research, the thesis used remote sensing (RS) and geographic information system (IS) methodologies. Using categorization and change analysis of satellite imagery, the LULC alterations were examined. The change in urban sprawl was analyzed using statistical analysis and the future simulation was done using machine learning of trend and simulation using Cellular Automata (CA) Markov model.

Satellite image analysis for trend analysis of urban sprawl in Dhanusha district was achieved for different six classes; Water, Developed, Sand/Barren, Forest, Shrubland and Cultivated/Planted areas. During the period of 1993 and 2021 the developed areas increased by more than three-fold by 4.9% from 18.33 Sq km. to 76.56 Sq km. The decrease in agricultural land in the same period was 11.4% of the total area from 743.46 Sq km. in 1993 to 608.64 Sq km. in 2021. The developed areas had sprawled around the roadway intersections of the district and mainly concentrated in Janakpur sub-metropolitan area. During the period of 1993 to 2013 there was gradual increase in urban areas which peaked after 2013 to 2021. In the simulated image the developed area was 63.77 Sq. Km. and 5.4%. The result of 2003 and 2013 simulation had more accuracy which was used for the simulation of 2033 and 2043. The result showed increase in developed area to 99.52 Sq. Km in 2033 and again increase in developed area in 2043 to 130.58 Sq. Km. Small settlements along the roadway intersections turned into dense settlements during the period. This study has importance in understanding the future urbanization sprawling patterns following current trend which can be used for proper management and planning of the area to ensure proper infrastructure development and management for sustainable development.

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Acronyms and Abbreviations

ARD	Analysis Ready Data
CA	Cellular Automata
DEM	Digital Elevation Model
ESRI	Environmental Systems Research Institute
ETM	Enhanced Thematic Mapper
GIS	Geographic Information System
GUI	Graphical User Interface
LULC	Land Use Land Cover
MSS	Multispectral Scanner
MOLUSCE	Modules for Land Use Change Evaluation
OLI	Operational Land Imager
RS	Remote Sensing
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
USGS	United States Geological Survey

Chapter-1: Introduction

1.1. Background

The global population has shifted from an agricultural rural area to urban cities and metropolis, largely after the industrial revolution in 18th century has created a major wave of urbanization. Globally, the urban population has increased by approximately six times since 1950, from 751 million to 4.2 billion as of 2018, and over the following decades, it is anticipated that the rural population would finally diminish and the urban population will increase to six billion and more (Ghosh, 2019). As per Mundhe & Jaybhaye publication they define urbanization as the urban development strategy that results in population growth, built-up area expansion, population densification, and urban lifestyle (Mundhe & Jaybhaye, 2014). Human population densification, economic progress and the expansion of construction land represents the leading driving forces in land use changes (Qiu et al., 2019).

Land Use land Cover (LULC) is defined as two terms where land use is referred as human activities on/in relation to the land (Lo, 1986) while the term "land cover" refers to the plant and man-made structures that cover the land (Alam et al., 2020; Burley, 1961). Since the 20th century, land use change has had a significant impact on ecology and has been one of the determining forces for altering the surface of the Earth. (Bielecka, 2020; Chapin et al., 2002). LULC changes under rapid urbanization has been a most important driving force that has influenced and altered the global and regional eco-environmental conditions (Qiu et al., 2019). Uncontrolled and unmanaged urbanization and LULC changes raises many issues like unapproved urban sprawl, loss in agricultural land, unregulated rise in land value and other many problems (Mundhe & Jaybhaye, 2014).

Nepal is one of the least urbanized country but at the same time is also one of the fastest urbanizing country (Bakrania, 2015). Urban development in Nepal has been a

spontaneous process such that the positive aspects of urban areas as engines of economic development and therefore national development have not been appreciated by policymakers and development experts (Tiwari, 2008). Urbanization in Nepal has mainly been observed in the capital city, along highways and towns on the southern border with India. After 1950, there was a significant influx of people from mountainous and hilly regions into Nepal due to the building of east-west routes and the elimination of malaria in the Terai region (Devkota, 2012). Due to changes mostly resulting from anthropogenic and natural factors effecting the national and regional environment, LULC in Nepal has altered continuously over the recent past (Paudel et al., 2016).

Population in the Terai areas increased from 37% to 47% from 1971 to 1991 with 31% increased population density and similarly urban areas increased from 10 to 33 to 36 in 1951 to 1987 and 1991 in Terai increases were from 5 to 21 urban centers (Satterthwaite et al., 2010). The Terai region of Nepal is regarded as the nation's food basket, but since 1988/1989, metropolitan areas have grown at an average annual pace of 12%, endangering the area's valuable agricultural land (Rijal et al., 2020). In the mountain and hilly areas of the country, the tough physical conditions and lack of arable lands have become major push factors while pull factors in the Terai region which area plains are the job opportunities and the availability of farming lands (Satterthwaite et al., 2010).

The rapid urbanization in country has intensified the deficit of urban infrastructures, access to piped water supply had declined from 68% in 2003 to 58% in 2010, solid waste collection is low and inadequate resulting in open piles (Elisa & Gabriela, 2013). Similarly, the haphazard urban expansion has contributed to the other problems like inadequate housing infrastructures, pollution, urban slums, traffic congestion and decline of agricultural lands. The country's constitution prohibits the government from enforcing any restrictions on the use of private property, which creates additional challenges for urban governance in Nepal while increasing the vulnerability of the urban population to multiple

hazards, especially the urban poor (Timsina et al., 2020).

Rural villages and markets are urbanizing quickly yet lack the most basic infrastructure (Satterthwaite et al., 2010). The problem of urban pollution has been a major concern for officials and planners. The problem of grey and black water stagnation has been more significant in the cities of terai plains because of low gradient for water flow. The haphazard urbanization has caused more pressure on these already existing problems. Historic cities like Janakpur are more vulnerable as their cultural and historical artifacts are in more need for preservation. Urban land use and cover in Nepal has changed significantly over the past 30 years due to the unprecedented rate of expansion, necessitating intensive historical LULC study for future change analysis (Paudel et al., 2016).

GIS has been extensively used for LULC change analysis. Development of computational power and One could think of a GIS-based spatial information management system as an integrated software and hardware set. The capabilities of trend analysis, modeling, mapping, and spatial tabular display as well as a framework for decision-makers and specialists are improved by the integration of GIS with satellite imagery. Landsat has been one of the widely used satellite imagery for various geographical analyses ranging from land changes to environmental and climate studies. The free and easy availability of the imagery contributes to the wide use of the imagery. The medium resolution imagery with wide range of spectral band makes it perfect for land change analysis.

LULC analysis provides a spatial outlook for the current situation and changes in the environment. This analysis is used to understand and manage the land uses. LULC analysis has widely been used in urban planning and management. Urban sprawl modelling is used in LULC analysis and planning to identify the probable high urbanization potential areas by looking into the trend of past urban pattern. The model can be helpful in directing future LULC. One of the most crucial considerations is the utilization of the land

in sustainable development so the look into land use of past and future can be important for the urban planning and rural planning with most benefit and little financial and technical resources for plan implementation.

1.1.1. Need Assessment

Increase in global population and global economy has caused more people living in cities and development of lands for built-up areas. Urbanization is one of the most serious and dynamic global issue at present resulting in haphazard and unplanned growth of cities and creating pressure of an ever growing population burdening the public services which are nearly crumbling (Mundhe & Jaybhaye, 2014). LULC study can be a key to understanding the human impact on the natural environment. The past urbanization trend and the direction of future urbanization can help create sustainable urban plans and implementation mechanisms and enhance the understanding of the factors that need to be addressed for sustainable built-up development. Similarly, climate change issue and ecological preservation need to be addressed which require the knowledge of urban trend. In order to evaluate urban growth trends, local and regional planning studies must continuously monitor LULC changes based on accurate and current LULC information (Mundhe & Jaybhaye, 2014).

Kathmandu valley and almost all the districts in terai zone have high to very high levels of in-migration (Tiwari, 2008). In Nepal, the expansion of urban areas due to the increase in population growth has put high pressure on the very limited resources namely, scarcity of water, land fragmentation for housing, slums, management of garbage in the cities has become a major challenge for governments and planners (Devkota, 2012). The population rise in the urban centers of these areas followed by the lack of the understanding of the changes in land use and future trends have created a planning void between the policymakers, planners, and urbanization. Though the study area is a rapidly urbanizing region of Nepal the LULC change trend and the future situation of this trend is not yet

explored in the region.

Thus, the project is aimed to understand urbanization and built-up pattern in Dhanusha district and the future direction of urbanization. Using geographic information system (GIS) and remote sensing (RS) techniques, the study aims to identify locations that may experience significant strain from future urbanization. Application of RS has been widely employed for identifying land use and land cover. In combination with GIS, satellite imageries are very useful in trend analysis of built-up. Similarly, the modelling techniques can be used to analyze future scenarios of land use change.

1.1.2. Research Approach

A literature review is done as part of the research methodology for "Assessing the Land Use Land Cover Change and Urban Sprawl Modelling in Dhanusha District" using GIS and RS. Theories regarding to urbanization, urban sprawl, urban sprawl in Nepal, sprawl measurement, urban sprawl modelling, simulation and machine learning. Multi-temporal satellite imageries of different time series were the primary data used in the study. Softwares were used for image analysis, modelling and all required tasks. LULC maps were generated for each Landsat imagery for the trend analysis for different time periods.

Recently RS and GIS technologies have been extensively used in mapping land surfaces features with significant improvement in mapping urban areas (Hadi et al., 2014). Remotely sensed images and GIS can be used for LULC change analysis. The integration of GIS and Satellite Imagery can enhance the capability of trend analysis, and mapping. Satellite images have become very important for analyzing land cover data and are widely used to monitor LULC change (Ridding et al., 2020). Landsat has been one of the widely used satellite imagery for various geographical analysis ranging from land changes to environment and climate studies. The free and easy availability of the imagery contributes to the wide use of the imagery. The medium resolution imagery with wide range of

spectral band makes it perfect for land change analysis.

LULC trend analysis provides a timely change in LULC which can help understand the trend in changes. Urban sprawl modelling can be used in LULC analysis and planning to identify the probable high urbanization potential areas by looking into the trend of past urban pattern. The model can be helpful in understanding the direction of future LULC. As the importance and also the demand for understanding LULC change has increased, a considerable number of software programs have been developed to model these changes (Ridding et al., 2020). The use of open-source software QGIS for modelling of LULC changes for the year 2033 and 2043.

The Landsat images of 1993, 2003, 2013 and 2021 will be used in analysis of land use changes in the past. The land uses will be classified of these satellite images. The LULC images of 1993, 2003, 2013 and 2021 will be used for identification of optimal change analysis accuracy. The LULC 1993 and 2013 will be used for LULC modelling of 2021 and 2003 and 2013 will be used for LULC modelling of 2021. Of the two models the accuracy will be checked with LULC classified image of 2021. The model which gives more accuracy will be used for the land use modelling of 2033 and 2043. The roads and elevation will be used as the variables that may influence future land use in the study area for modelled LULC.

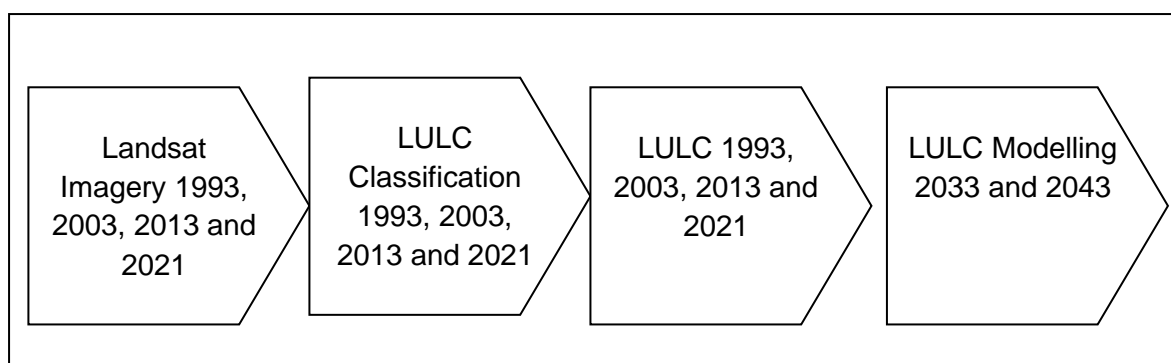


Figure 1. Research Approach

1.2. Objective

The main goal and objective of this project is to employ Landsat imagery and analysis method using GIS for identification of LULC change and urban sprawl modelling in Dhanusha District of Nepal. The study has the following main Specific objectives which are listed below:

1. To assess the LULC change between 1993-2021.
2. To model urban sprawl in 2033 and 2043.

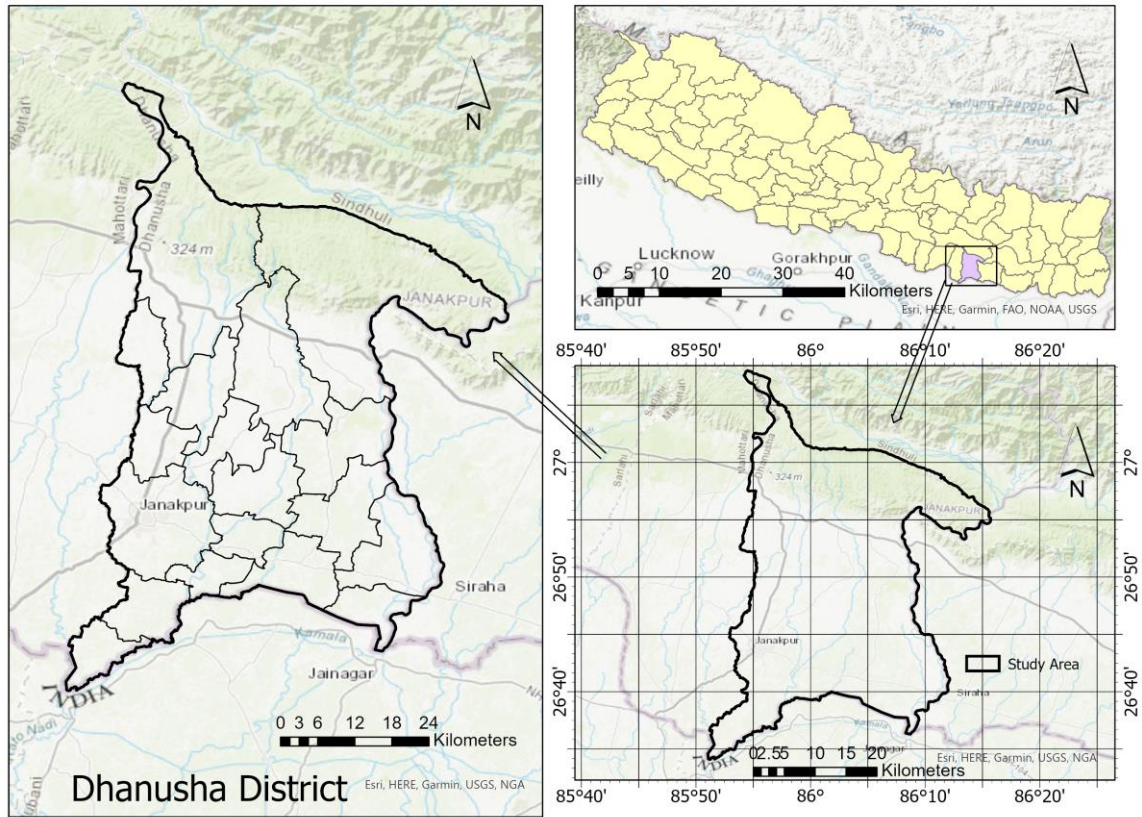
1.3. Location and General Description of Study Area

Dhanusha district is administratively a part of the Madhesh province of Nepal and geographically situated in the outer terai region. Dhanusha district lies on the southern border with India. The most spoken language in the district is Maithali. Dhanusha district covers an area of 1180 Km² of Nepal. According to the National census in 2021 the district had a population of 754,777 an increase from 671,364 from census 2011. The district is bounded by Siraha district to the east, Mahottari district to the west, Sindhuli district to the north, India to the south and Udayapur district to the North-East.

The district is located between 35° - 27.5° N and 85.5° - 86.2° E on the southern slopes of the Churia hills. The district is 350 Km south-east of the capital of the country, Kathmandu. A subtropical climate with spring, monsoon, and winter seasons, with mean monthly minimum/maximum temperatures of 9.3/21.4 °C in January and 26.7/39.6 °C in April, with an average annual rainfall of 2,199 mm, prevails at an average height of 95 meters above sea level. The major city in the district is Janakpur sub-metropolitan city which is also a historic city with rich culture and traditions. The city is a major tourist attraction for internal as well as external tourists. Dhanusha district is one of the popular pilgrimage destinations for Hindu people. The district offers many tourist destinations

including temples and ponds. The district has a national airport and the only railway line of Nepal which connects with Indian town of Jayanagar.

STUDY AREA



Prepared By: Prashant Shah UNIGIS ID: U105555

Map 1. Location Map of Dhanusha District

1.4. Literature Review

Literature review is an important part of academic writing for understanding of core concepts of the subject matter and understanding current knowledge of the subject. Literature review is done in this report for understanding the concept of urbanization, history of urbanization, current trend of urbanization, future projections of urbanization, urbanization in cities around the world, the concept of urban sprawl, current knowledge of sprawl, trends of sprawl, urban sprawl in Nepal, modelling and the process of measurement of urban sprawl. The knowledge acquired for literature review was used in

analysis of the problem and in achievement of the results in this report.

1.4.1. Urbanization

According to the Geographical Society of the United States, According to Urbanization | National Geographic Society, 2022, "Urbanization is the process by which the cities grow and higher percentages of the population migrate to live in the city". The process by which many people permanently congregate in a small area to form cities is known as urbanization, according to Britannica (Kuiper et al., 2009). But across time and in different places, different people have different ideas about what a city is. The United Nations (UN) adheres to the definitions established in each nation and does not have its own concept of "urban" For instance, In Peru, the term "erm" is used to describe areas of high population density with 100 or more homes, but in the United States, the term "urban place" refers to any location with more than 2,500 individuals.

The development of human civilization in past was largely supported by people living sparsely in rural areas engaging in activities like agriculture, fishing, and trading but with time rural population grew resulting in the development if cities (Urbanization | National Geographic Society, 2022). Less than 3% of the world's population lived in cities with 20,000 or more people in 1800; this number rose to nearly a quarter by the mid-1960s; and by the early 21st century, more than half of all people lived in urban regions (Kuiper et al., 2009).

Currently, about half of the world's population is urban with a rise in polycentric regions and a decline in urban densities (McGranahan, 2015). Towards the future in the 21st century, the urban areas and urban population are likely to continue to grow (Urbanization | National Geographic Society, 2022). The vast majority of people on earth now live in cities due to the concentration of many employees and their families there as well as industrialization (Kuiper et al., 2009). More over half of the world's population (55%)

resides in urban regions, and according to the UN, the historic moment when the number of urban residents surpassed that of rural residents happened in 2007 as shown in Figure 2 (Ritchie & Roser, 2018). The urban population crossing the rural population is a significant event for the urban future. The number of people living in rural areas was always high throughout the history. However, as the urban population grew throughout time, people's lifestyles altered to the point where the urban population eventually surpassed the rural population and is now expected to reach its peak in the near future.

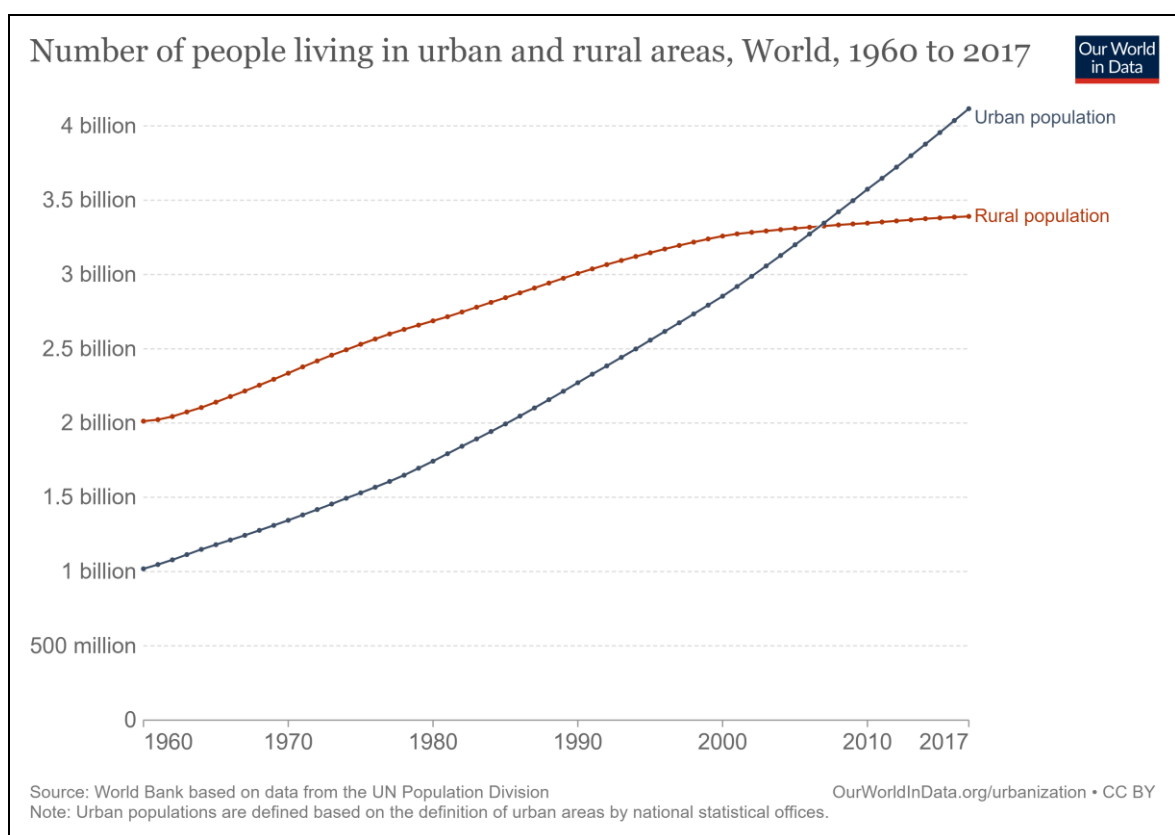


Figure 2. Number of people living in urban and rural areas, World, 1960 to 2017 (Ritchie & Roser, 2018)

Urbanization is the process of increasing the percentage of a region's population who live in cities and/or towns concentrated in larger settlements of the territory with higher population density. It involves a complex set of demographics, cultural, social, economic,

technological, and environmental processes (Knox, 2009). The global population has increased significantly as economies around the world have increasingly industrialized from the beginning of the eighteenth century which has resulted in a large number of people moving to the cities from rural areas with increased jobs, professions and opportunities of education and entertainments in cities (Urbanization | National Geographic Society, 2022).

In addition, the demographic processes of immigration and movement, population increase, etc., are significant urbanization-related determinants. Levels of urbanization are connected with levels of economic development, while rates of urbanization are inversely correlated with levels of economic development (Knox, 2009). Uncontrolled and fragmented urban growth is a significant global trend that fuels competition for land resources (Jaeger et al., 2010). Urbanization creates economic growth but also has caused numerous worldwide environmental constraints that frequently result in social and economic inequities, which presents opportunities as well as problems for sustainable development (McGranahan, 2015).

By 2050, the world population is expected to reach 9.8 billion, with more than twice as many people living in urban areas (6.7 billion) than in rural areas (3.1 billion), according to the UN's medium fertility scenario. As of 2018, there were approximately 7.6 billion people on Earth (4.2 billion in urban areas and 3.4 billion in rural areas) billion and it's projected that the majority of countries will have a majority (more than 50 %) people living in urban areas as shown in Figure 3 (Ritchie & Roser, 2018).

The population graph shows that population increase in urban areas started to peak around the middle of 1900. Even under mid-fertility scenario the urban population is projected to grow significantly then rural population. Around 2030 the population of rural areas is shown to start declining which shows more immigration to urban areas in that time.

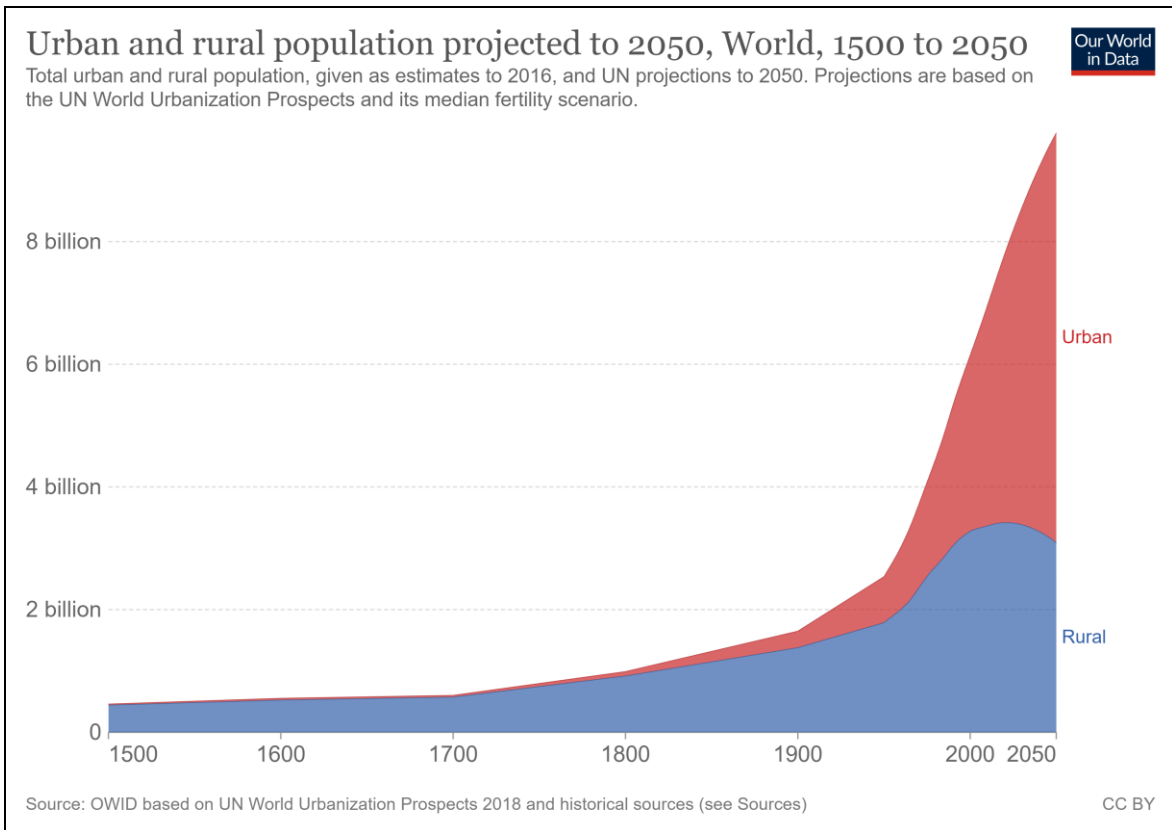


Figure 3. Urban and rural population projected to 2050, World, 1500 to 2050 (Ritchie & Roser, 2018)

1.4.2. Urbanization Case Study

The development of Chinese cities depends increasingly on the management of land resources in urban regions (Shin, 2015). The main effect of urban development on agricultural land use is that it permanently and irreversibly converts agricultural land to urban use, endangering the viability of agriculture-based industries (Beesley & Ramsey, 2009). The increased pressure in land values creates pressure on farmers and rural landowners to receive money by selling land for other use rather than farming which they can no longer be able to justify economically (Beesley & Ramsey, 2009).

As of 2015, 52% of the world's population resided in urban centers, 33% in urban clusters, and 15% in rural areas, totaling 85% of the world's population, or more than 6.1 billion people, as illustrated in Figure 3 (Ritchie & Roser, 2018).

Share of the population living in urban area as estimated by the European Commission. The European Commission combines satellite imagery with national census data to derive urban and rural populations based on its own standardized definitions. In contrast to UN statistics, which are based on nationally determined urban definitions, the outcome is different (European Commission, Atlas of the Human Planet, 2016).

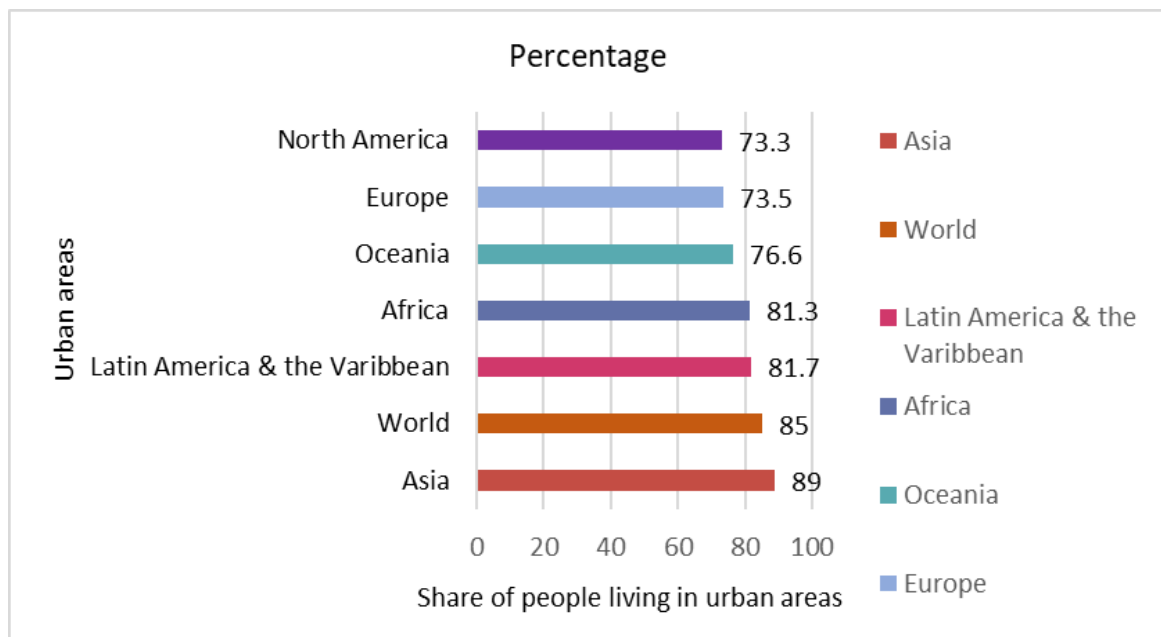


Figure 4. Share of people living in urban areas, 2015 (Ritchie & Roser, 2018)

Rapid urbanization has resulted in the establishment of large metropolitan areas, which have caused the transition of natural surfaces into built-up areas that change their physical and biological characteristics (Vinayak et al., 2022). Megapolis, or concentrated urban areas, have developed throughout the 20th and 21st centuries in a number of locations, including the Netherlands and central Belgium, the Tokyo-Saka-Kyoto complex in Japan, the region between London and the Midland cities in Great Britain, and the northeastern seafont as well as along the Californian coast (Kuiper et al., 2009).

In contrast to Japan, where urbanization was fairly low until the 20th century, the United States. During the 19th century, urbanization in states increased dramatically, reaching 40% by

1900, 64% by 1950, and over 80% by 2000 (Ritchie & Roser, 2018). China's rate of urbanization increased quickly in the 1990s and 2000s, and its urban share nearly doubled to 58%, while India's urban population has increased to over 90% today. Up until the late 1980s, both countries had about one-fourth of their populations living in urban areas. Japan's urbanization rate topped one in ten by 1900, and it continued to grow quickly, exceeding the USA to over 90% today by 2000, Comparatively, it increased to almost 80% by 1950 and more than 50% by 2000 (Ritchie&Roser,2018).

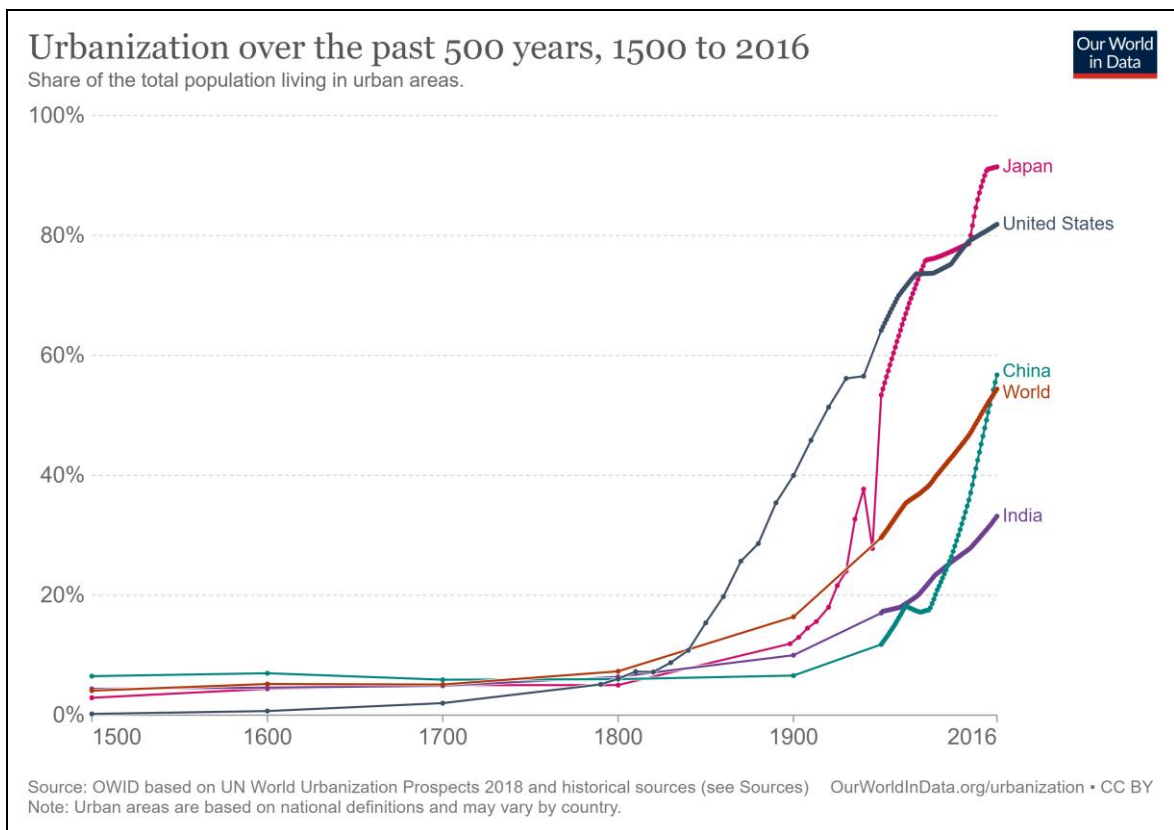


Figure 5. Urbanization over the past 500 years, 1500 to 2016 (Ritchie & Roser, 2018)

It is projected that by the middle of the twenty-first century, at least 50 percent of South Asian people will be living in urban areas, with 1.2 billion urban population in this region which is more than the urban population of many developed countries in the world (Devkota, 2012).

1.4.3. Urban Sprawl

Urban sprawl has been the focus of public debate and policies from governments and other organizations, although there is little consensus on its definition, effects, and policy models that foretell the presence of sprawl and decision support models (Johnson, 2016). (Fulton et al., 2001) implies that urban sprawl occurs when the rate of land consumption exceeds the rate of population expansion. Urban sprawl is a form of low-density development that has residential, commercial, and office districts, is rigorously divided, lacks activity centers, and offers few transportation options (Ewing et al., 2002). According to (Glaeser & Kahn, 2003), urban sprawl is the dominant form of city living based on automobiles. (Hasse & Lathrop, 2003) define urban sprawl as the dispersed and inefficient growth of urban areas. Urban sprawl is termed the low-density expansion of a city footprint (Nechyba & Walsh, 2004). According to (Burchell et al., 2005), urban sprawl has a specific spatial layout that allows low-density development to expand indefinitely and leapfrog. Urban sprawl is defined as the spread of urban land uses onto non-urban territories by (Liu et al., 2011).

Table 1. Definitions of "Urban Sprawl" (Jaeger et al., 2010)

Definitions	Source
The definition of sprawl is the "process of the spilling-over of settlement areas and of extreme use of the open landscape by haphazardly, mostly weakly condensed extensions of settlement areas in the fringes of urban accumulations" (Ermer, 1994).	(Ermer, 1994)
Sprawl is defined as "(1) leapfrog or scattered growth; (2) development of commercial strip; and (3) large expanses of low-density and/or single-use developments—as well as the low accessibility and lack of functional open space"(Ewing & Rong, 2010).	(Ewing & Rong, 2010)

<p>"Sprawl" is the unrestrained urbanization that is currently occurring. The risk of sprawl is particularly significant in areas on the outskirts of large cities, where it is not only caused by activities such as sprawling residential construction but also by economic institutions such as industrial firms, airports, and industrial complexes. Through growing construction of vacation homes, sprawl has recently put attractive adjacent recreational areas at danger (Leser & Huber-Fröhli, 1997).</p>	<p>(Leser & Huber-Fröhli, 1997)</p>
<p>Sprawl is defined as "low-density expansion beyond the edge of service and occupation, which isolates people's places of residence from their places of employment, recreation, and education, necessitating the use of automobiles to move between neighborhoods" (1999, Sierra Club).</p>	<p>(Sierra Club, 1999)</p>
<p>The definition of sprawl is "a specific type of out-of-town development characterized by very low-density settlements, both residential and non-residential; dominance of movement by use of private vehicles; unlimited outward development of new subdivisions and leap-frog expansion of these subdivisions; and segregation of land uses by activity" (USHUD, 1999).</p>	<p>(USHUD, 1999)</p>
<p>"Sprawl" is defined as the disruption or extinction of the landscape and ecosystems as a result of settlement spillover outside of enclosed built-up regions (1999, ARL & VLP).</p>	<p>(ARL & VLP, 1999)</p>
<p>The process of development outpacing population growth by a significant margin is called sprawl. The landscape that sprawl produces has four distinct characteristics: a population that is dispersed widely across low-density development; homes, businesses, and workplaces that are strictly segregated; a network of roads with large blocks and poor access; and a lack of clearly defined, thriving activity centers, such as city centers and town centers. These circumstances are the cause of the majority of the additional factors that are often associated with sprawl, such as the scarcity of alternative</p>	<p>(Ewing et al., 2002)</p>

<p>modes of transportation, the homogeneity of available housing options, or the discomfort of walking (Ewing and others, 2002).</p>	
<p>Low-density, limitless outward extending growth is referred to as sprawl. In other words, sprawl is an area that has seen a major growth in either residential or non-residential development while remaining mostly undeveloped. This development is low concentration, has surpassed nearby development to establish itself in a remote place, and its very location suggests that it is unbounded in almost every case(Burchell & Galley, 2003).</p>	<p>(Burchell & Galley, 2003)</p>

(Downs, 1998) points out a few traits of urban sprawl including unlimited outward development, no control over land uses or no centralized plan, fiscal disparities among localities, few planning provisions for low-income housing, and strip development.

Due to its negative effects on the environment, urban expansion and rapid urbanization have become important global concerns (Jaeger et al., 2010). (Brueckner, 2016) argues that urban spatial expansion or sprawl is the result of powerful forces namely growing population, rise in income, and falling cost of commute.

On one hand urban sprawl is associated with improvement in quality of life (Glaeser & Kahn, 2003) but on the other hand, Road congestion, high levels of vehicle pollution, the loss of open space, the unequal distribution of public amenities, and the rise in residential segregation are all attributed to urban expansion (Nechyba & Walsh, 2004).

1.4.4. Urban Sprawl Case Studies

The urban sprawl as witnessed in last century in many parts of the world has been because of the expansion of the transportation network for automobile based

development which encouraged sprawl of cities (Glaeser & Kahn, 2003). In response to the significant opposition to urban expansion that has grown in the US, some local and state governments have implemented legislation (Brueckner, 2016). One of the main factors influencing changes in land use and land cover in the United States is the sprawling of urban development (Hasse & Lathrop, 2003). For the past 50 years, suburban sprawl has dominated American metropolitan areas' growth (Downs, 1998).

Urban sprawl, which is evident in American cities and other cities throughout the world, has been linked to large socioeconomic and environmental consequences and will provide a huge land use management challenge in the twenty-first century (Hasse & Lathrop, 2003). (Jaeger et al., 2010) hypothesizes that the degree of urban sprawl increases with the amount of urban area present in a landscape, as illustrated in Figure 6 below.

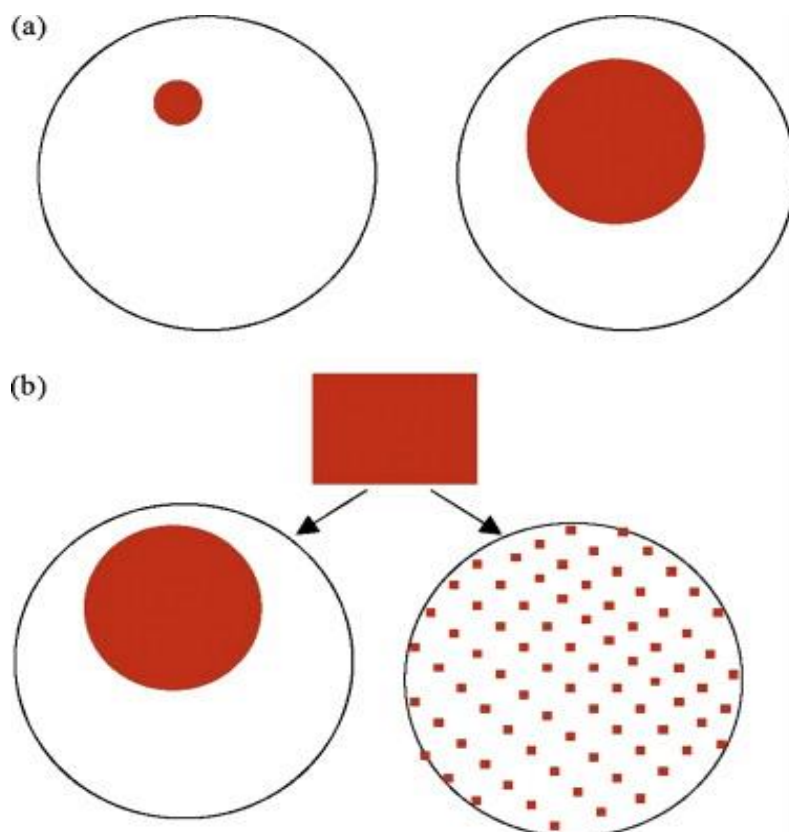


Figure 6. Two major dimensions of urban sprawl: (a) low amount vs high amount urban area (b) compact urban area vs uniformly dispersed urban area

According to Frenkel and Ashkenazi (2008), measuring urban sprawl can be done from a variety of viewpoints, including urban research, ecological research, and fractal geometry. The various, conflicting definitions of the word "urban sprawl" used in the various techniques of assessing it are unclear. Similar to how urban sprawl is defined differently, there are numerous techniques to assess urban sprawl as well as numerous methodologies for researching its various facets (Banai & DePriest, 2014).

(Galster et al., 2010) identified eight measurable dimensions of urban sprawl which are density, continuity, compactness, concentration, centrality, diversity, nuclearity, and proximity. Some restrictions on this application were noted by (Lopez & Hynes, 2003), particularly in the comparative evaluation of metropolitan sprawl, population density, dwelling unit density, or decentralized employment among simple measures of sprawl. According to (Bourne & Rpp, 2001), demographics that separate population cohorts according to urbanization/suburbanization are more important indicators of the changing urban structure. Another indicator of sprawl is the population's separation from the city center (Banai & DePriest, 2014).

1.4.5. Urban Sprawl in Nepal

With 15 of the world's 20 largest cities located in these nations, developing nations have taken the lead in pushing global urbanization (Brinkoff, 2009). The global population growth will mainly concentrate in urban Asia and Africa in coming decade (McGranahan, 2015). Urban sprawl is a global phenomenon but recently is taking place in rapidly developing regions (Lv et al., 2012). Under management of urban areas and under regulations for controlling urban development in rapidly developing economies have sprawled for the availability of cheaper lands.

Nepal was an agricultural country. The country had been divided into small kingdoms with kings of each kingdom building their fort mostly on the hilltops while peasants lived in

villages outside the forts and engaged in trade and agriculture. There were small towns like Kathmandu and Bhaktapur, but the traces of large cities did not exist at those times. Historical documents suggest castles like Janaki Temple in Janakpur having a major importance in past with mention in Hindu writing of "Ramayana". After the 1950s, commerce of products to peri-urban centers and the expansion of decentralization of government administration and the military led to an increase in people in the mid hills (Devkota, 2012). Similarly, some small towns sprawled along the north south corridor for trade between India and China. These towns were mostly settled by traders along the trade route which gradually formed communities and attracted more settlers. Some communities developed along the fertile lands on the riverbanks. Kathmandu valley along with major towns in along the Terai plains along the southern part of the country saw the first traces of modern urbanization since after 1960 and 1970.

The agricultural sector used to provide economic support for 80% of the total population of the country and in 1991, the urbanization rate in the South Asian region has been the greatest in Nepal (7.3% compared to 6.1% in Bangladesh and 3.7% in India), with a population density of 130 people per square kilometer and 9% of the total population living in urban areas (Satterthwaite et al., 2010). In Nepal, urban sprawl has been a major contributor to the loss of open spaces and fertile agricultural lands. Nepal is mostly hilly so most of the fertile lands of the country have historically been used for agricultural purposes. With the ease of trade and change of farming tradition people have less use for agricultural fields but have rather converted agricultural fields to urban areas with infrastructure construction. The land use conversion has also affected forest areas as there have been many forests encroachment by locals in many parts of Nepal.

Three factors contributed to Nepal's urbanization: natural population expansion, rural-to-urban migration, and the categorization of rural areas as urban. Physical conditions, public service accessibility, economic opportunities, the land market, population growth, the

political climate, and plans and policies are just a few of the seven driving factors that have had a considerable impact on the dynamic pattern of urban growth in the Kathmandu Valley (Devkota,2012). Kathmandu is the most populated and urbanized hub, followed by Biratnagar, Pokhara, and Birganj. The central and eastern parts of Nepal have seen quicker urban growth than the western, mid-western, and far western regions (Satterthwaite et al., 2010).

1.4.6. Urban Sprawl Modelling

One of the tools for analyzing urban sprawl is the modeling of urban sprawl trends. Urban sprawl trend is analyzed using land use land cover changes in the past usually the change of built-up land use which is the major contributor to land use change. The changes in 2, 3, or more years of built-up land use have been used to simulate future land use. Modeling future LULC dynamics under various scenarios can help us better understand how human activities, potential resource usage, and conservation can be improved in the future (Kindu et al., 2018). LULC change models are crucial for scientists, decision-makers, and planners in developing plans for confronting environmental and sustainable development issues (Munthali et al., 2020).

1.4.7. Simulation and Machine Learning

Population growth is a driving factor for urbanization, Therefore, by assigning urban and/or non-urban labels to each plot of land, growth models can be used to estimate urban expansion (Gómez et al., 2020). The value of these algorithms lies in their ability to create machines that can automatically calibrate and process with the advancement of processing capacities and the volume capacity the learning algorithms have been widely applied in practice in various domains like urban planning (Tekouabou et al., 2021). Learning algorithms are widely used in many real-life applications because of their distinctive problem-solving nature.

Ecology, economics, geography, and other related sciences that use a model-driven or data-driven method all have active growth modeling study areas, and in model-driven method models are required (Gómez et al., 2020). Applications of machine learning algorithms for the modeling of urban forms have evolved considerably in recent years for addressing the challenges of urban planning (Tekouabou et al., 2021).

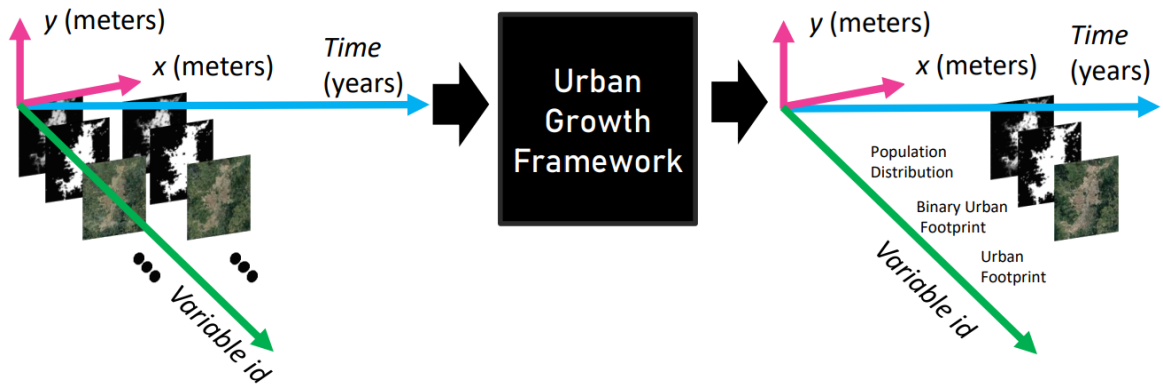


Figure 7. Urban Growth Framework (Gómez et al., 2020)

The different machine learning techniques and their advantage is shown in table.

Table 2. Machine Learning Techniques, advantages and disadvantages (Chaturvedi & de Vries, 2021)

Machine Learning Algorithms	Advantage/Useful When/Appropriate for Applications Related to
Support vector machines (SVMs)	<ul style="list-style-type: none"> - SVMs have a propensity to generalize effectively after the hyperplane is established. - The vast majority of training data is redundant after the hyperplane's boundary is defined. - Powerful algorithm for recognizing

	<p>patterns in land usage.</p> <ul style="list-style-type: none"> - Capability of contextual feature extraction.
Markov random field (MRF)	Pixel and area information are combined by MRF.
Convolutional neural network (CNN)	CNN is suitable for feature extraction since the input image has local spatial coherence.
Random forest (RF)	<ul style="list-style-type: none"> - Can deal with large number of features. - It uses spectral bands as well as additional feature selection layers including the soil index, water index, and NDVI. - It uses textural features, such as metrics like entropy, variance, morphology, and line features, for categorization. - It avoids overfitting.

The fundamental tenet of the models is the presumption that the initial state is in time- and space-equilibrium and that it evolves in response to an exogenous stimulus to a new equilibrium state following the application of the exogenous stimulus (Gharbi et al., 2018).

Table 3. Modelling Techniques (Chaturvedi & de Vries, 2021)

Machine Learning Models	Advantages	Disadvantages	Particularly Useful for Applications of
Spatial logistic regression	- Can incorporate socio-economic and demographic	- Insufficient temporal dynamics	<ul style="list-style-type: none"> ▪ Urban growth, land use

	<p>elements.</p> <ul style="list-style-type: none"> - Multi-scale calibration is possible using logistic regression since it requires less computational resources. 	<ul style="list-style-type: none"> - Disregards location preferences and policies. 	<ul style="list-style-type: none"> ▪ change, land allocation
Cellular automata	<ul style="list-style-type: none"> - CA models are effective at simulating sprawl phenomena. - The outputs from CA models follow the transitional rules. 	<ul style="list-style-type: none"> - High demand for processing power. - Ability to deal with temporal dynamics. 	Land use change, land allocation
Agent based modeling	<ul style="list-style-type: none"> -It incorporates human behavior -Bottom-up approach 	<ul style="list-style-type: none"> - Variability in the outcomes due to the initialization of the agents randomly for a combination of parameter settings. -Hard to calibrate 	Urban growth and land use change

The classification approach in Support Vector Machine (SVM) does not require huge training samples, and it is popular for its use of non-linear boundaries and ability to detect the boundary of training data (Chaturvedi & de Vries, 2021). As it can handle numerous variables like contextual, texture, spatial, spectral, and structural aspects without affecting the classification's overall accuracy, the random forest can be used to classify satellite and aerial images (Chaturvedi & de Vries, 2021).

1.4.8. Neural Network

In comparison to other statistical classification methods, the Artificial Neural Network (ANN) (multi-layer preceptor) method has a clear advantage in modeling because it is non-parametric, requires little to no prior knowledge of the distribution model of the input data, and includes parallel processing with the ability to estimate the non-linear association between the input data and the outputs. Finally, it is quick to generalize (Chaturvedi & de Vr, 2021).

1.4.9. Cellular Automata Simulation

The main distinction between agent-based models and cellular automata models—which are sometimes referred to as the same thing—is that while spatial entities serve as the basic units for the simulation in agent-based models, the relationship between these units is dynamic and flexible (Chaturvedi & de Vries, 2021). The CA model is based on a grid of physical zones, or cells, that are distinguished by a condition of land use that shifts over time in accordance with a set of transitional rules (Gharbi et al., 2018).

Since Tobler adopted the concept for geographical modeling whose dynamic changes are impacted by environmental and socio-economic elements and their relations on multiple spatial and temporal scales, cellular automata (CA) have been frequently employed to predict urban growth (Hassan et al., 2020). CA can use simple rules to simulate complicated spatiotemporal active processes and can then be integrated with high-resolution images, GIS, CA, and CA-based models for the simulation of urban growth in the past (Hassan et al., 2020). The ability to represent individual decision-makers and their interactions, to include numerous social and non-financial processes in decision-making, and to link social and environmental processes are the key benefits of the agent-based approach (Chaturvedi & de Vries, 2021).

1.5. Conclusion

This chapter consists of the important parts on understanding the topic of the study in detail. The knowledge of urban planning, urbanization and impacts of urbanization are the basis for this study. The increase in urbanization population creates problems in urban areas which can be solved by modelling technology. The use of geographic information such as LULC for past evaluation and prediction of future creates a framework for future development.

Chapter-2: Methodology

LULC and Urban Sprawl modeling in the Dhanusha district was based on temporal remote sensing data of the study area. The study mainly investigated the trend of land use and cover changes in the Dhanusha district, with the application of temporal Landsat images. Temporal images from 1993, 2003, 2013, and 2021 were used for analyzing the changes focused on built-up. ArcGIS Pro was used for processing images and LULC mapping and the urban sprawl model was created using the QGIS MOLUSCE plugin. The following sections provide the process's specifics.

2.1. Workflow

The methodology workflow for the study of land use land cover change in the Dhanusha district and urban sprawl modeling is presented in Figure 17.

- Landsat Imagery covering the Dhanusha district for 1993, 2003, 2013, and 2021 was downloaded from the USGS website. The images were selected with no cloud cover over the study area for all four years.

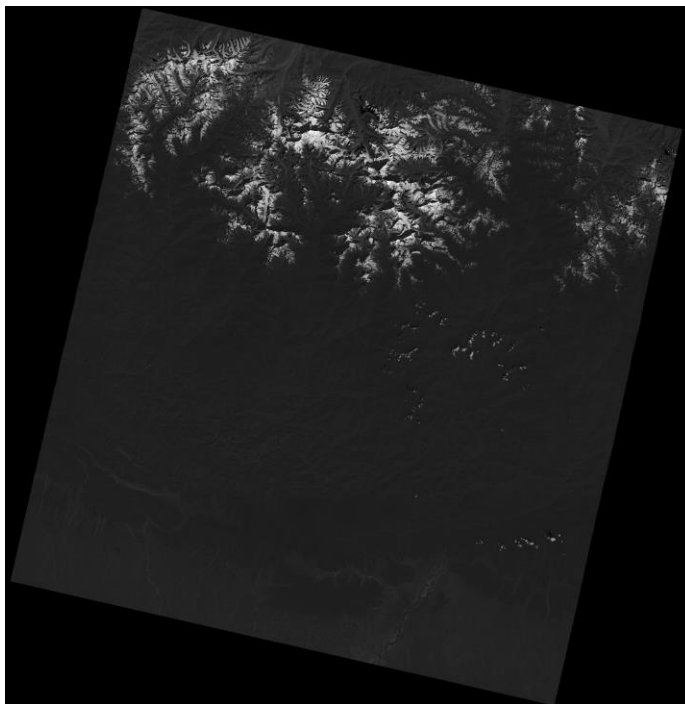


Figure 8. Band 1 sample of Satellite Image of 2021

- Landsat 4-5 imagery of 1993 contained 7 bands each in GeoTIFF format and other supporting files. The study area was not covered by a single image so an adjacent imagery was acquired with same specification for same date. ArcGIS Pro's "Composite Bands" tool was used to combine the picture bands into a single image, and the "Mosaic" tool was used to combine the two neighboring images into a single mosaic.

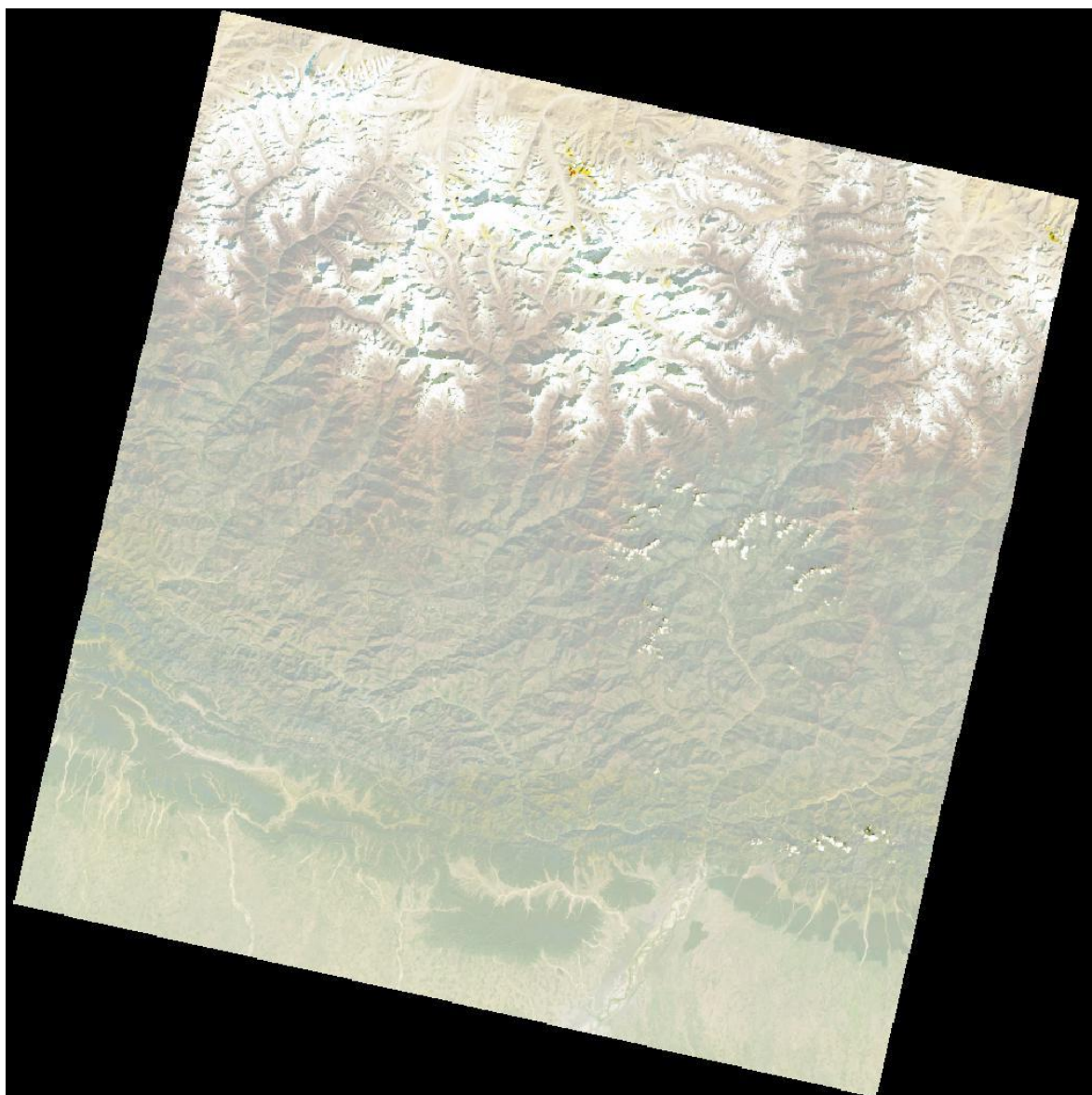


Figure 9. Thumbnail of composite image for 2021

- Similarly, Landsat 7 imagery of 2003 containing 9 bands was acquired. A single tile could not cover the study area so two adjacent images were mosaiced.
- Landsat 8 images of 2013 and 2021 with 11 number of spectral bands were

acquired. A single tile in 2013 was sufficient for enclosing the study area but the image of 2021 was not sufficient so two adjacent images were mosaiced for the study area.

- The downloaded images were first composited to a single image then the study area boundary was used to clip the study area region from the entire downloaded imagery. The “Clip” tool in ArcGIS Pro was used for obtaining the satellite imagery for the study area for 1993, 2003, 2013 and 2021.

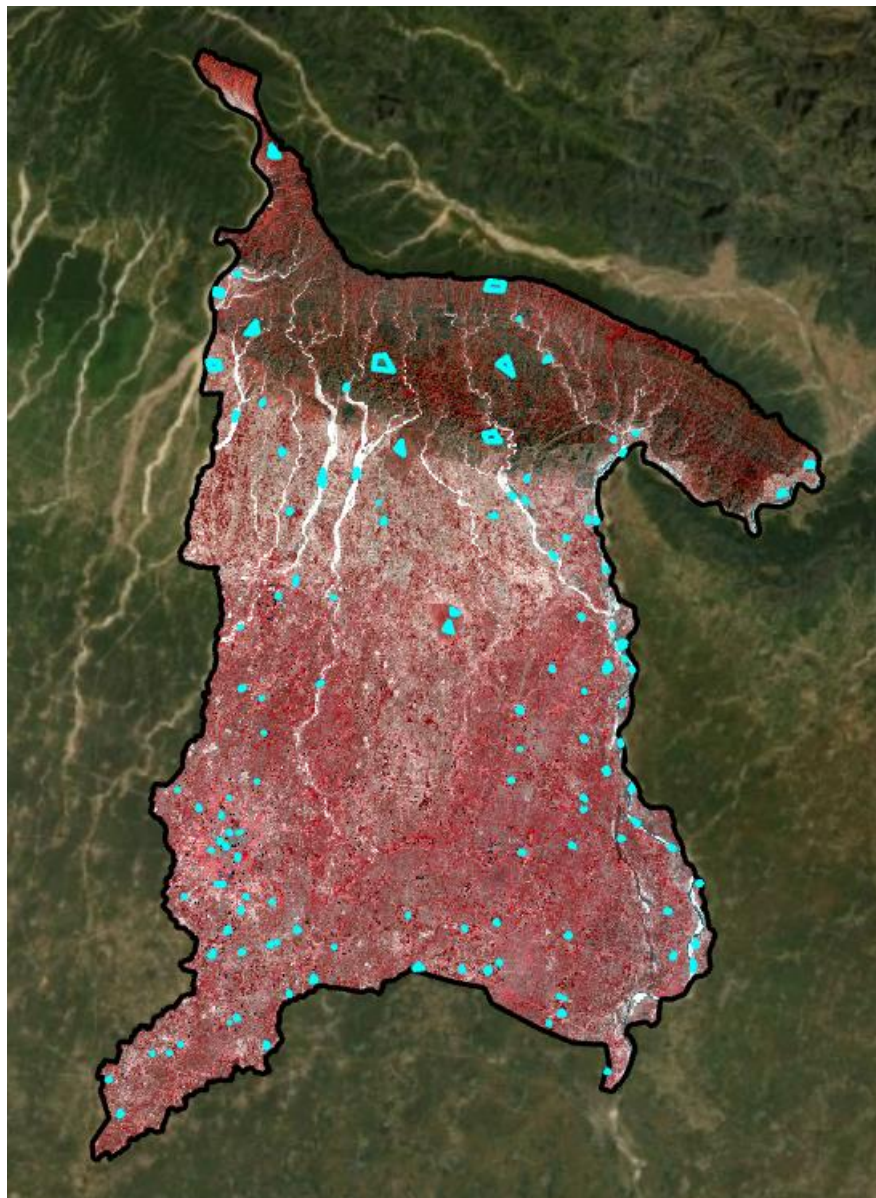
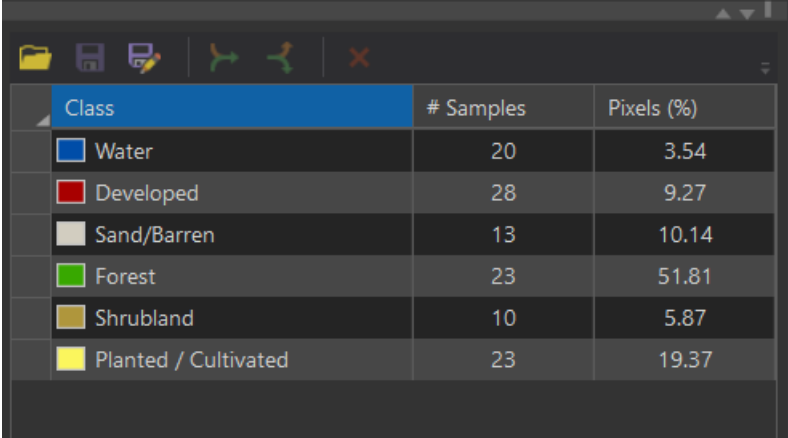


Figure 10. Creating training samples

- Each imagery from 1993, 2003, 2013 and 2021 were classified in ArcGIS Pro. The classification method used was pixel-based image classification technique. The training samples for each image was prepared for each LULC classes.



The screenshot shows a table with three columns: 'Class', '# Samples', and 'Pixels (%)'. The table lists six LULC classes with their respective sample counts and pixel percentages. The classes are Water, Developed, Sand/Barren, Forest, Shrubland, and Planted / Cultivated.

Class	# Samples	Pixels (%)
Water	20	3.54
Developed	28	9.27
Sand/Barren	13	10.14
Forest	23	51.81
Shrubland	10	5.87
Planted / Cultivated	23	19.37

Figure 11. Training samples and pixels

- The LULC maps were generated for 1993, 2003, 2013 and 2021 using the layout function and cartographic tools in ArcGIS Pro.

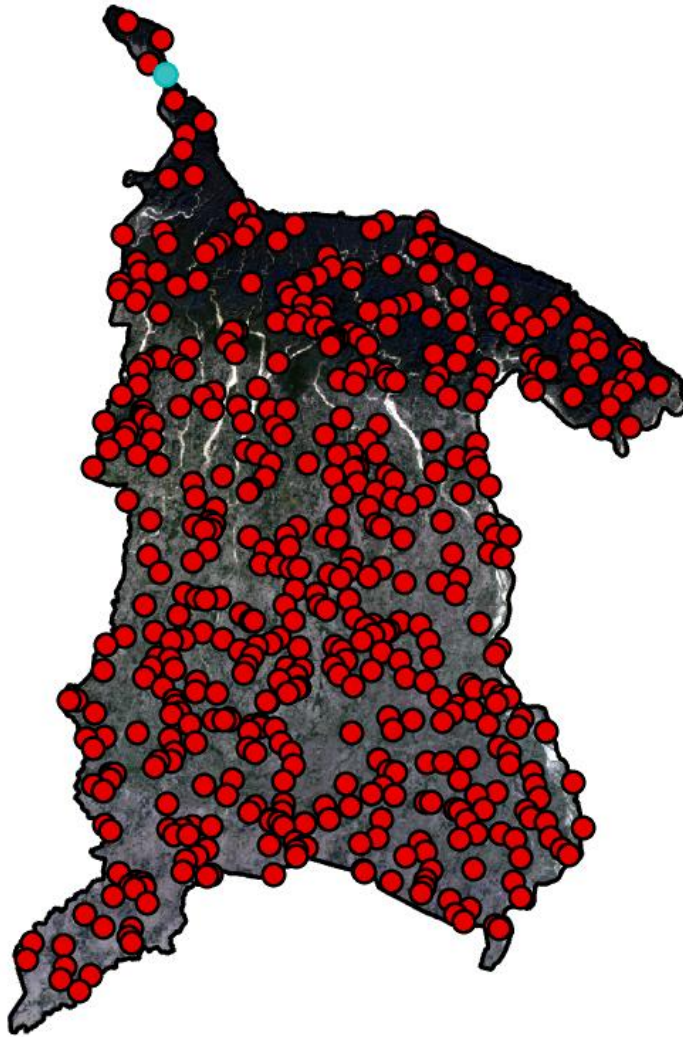


Figure 12. Accuracy Assessment Points

- The accuracy assessment of the classification was analyzed using “Create accuracy assessment points”. The accuracy assessment points were generated for images from 1993, 2003, 2013, and 2021. The points were opened in attribute view and each point was analyzed to be in proper classification or not.
- The confusion matrix was then generated for each points layer using “Create confusion matrix” and the table obtained was saved as the table in excel using the “Table to Excel” tool in ArcGIS Pro.
- After analyzing the accuracy to be more than 80% for each layer, the LULC maps were generated for 1993, 2003, 2013 and 2021 and saved as .Tiff file format for processing in QGIS.

- Data from the Shuttle Radar Topography Mission (SRTM) was used to create Digital Elevation Model (DEM) files. Single - tile Images could not fill the entire area. Four elevation images were merged using the “Mosaic” raster function. The layer was then clipped to get the DEM of the study area. The DEM was saved as. Tiff format.



Figure 13. DEM of Dhanusha

- Roads of Nepal data was downloaded from International Centre for Integrated Mountain Development (ICIMOD) Nepal database. The layer was clipped to obtain roadways in the study area and saved as. Tiff format.
- The LULC files, DEM, and Road files were loaded in QGIS for change analysis

and simulation.

- Firstly, LULC change was analyzed using Initial Image: LULC 1993 and Final Image: LULC 2013. The DEM and roads layers were used as spatial variables. After checking their geometries.

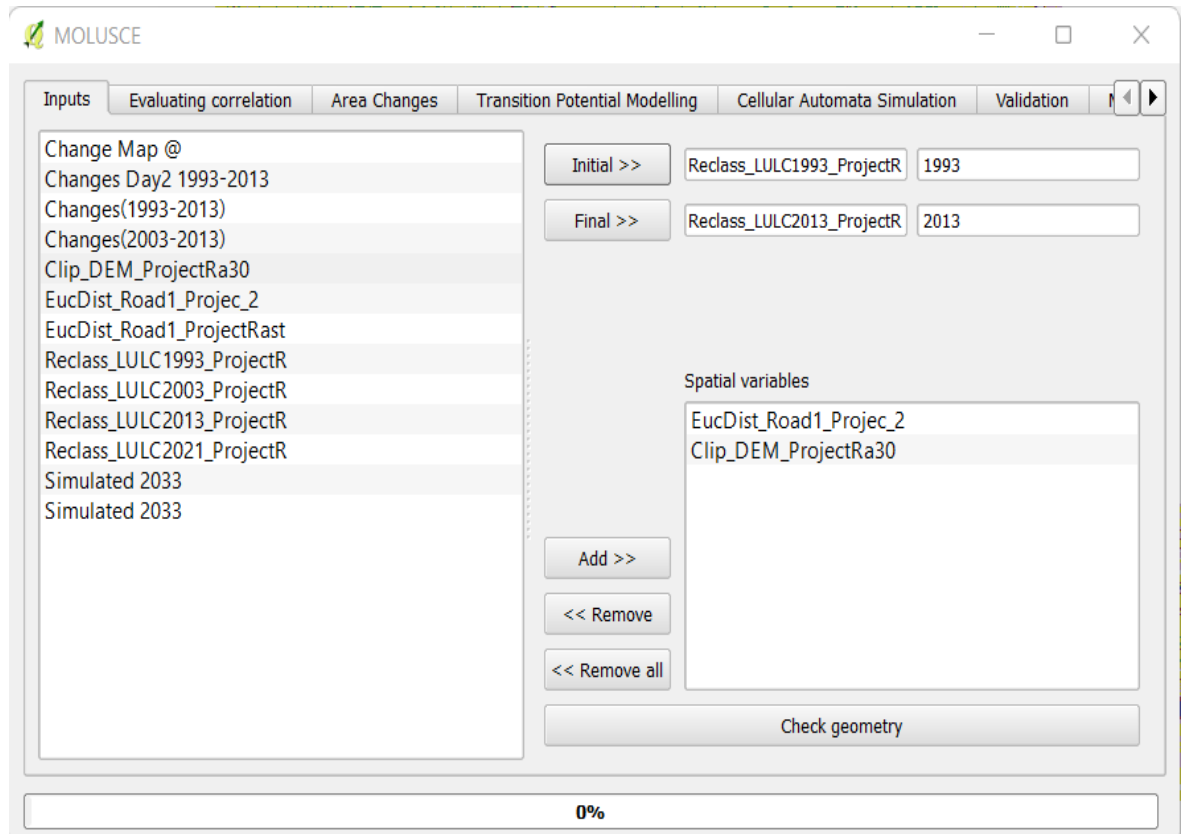


Figure 14. Input for LULC Simulation

- Evaluation correlation was checked for first and second raster using Pearson's Correlation. The class statistics and Transition matrix were evaluated for area changes from 1993 to 2013.
- Transition potential modelling was done using neural network learning curve and LULC was simulated for 2021 using cellular automata simulation.
- The process of simulation was again done similarly using initial image of 2003 and final image of 2013.

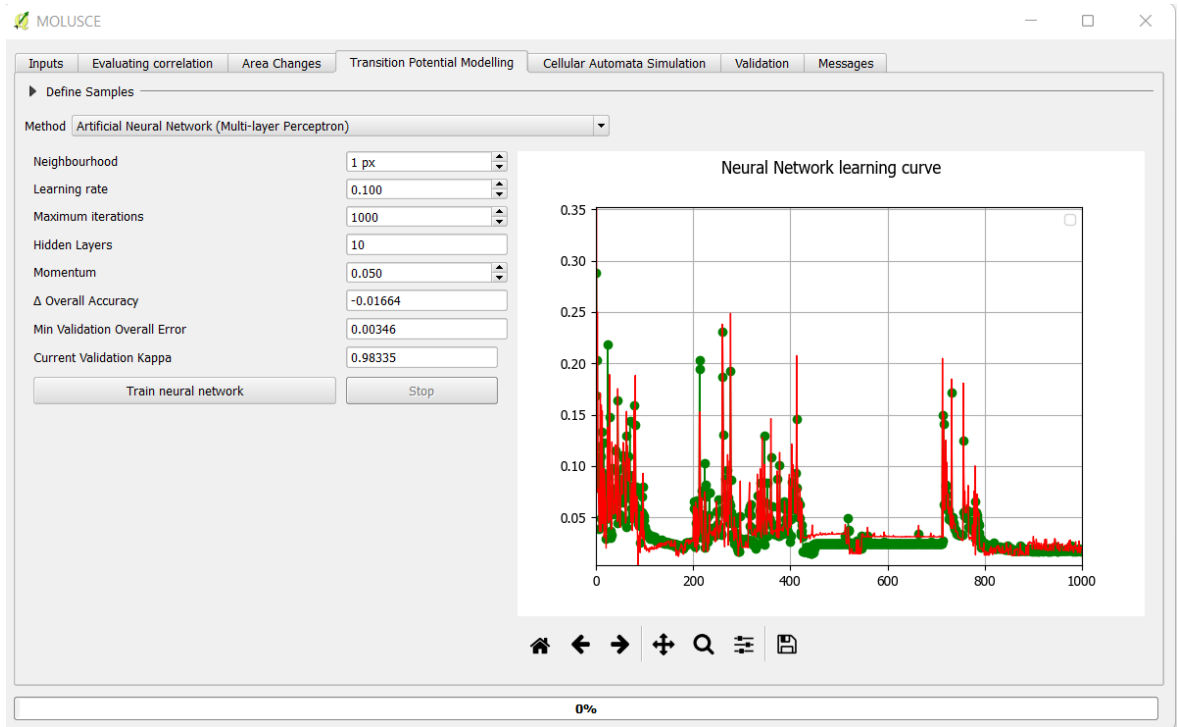


Figure 15. Transition Potential Modelling LULC Simulation

- The result of simulated 2021 was validated with LULC image of 2021 for both simulation results. The accuracy for the model using 2003 and 2013 was more than 80% so the model was used for simulation for 2033 and 2043.

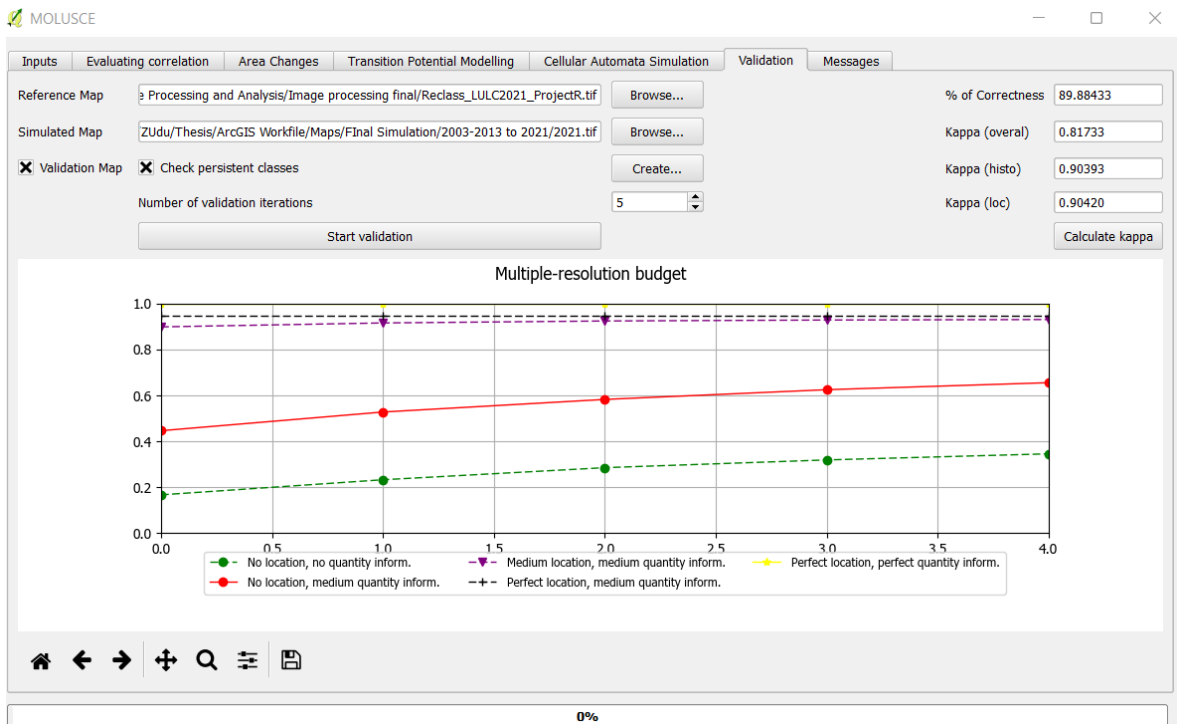


Figure 16. Simulation Validation

- The modeled maps were saved to the computer in GeoTIFF format for use in ArcGIS.
- The calculation of every land use class was done in ArcGIS by uploading the files into ArcGIS work file.
- The maps were created for LULC of 1993, 2003, 2013, 2021, 2033 and 2043. Again, the map of roads in Dhanusha and map of DEM was plotted in ArcGIS with scale, outline, legend and other features.
- The calculations of each map were done using reclassify tool in ArcGIS. The data was exported in Microsoft excel which was used for making the graphs and tables of the features.

The workflow of the study is divided into data acquisition and data preparation, data processing and analysis and result and verification. The workflow of the study is presented in Figure 17.

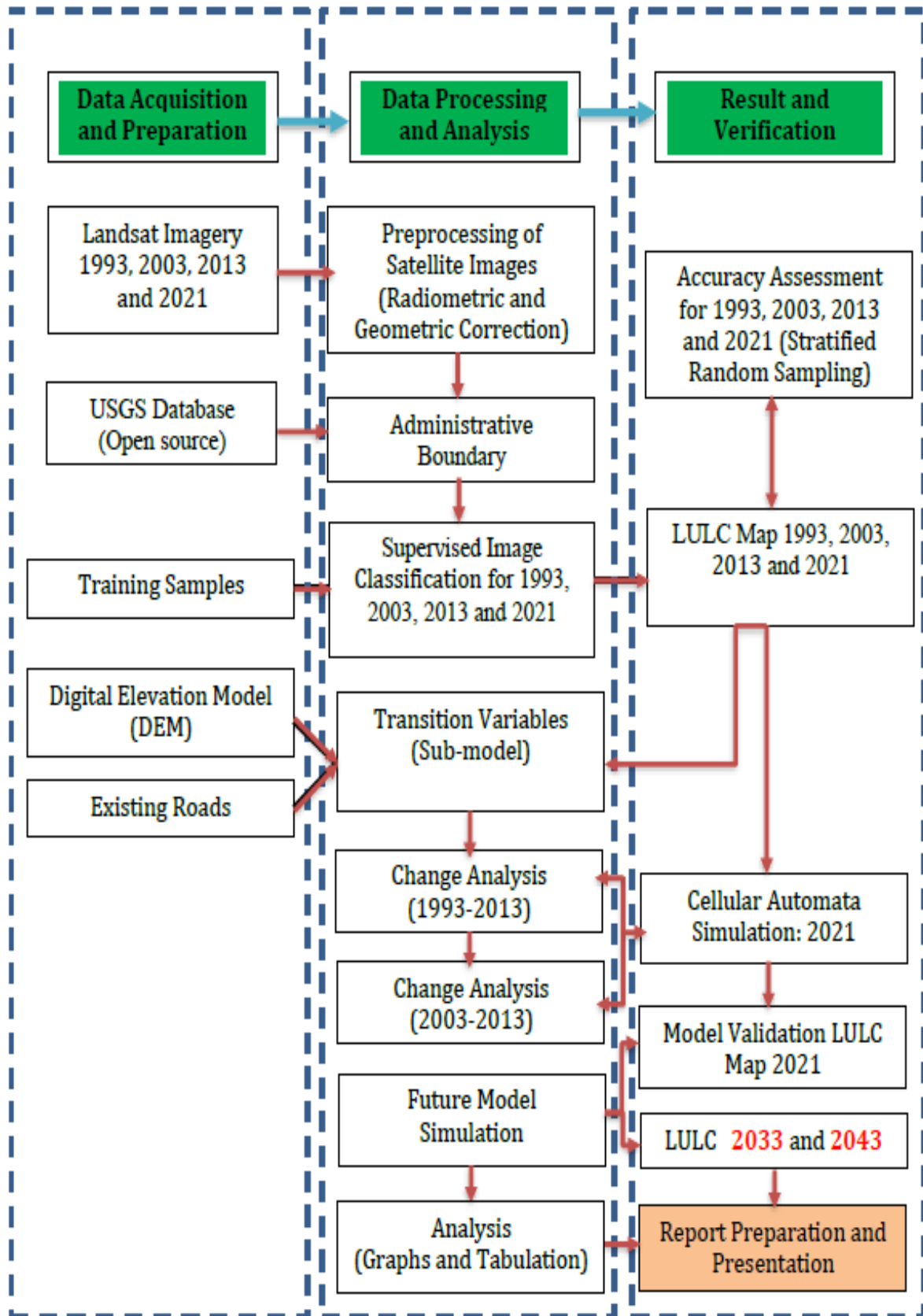


Figure 17. Workflow of LULC analysis

2.2. Data Used

2.2.1. Landsat Imagery

The United States Geological Survey (USGS) Earth Explorer website offers free access to photographs of Landsat satellites. The area of interest can be defined using a polygon, circle, or predefined area in an interactive world map. The date range can be specified for obtaining images of the required date-time. Similarly, the cloud cover percentage can be defined as limiting the cloud cover of the imageries. Landsat Collection 2 level 2 data, Landsat Collection 2 level 1 data, Landsat C2 atmospheric auxiliary data, Landsat Collection 1 datasets, and Landsat Legacy datasets are among the datasets included under Landsat. Landsat 8-9 Operational Land Imager (OLI) / Thermal Infrared Sensor (TIRS) C2 L2, Landsat 7 Enhanced Thematic Mapper (ETM+), and Landsat 4-5 Thematic Mapper (TM) C2 L2 are among the level-2 data from Landsat Collection 2 that can be downloaded.

The Landsat satellites collect imagery using a variety of frequency bands across the electromagnetic spectrum. Landsat 1,2,3,4 and 5 carried Multispectral Scanner (MSS) collected 4 range of bands. Later, Landsat 4 and 5 included new thermal bands and shortwave infrared with the 4 range of previous bands. Landsat 7 added a new panchromatic band to the previous bands with its ETM + sensor. The Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) were two sensors carried by Landsat 8, as opposed to the preceding satellites' single sensor. Recently, Landsat 9 has been launched and is in operation which has the instruments as improved copies of the Landsat 8 sensors but this satellite is out of the scope of this study.

The Multispectral Scanner (MSS) used by Landsat 1-5 produced images with four spectral bands and a spatial resolution of 60 meters. The scene sizes are approximately 170 km north-south and 185 km east-west. In Landsat 1-3 and Landsat 4-5, distinct bands have

different labels. Table 4 displays the Landsat 4-5 band parameters.

Table 4. Landsat 4-5 Bands Specification (USGS, 2021)

Landsat 4-5		
Acquisition Dates: 18-01-2018		
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	0.77-0.90	30
Band 5	1.55-1.75	30
Band 6	10.40-12.50	120 (30)
Band 7	2.09-2.35	30

Similar to this, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images were composed of eight spectral bands, with Bands 1 through 7 having a spatial resolution of 30 meters and Band 8 (Panchromatic band) having a resolution of 15 meters. For greater radiometric sensitivity and dynamic range, these bands can gather data at either one of two gain settings: low or high. Band 6 is able to gather all scenes' high and low gain. Landsat 7's scene size is roughly 170 km north-south and 183 km east-west. The band specifications for Landsat 7 are shown in Table 5.

Table 5. Landsat 7 Bands Specification (USGS, 2021)

Landsat 7		
Acquisition Date:18-01-2001		
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 – Short Waved Infrared (SWIR)	1.55-1.75	30
Band 6 – Thermal Infrared	10.40-12.50	60 (30)
Band 7 – Short wave Infrared	2.09-2.35	30
Band 8 – Panchromatic	0.52-0.90	15

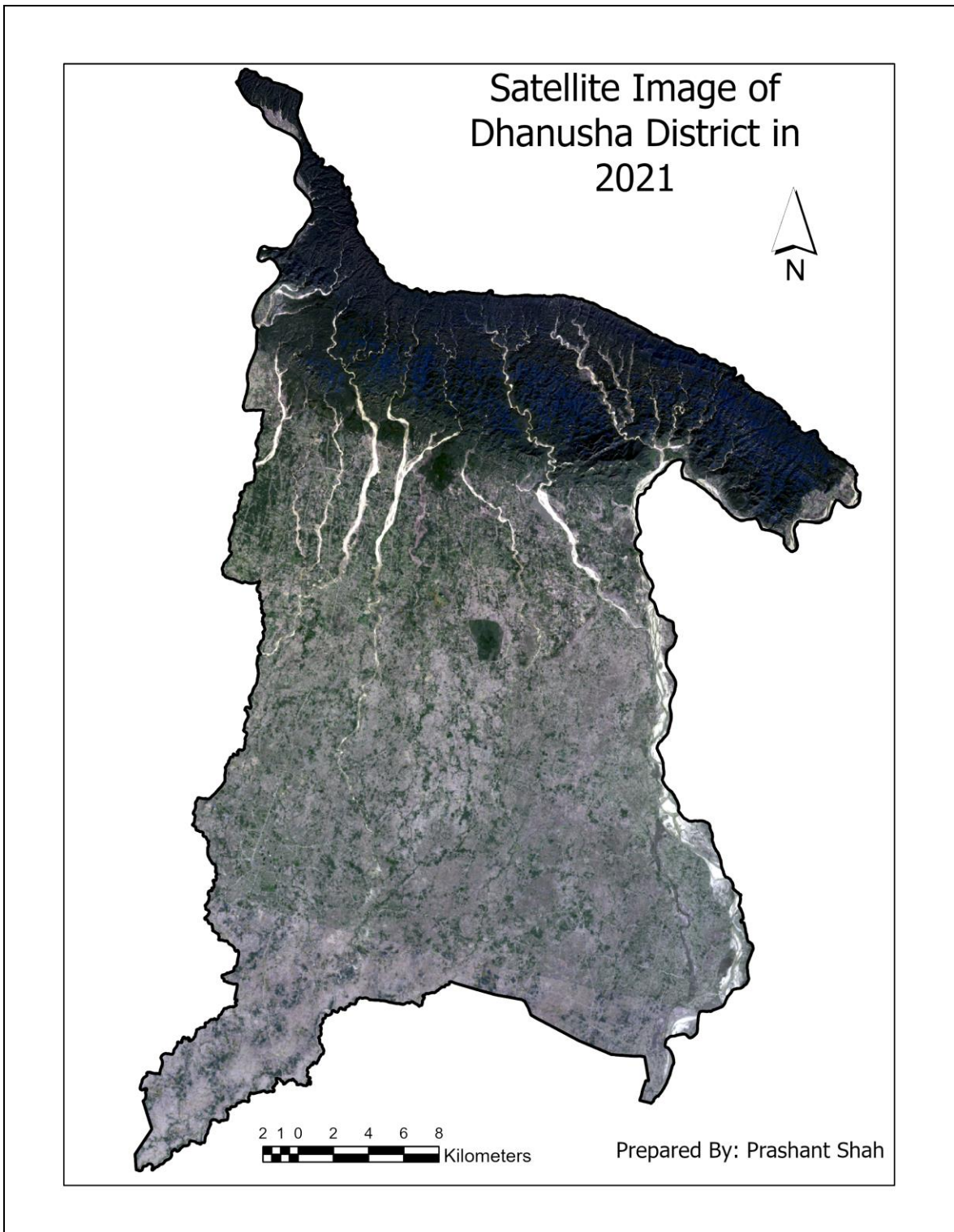
Bands 1 through 7 and 9 of the Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensors (TIRS) pictures each have a spatial resolution of 30 meters. The bands have different importance studies such as Band 1 which is ultra-blue used for coastal and aerosol studies and Band 9 is used for cirrus cloud detection. Band 8, the panchromatic band, has a spatial resolution of 15 meters. Two thermal bands, 10 and 11, are employed to provide surface temperatures that are gathered with a 100-meter resolution. The approximate scene sizes of Landsat 8 images are 170 km north-south by 183 km east-west. The band specification for Landsat 8 is presented in Table 6.

Table 6. Landsat 8 Bands Specification (USGS, 2021)

Landsat 8		
Acquisition Dates: 21-01-2016		
Bands	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 - SWIR 1	1.57-1.65	30
Band 7 - 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

The Landsat 8 image of 2021 December 19, which was merged from two image tiles downloaded to cover the entire study area and clipped to the study area is shown below.



Map 2. Satellite Image of Dhanusha District

The specification of Landsat 8 image used for the image processing are shown below:

Table 7. Image Specification 2021 (I)

LANDSAT_PRODUCT_ID = "LC08_L2SP_140042_20211219_20211223_02_T1"	
PROCESSING_LEVEL = "L2SP"	TARGET_WRS_PATH = 140
COLLECTION_NUMBER = 02	TARGET_WRS_ROW = 42
SPACECRAFT_ID = "LANDSAT_8"	DATE_ACQUIRED = 2021-12-19
SENSOR_ID = "OLI_TIRS"	SCENE_CENTER_TIME= "04:42:53.734885Z "
WRS_TYPE = 2	STATION_ID = "LGN"
WRS_PATH = 140	CLOUD_COVER = 0.41
WRS_ROW = 42	SUN_AZIMUTH = 154.71918152
NADIR_OFFNADIR = "NADIR"	SUN_ELEVATION = 36.17497210

Table 8. Image Specification 2021 (II)

LANDSAT_PRODUCT_ID = "LC08_L2SP_140041_20211219_20211223_02_T1"	
PROCESSING_LEVEL = "L2SP"	TARGET_WRS_PATH = 140
COLLECTION_NUMBER = 02	TARGET_WRS_ROW = 41
SPACECRAFT_ID = "LANDSAT_8"	DATE_ACQUIRED = 2021-12-19
SENSOR_ID = "OLI_TIRS"	SCENE_CENTER_TIME= "04:42: 29.8396100Z "
WRS_TYPE = 2	STATION_ID = "LGN"
WRS_PATH = 140	CLOUD_COVER = 5.29
WRS_ROW = 41	SUN_AZIMUTH = 155.41974796
NADIR_OFFNADIR = "NADIR"	SUN_ELEVATION = 34.96790866

Table 9. Image Specification 2013

LANDSAT_PRODUCT_ID = "LC08_L2SP_140041_20131127_20200912_02_T1"	
PROCESSING_LEVEL = "L2SP"	TARGET_WRS_PATH = 140
COLLECTION_NUMBER = 02	TARGET_WRS_ROW = 41
SPACECRAFT_ID = "LANDSAT_8"	DATE_ACQUIRED = 2013-11-27
SENSOR_ID = "OLI_TIRS"	SCENE_CENTER_TIME= "04:43:46.6574010Z"
WRS_TYPE = 2	STATION_ID = "LGN"
WRS_PATH = 140	CLOUD_COVER = 7.18
WRS_ROW = 41	SUN_AZIMUTH = 157.16952323
NADIR_OFFNADIR = "NADIR"	SUN_ELEVATION = 38.01520498

Table 10. Image Specification 2003

LANDSAT_PRODUCT_ID = "LE07_L2SP_141041_20031104_20200916_02_T1"	
PROCESSING_LEVEL = "L2SP"	TARGET_WRS_PATH = 141
COLLECTION_NUMBER = 02	TARGET_WRS_ROW = 41
SPACECRAFT_ID = "LANDSAT_7"	DATE_ACQUIRED = 2003-11-04
SENSOR_ID = "ETM"	SCENE_CENTER_TIME= "04:37:04.0203102Z"
WRS_TYPE = 2	STATION_ID = "SGS"
WRS_PATH = 141	CLOUD_COVER = 5.00
WRS_ROW = 41	SUN_AZIMUTH = 136.78496205
NADIR_OFFNADIR = "NADIR"	SUN_ELEVATION = 46.21267933

Table 11. Image Specification 1993

LANDSAT_PRODUCT_ID = " LT05_L2SP_140041_19931210_20200914_02_T1"	
PROCESSING_LEVEL = "L2SP"	TARGET_WRS_PATH = 141
COLLECTION_NUMBER = 02	TARGET_WRS_ROW = 41
SPACECRAFT_ID = "LANDSAT_5"	DATE_ACQUIRED = 1993-12-10
SENSOR_ID = "TM"	SCENE_CENTER_TIME= " 04:04:27.2000380Z"
WRS_TYPE = 2	STATION_ID = "ISP"
WRS_PATH = 140	CLOUD_COVER = 10.00
WRS_ROW = 41	SUN_AZIMUTH = 116.29001820
NADIR_OFFNADIR = "NADIR"	SUN_ELEVATION = 53.64857021

2.2.2. Digital Elevation Model (DEM)

SRTM data are enhanced void-filled Digital Elevation data. Among the datasets available are SRTM Non-void filled data, SRTM Void filled data, and SRTM 1 Arc-Second Global data. Earth Resources Observation and Science (EROS) Center specifies product specification of SRTM Products as shown in Table 12.

Table 12. SRTM Product Specifications

Projection	Geographic
Horizontal Datum	WGS84
Vertical Datum	EGM96 (Earth Gravitational Model 1996)
Vertical Units	Meters
Spatial Resolution	1 arc-second for global coverage (~30 meters)

3 arc-seconds for global coverage (~90 meters)	
Raster Size	1-degree tiles

2.3. Software Used

The software used for the main analysis and mapping was ArcGIS Pro. Similarly, the QGIS MOLUSCE plugin was used for the change analysis and change prediction for future LULC. The report preparation was conducted in Microsoft Word and the charts and tables were analyzed in Microsoft Excel.

2.3.1. ArcGIS Pro

The main software used for most of the work was ArcGIS Pro. The software is a product of Environmental Systems Research Institute (ESRI). The image preprocessing of the imagery, bands composite, clipping to the study area, mosaicking images, training samples, image classification, and accuracy assessment of classified images processes were done in ArcGIS Pro. The creation of maps as required for the study were all done in ArcGIS Pro using layout function. The toolbar in ArcGIS pro were used for the analysis. The raster functions were also used for image processing.

QGIS MOLUSCE

QGIS is an open-source platform for spatial GIS analysis. A plugin for QGIS is called Modules for Land Use Change Evaluation (MOLUSCE). The plugin is used for land use change simulations using the QGIS platform and was designed for the analysis, modeling, and simulation of land use changes. The MOLUSCE Graphical User Interface (GUI) has seven main components as shown in Figure 18. The Input section uses the specification of the initial time and final time of LULC changes and other spatial variables like

DEM.

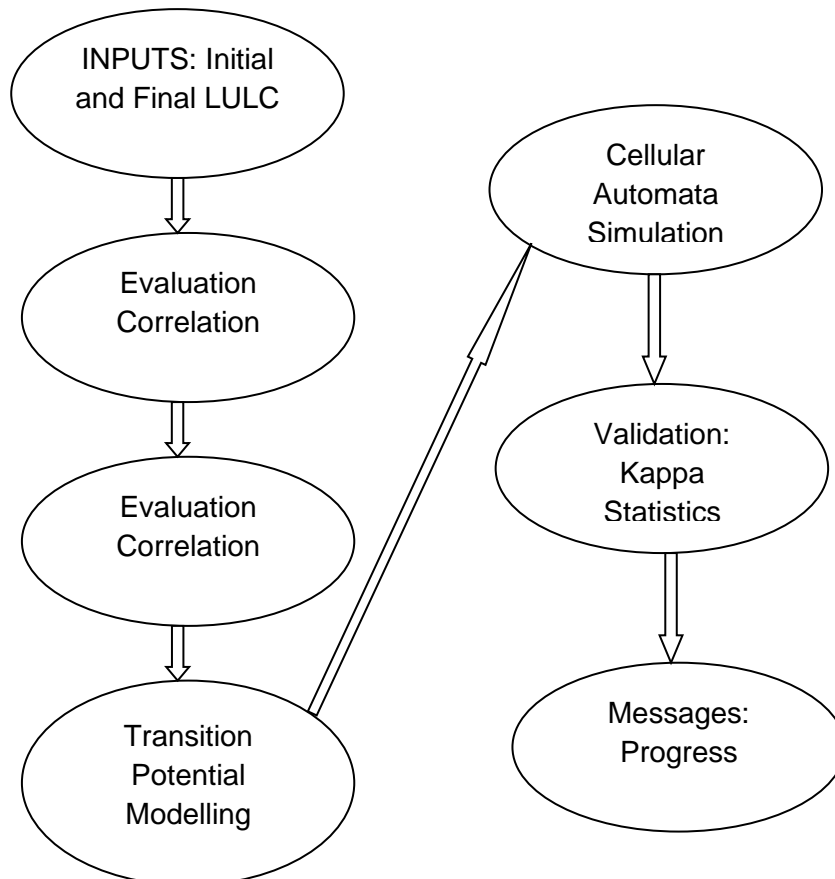


Figure 18. Seven Main Components of MOLUSCE

The Asia Air Survey developed the MOLUSCE plugin as an open-source model compatible with QGIS 2.0 and higher versions for the study, modeling, and simulation of the changes in land use/cover (Muhammad et al., 2022). The plugin has many advantages for use for analysis, simulation, and modeling, the main advantage is its open source which provides users this capability without any cost. It incorporates many well-recognized processes, some of the algorithms are cross-tabulation techniques, utility modules, algorithmic modules, and examples. ANNs, weights of evidence, multi-criteria evaluation, logistic regression, and CA models (Muhammad et al., 2022).

Numerous researchers employ MOLUSCE, which estimates probable LULC changes using the CA model and the transition probability matrix (Kamaraj et al., 2021). A CA-ANN

model used in the MOLUSCE plugin is a reliable tool that can predict the future LULC and is utilized in land use planning this is being used for estimating LULC shift because it evaluates the current condition of pixels based on the initial situation and adjacent neighborhood (Kamaraj et al., 2021). Assessing spatial and temporal land-use changes, projecting transition possibilities, and modelling future scenarios are all made possible by the MOLUSCE plugin, which efficiently computes and models changes (Muhammad et al., 2022).

2.3.2. Conclusion

In this section, the workflow of the study is stated along with the flowchart of methodology. The datasets used for the study area were discussed. The use of remotely sensed satellite imagery was studied and the data availability from Landsat satellites for different study time were analyzed. The specification and bands availability of Landsat 4-5, Landsat 7, and Landsat 8 were studied. It was noted that Landsat imagery analysis would be effective in 30m spatial resolution for bands 1-7 to consistently use data over four study times.

Chapter-3: Results and Discussion

3.1. Land Use Land Cover Classification

The land use land cover of Dhanusha district in the year 1993 was mainly agricultural and forest area dominant. The area of 743.46 Sq km. was covered by planted/ cultivated lands which is the highest land use in the area with a percentage of 63.0%. The second major land use was forest areas which was calculated as 322.47 Sq km. and was covering 27.3% of Dhanusha. The third main land cover was Shrub areas which covered an area of 51.57 Sq Km. and was covering 4.4% of the area. The shrublands were formed along the riverbanks. The data of the LULC in the district is presented in Figure 19.

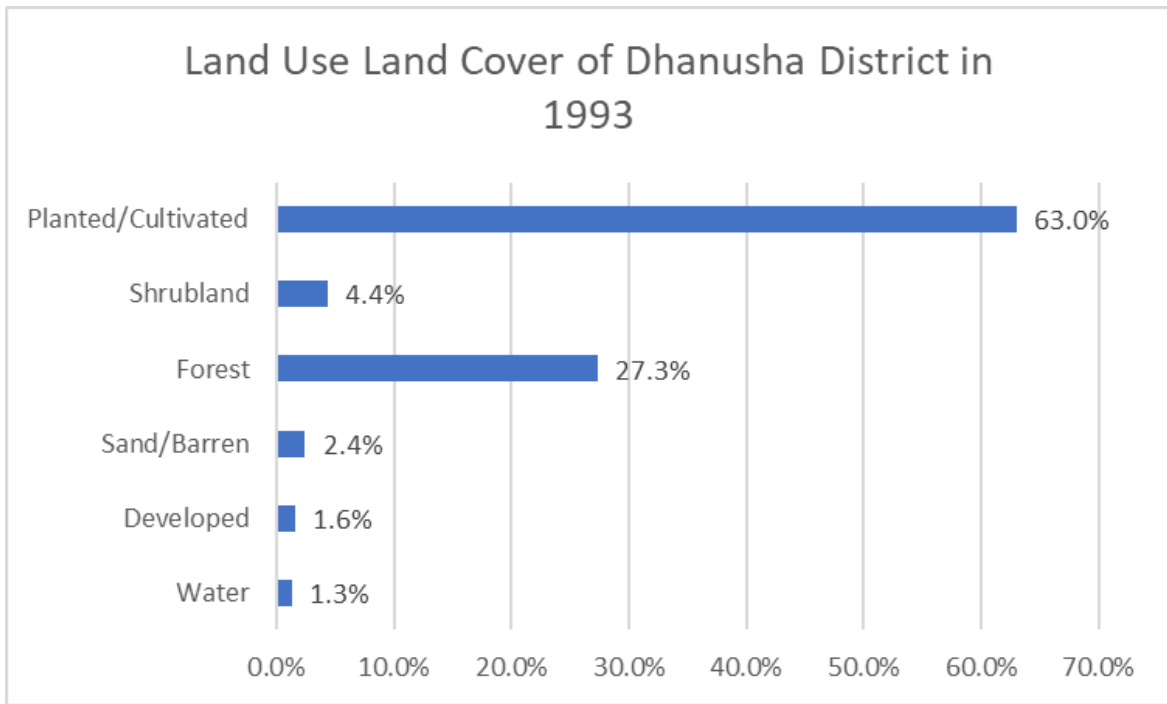
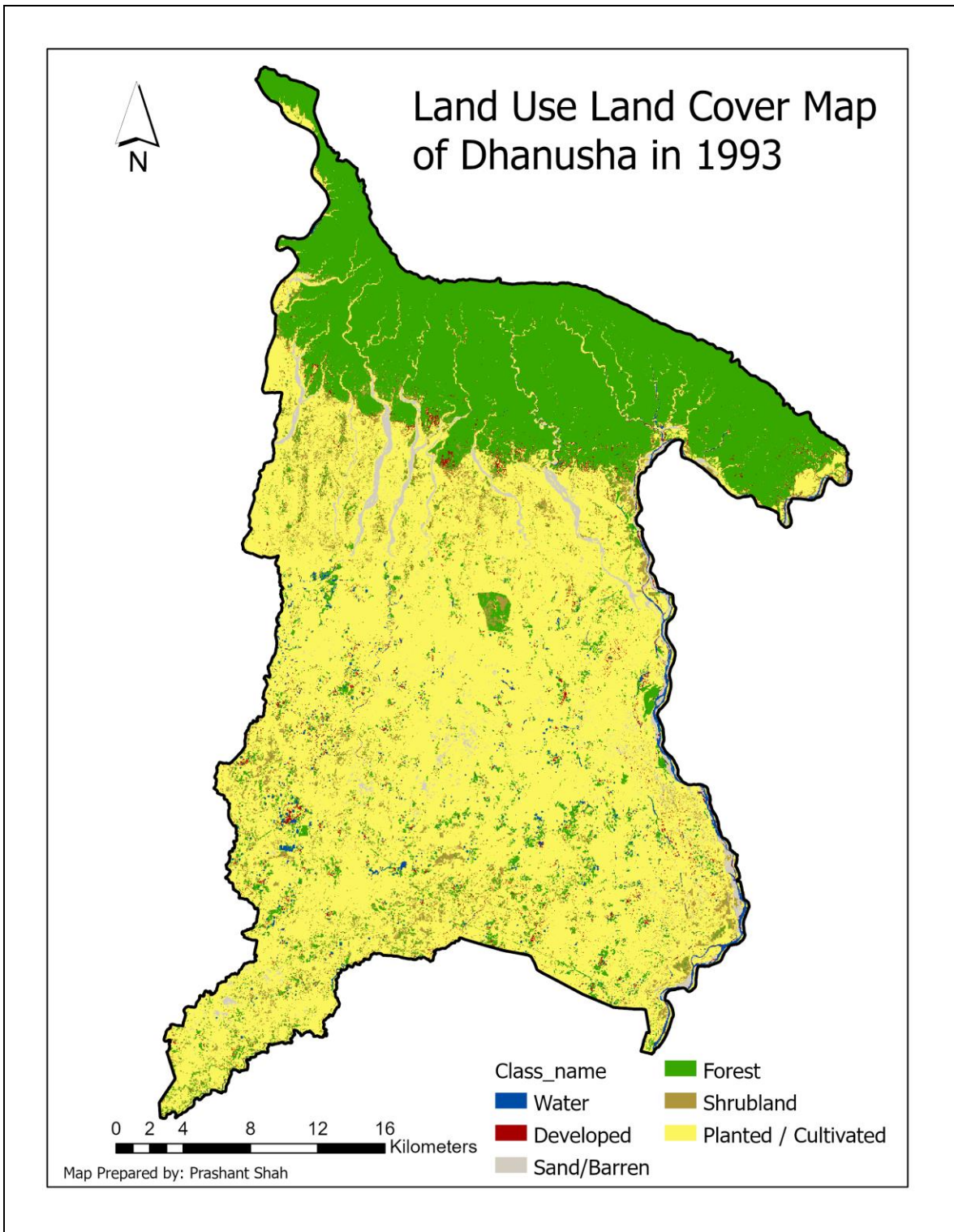


Figure 19. Land Use Land Cover Data in 1993

The least amount of study area was covered by water body which is 15.46 Sq km. which covered an area of 1.3%. The second lowest land use was developed which covered an area of 18.33 Sq km. in the district and had a 1.6% coverage in the area. The Sand / Barren areas had a total area of 27.70 Sq km. and covered an area of 2.4% of the Dhanusha district.

The LULC map of the Dhanush District in 1993 is presented in the Map 3.



Map 3. Land Use Land Cover Map of Dhanusha District in 1993

The land uses land cover of the Dhanusha district in the year 2003 was like the year 1993 with mainly agricultural and forest areas dominant. The agricultural areas decrease by 2.9% in 2003. The area of 708.83 Sq km. was covered by planted/ cultivated lands which

is still the highest land use in the area with a percentage of 60.1%. The second major land use was forest areas which was calculated as 360.07 Sq km. and was covering 30.5% of Dhanusha. The third main land cover was Sand/Barren areas which covered an area of 37.05 Sq Km. and was covering 3.1% of the area. The shrubland and barren areas changed significantly from 1993 to 2003. The barren/ sandy areas were formed along the riverbanks. The data of the LULC in the district is presented in Figure 20.

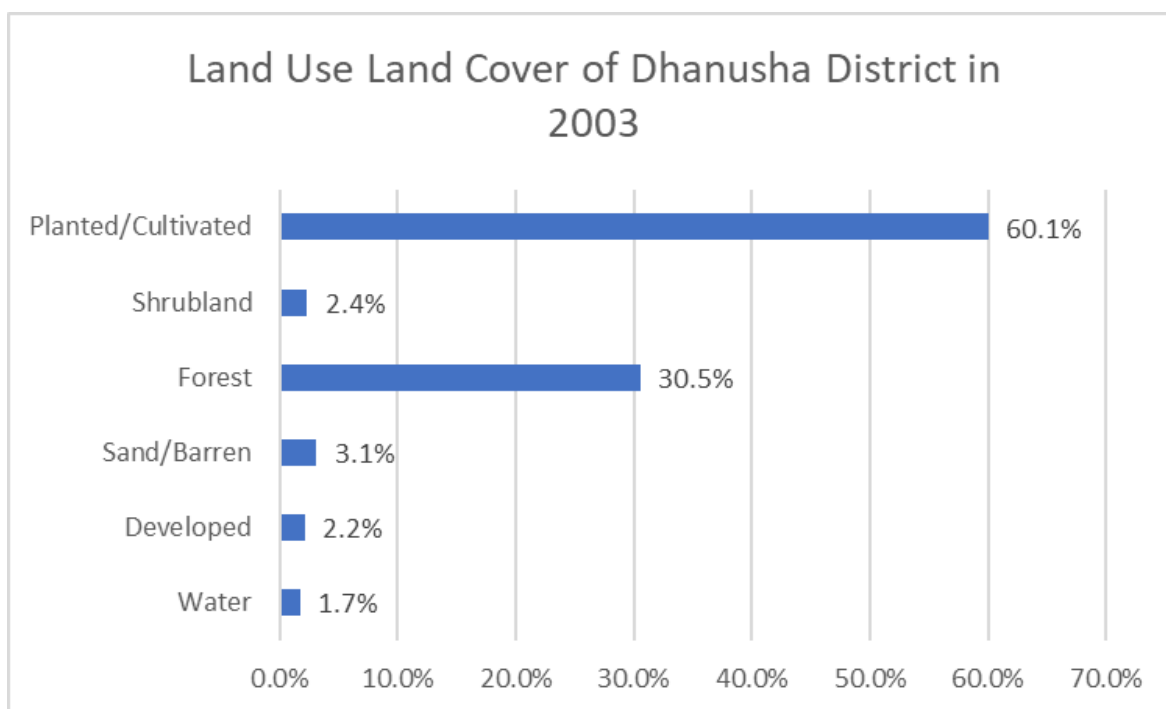
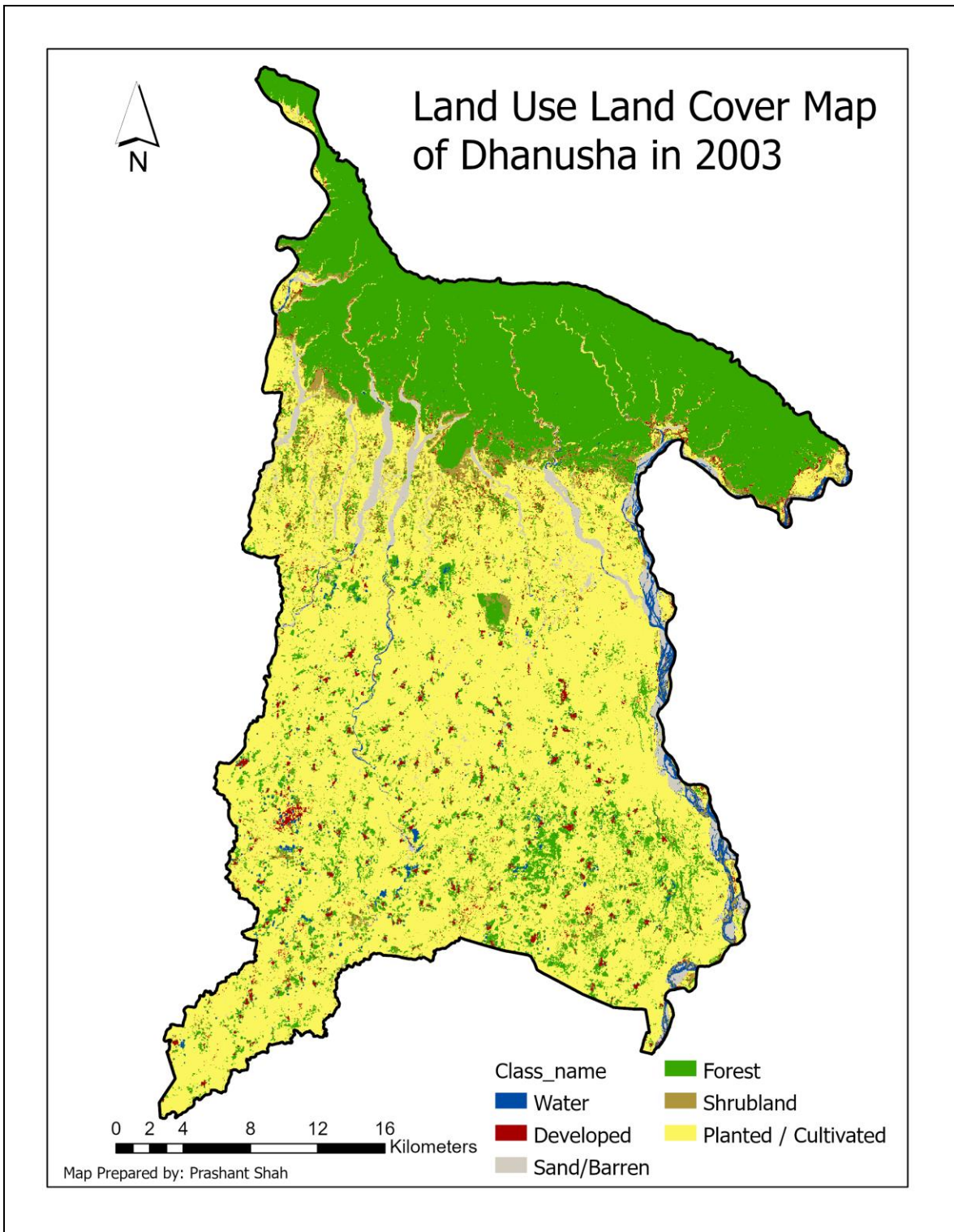


Figure 20. Land Use Land Cover Data in 2003

The least amount of study area was covered by water body which is 20.60 Sq km. which covered an area of 1.7%. The second lowest land use was developed which covered an area of 25.57 Sq km. in the district and had a 2.2% coverage in the area. The Shrubland areas had a total area of 27.87 Sq km. and covered an area of 2.4% of the Dhanusha district. The developed areas increased by 0.6% and in 2003 had an increase in coverage of 7.24 Sq km.

The LULC map of the Dhanush District in 2003 is presented in the Map 4.



Map 4. Land Use Land Cover Map of Dhanusha District in 2003

The land uses land cover of the Dhanusha district in the year 2013 was like the years 1993 and 2003 with mainly agricultural and forest areas dominant. The agricultural areas decrease by 3.1% in 2013. The area of 672.77 Sq km. was covered by planted/ cultivated lands which is still the highest land use in the area with a percentage of 57.16%. The second major land use was forest areas which were calculated as 368.03 sq km. and was covering 31.2% of Dhanusha. The third main land cover was Shrubland areas which covered an area of 57.16 Sq Km. and was covering 4.8% of the area. The shrubland and barren areas changed significantly from 1993 to 2013. The Shrubland areas were formed along the riverbanks. The data of the LULC in the district is presented in Figure 21.

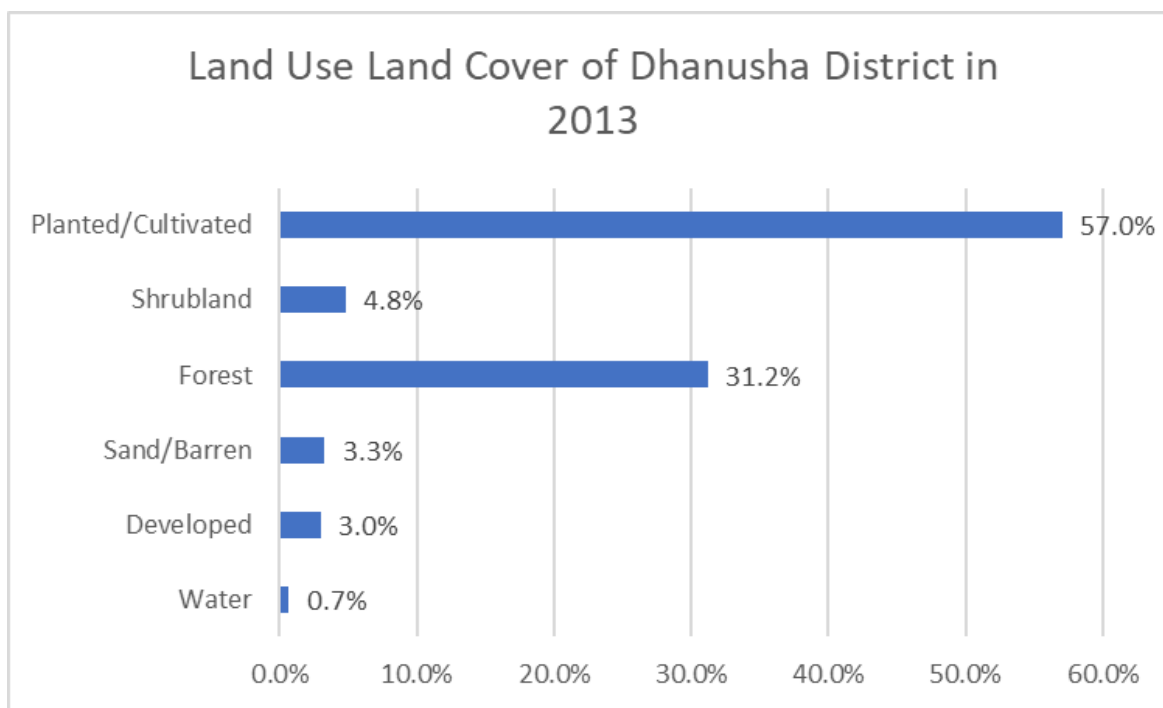
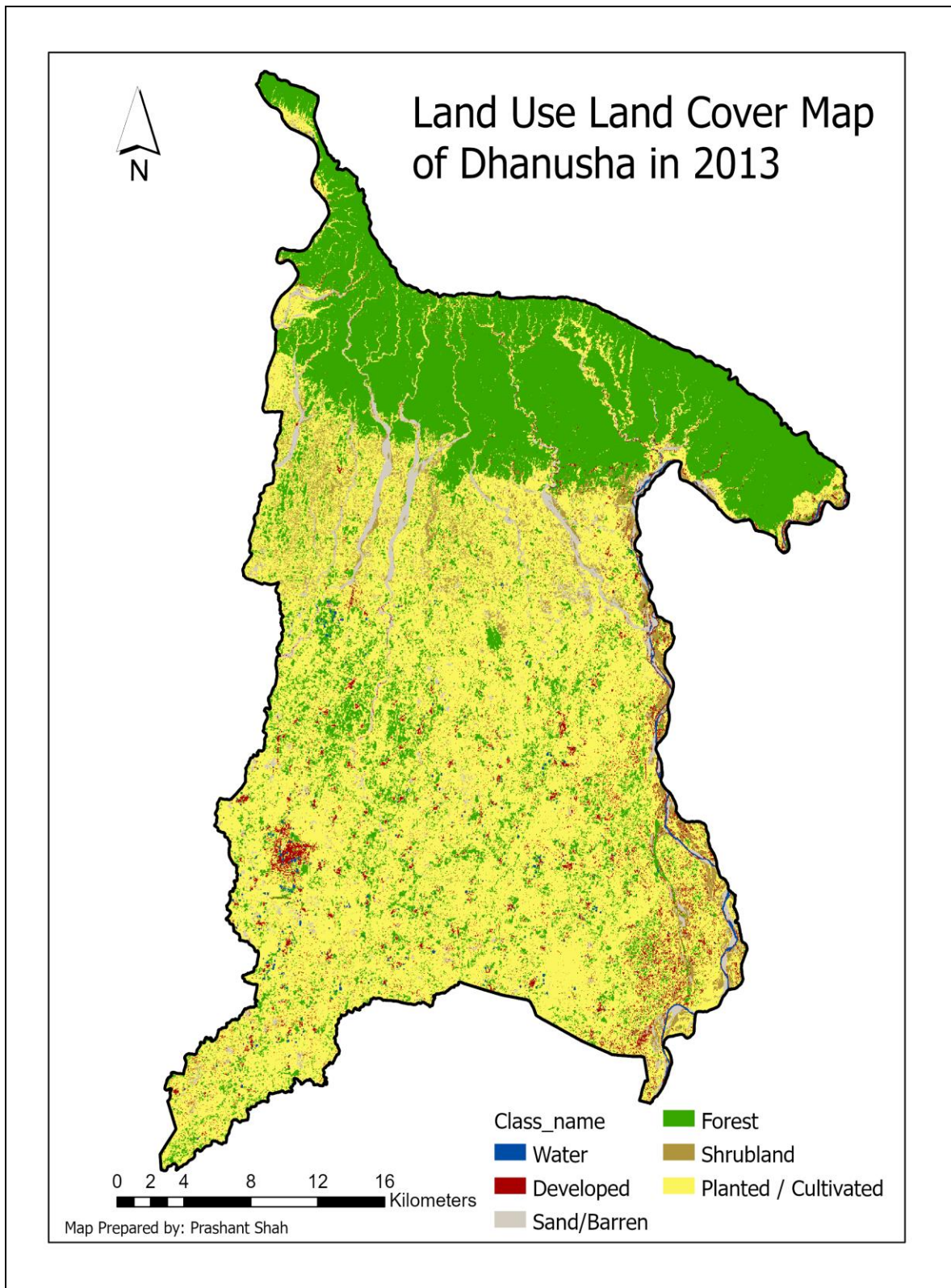


Figure 21. Land Use Land Cover Data in 2013

The least amount of study area was covered by water body which is 8.17 Sq km. which covered an area of 0.7%. The second lowest land use was developed which covered an area of 35.30 Sq km. in the district and had a 3% coverage in the area. The Barren/ Sandy areas had a total area of 38.57 Sq km. and covered an area of 3.3% of the Dhanusha district. The developed areas increased by 0.8% and in 2013 had an increase in coverage of 9.73 Sq km.

The LULC map of the Dhanush District in 2013 is presented in the Map 5.



Map 5. Land Use Land Cover Map of Dhanusha in 2013

The land use land cover of Dhanusha district in the year 2021 was similar to the year 1993, 2003 and 2013 with mainly agricultural and forest area dominant. The agricultural areas decrease by 5.4% in 2021 from 2013. The area of 608.64 Sq km. was covered by planted/ cultivated lands which is still the highest land use in the area with a percentage of 57.16%. The second major land use was forest areas which was calculated as 350.21 Sq km. and was covering 29.7% of Dhanusha. The third main land cover was Shrubland areas which covered an area of 88.10 Sq Km. and was covering 7.5% of the area. The shrubland and barren areas changed significantly from 1993 to 2021. The Shrubland areas were formed along the riverbanks. The data of the LULC in the district is presented in Figure 22.

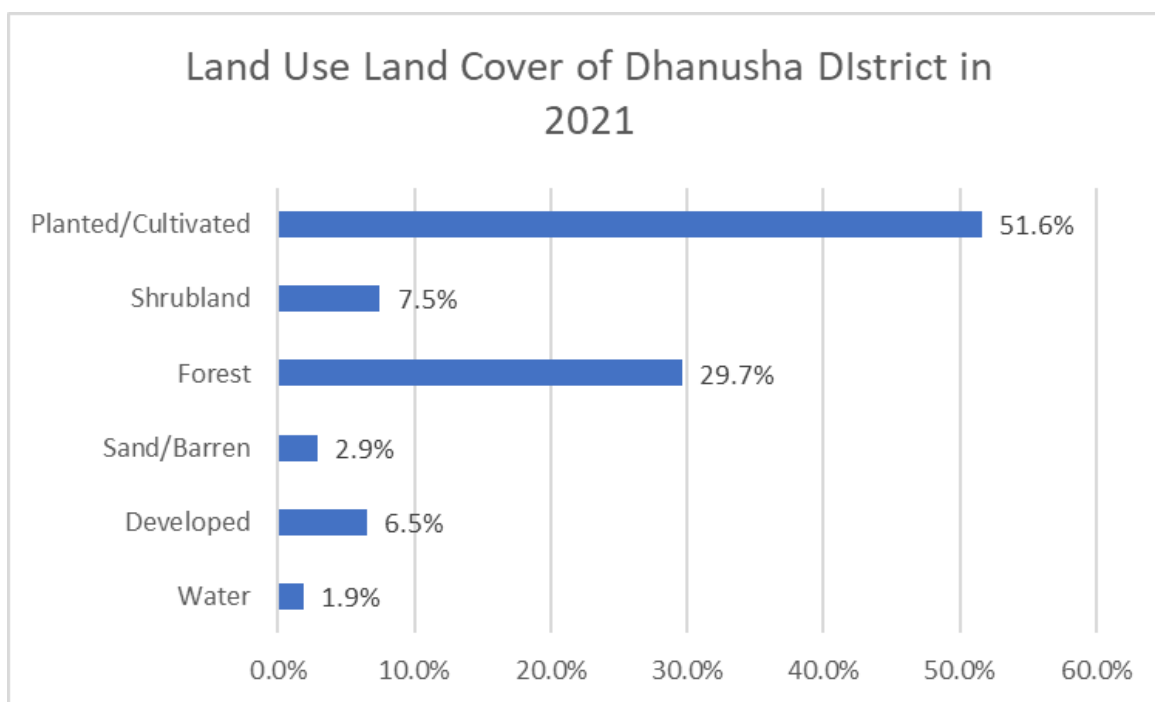
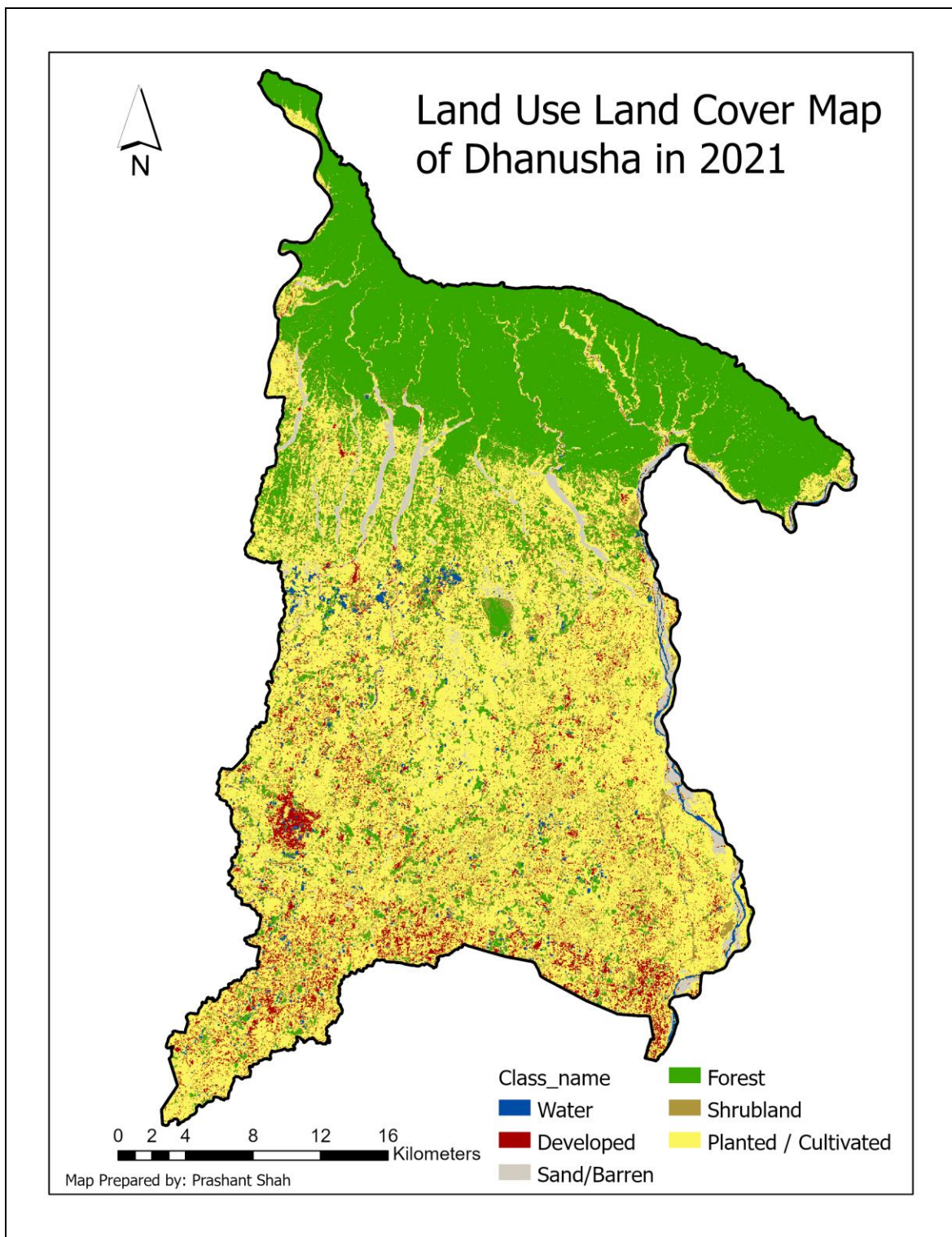


Figure 22. Land Use Land Cover Data in 2021

The least amount of study area was covered by water body which is 22.07 Sq km. which covered an area of 1.9%. The second lowest land use was Sand/Barren which covered an area of 34.43 Sq km. in the district and had a 2.9% coverage in the area. The Developed areas had increased significantly, and areas had a total area of 76.56 Sq km. and covered an area of 6.5% of the Dhanusha district. The developed areas increased by 3.5% and in 2021 had an increase in coverage of 41.26 Sq km.

The LULC map of the Dhanush District in 2021 is presented in the Map 6.



Map 6. Land Use Land Cover Map of Dhanusha District in 2021

3.2. Accuracy Assessment

The accuracy assessment was done in ArcGIS Pro. The accuracy assessment was done using sample points in each LULC image. The “Create accuracy assessment points” tool was used for creating assessment points in images. The stratified random sampling method involves population division into small groups called strata which allows researchers to get a sample population for the best representation of the entire study population (Adam, 2021).

The accuracy assessment was done with a confusion matrix. The confusion matrix measures user accuracy, the producer’s accuracy, and the Kappa coefficient. The classes of LULC are measured against how many were classified correctly and how many were classified in the wrong classes. The total of each right and wrongly classified class are weighted vertically and horizontally. 500 samples were created for each accuracy assessment of LULC. Some samples crossed the threshold of 500 points to more than 500. The confusion matrix was created in ArcGIS using create confusion matrix and it was managed in Excel. For the LULC of 1993, the producer’s accuracy and the user’s accuracy were 91%. The Kappa was 83%.

Table 13. Accuracy Assessment 1993

	Class Value	Water	Developed	Sand/ Barren	Forest	Shrubland	Planted/ Cultivated	Total	U_Accuracy	Kappa
1	Water	8	0	0	2	0	0	10	80%	0
2	Developed	1	5	0	1	0	3	10	50%	0
3	Sand/ Barren	0	0	11	0	0	1	12	92%	0
4	Forest	0	1	0	133	0	3	137	97%	0

5	Shrubland	0	0	0	2	11	9	22	50%	0
6	Planted/Cultivated	1	7	1	10	4	292	315	93%	0
7	Total	10	13	12	148	15	308	506	0%	0
8	P_Accuracy	80%	38%	92%	90%	73%	95%	0%	91%	0
9	Kappa	0	0	0	0	0	0	0	0	83%

The same method of confusion matrix was created for LULC 2003. The same approach of Stratified random sampling was used.

Table 14. Accuracy Assessment 2003

	Class Value	Water	Developed	Sand/Barren	Forest	Shrubland	Planted/Cultivated	Total	U_Accuracy	Kappa
1	Water	9	0	0	1	0	0	10	90%	0
2	Developed	0	5	0	1	3	2	11	45%	0
3	Sand/Barren	0	0	16	0	0	0	16	100%	0
4	Forest	1	0	0	142	0	10	153	93%	0
5	Shrubland	0	1	0	0	9	2	12	75%	0
6	Planted/Cultivated	2	6	0	9	4	279	300	93%	0
7	Total	12	12	16	153	16	293	502	0%	0
8	P_Accuracy	75%	42%	100%	93%	56%	95%	0%	92%	0
9	Kappa	0	0	0	0	0	0	0	0	85%

The samples were verified using google imagery and satellite image of 2003. After verification the confusion matrix was created. The matrix found the user accuracy 92% and the Kappa was 85%. The Kappa and accuracy were found to be accurate enough for the urban sprawl analysis study.

The accuracy assessment was again done for LULC in 2013. The stratified random samples were used for the creation of samples, the accuracy of points was analyzed and the confusion matrix was created. The user accuracy and producer accuracy were 94% and the Kappa was 90%.

Table 15. Accuracy Assessment 2013

	Class Value	Water	Developed	Sand/Barren	Forest	Shrubland	Planted/ Cultivated	Total	U_Accuracy	Kappa
1	Water	10	0	0	0	0	0	10	100%	0
2	Developed	0	6	0	1	3	1	11	55%	0
3	Sand/Barren	0	0	16	0	0	0	16	100%	0
4	Forest	1	0	0	147	0	5	153	96%	0
5	Shrubland	0	1	0	0	10	1	12	83%	0
6	Planted/Cultivated	1	2	0	9	3	283	298	95%	0
7	Total	12	9	16	157	16	290	500	0%	0
8	P_Accuracy	83%	67%	100%	94%	63%	98%	0%	94%	0
9	Kappa	0	0	0	0	0	0	0	0	90%

The accuracy assessment of the LULC of 2021 was done using stratified random sampling and confusion matrix. The samples were verified using google earth images and satellite images. The confusion matrix showed user and producer accuracy of 93% and Kappa of 87%.

Table 16. Accuracy Assessment 2021

	Class Value	Water	Developed	Sand/Barren	Forest	Shrubland	Planted/ Cultivated	Total	U_Accuracy	Kappa
1	Water	10	0	0	0	0	0	10	100%	0
2	Developed	0	6	0	1	3	1	11	55%	0
3	Sand/Barren	0	0	16	0	0	0	16	100%	0
4	Forest	1	0	0	145	0	7	153	95%	0
5	Shrubland	0	1	0	0	9	2	12	75%	0
6	Planted/Cultivated	1	5	0	12	3	277	298	93%	0
7	Total	12	12	16	158	15	287	500	0%	0
8	P_Accuracy	83%	50%	100%	92%	60%	97%	0%	93%	0
9	Kappa	0	0	0	0	0	0	0	0	87%

The accuracy assessment of all the land use images was accurate enough, i.e., more than 80% Kappa, the analysis of the trend in land use changes for 1993, 2003, 2013, and 2021.

3.3. Urban Sprawl Modelling

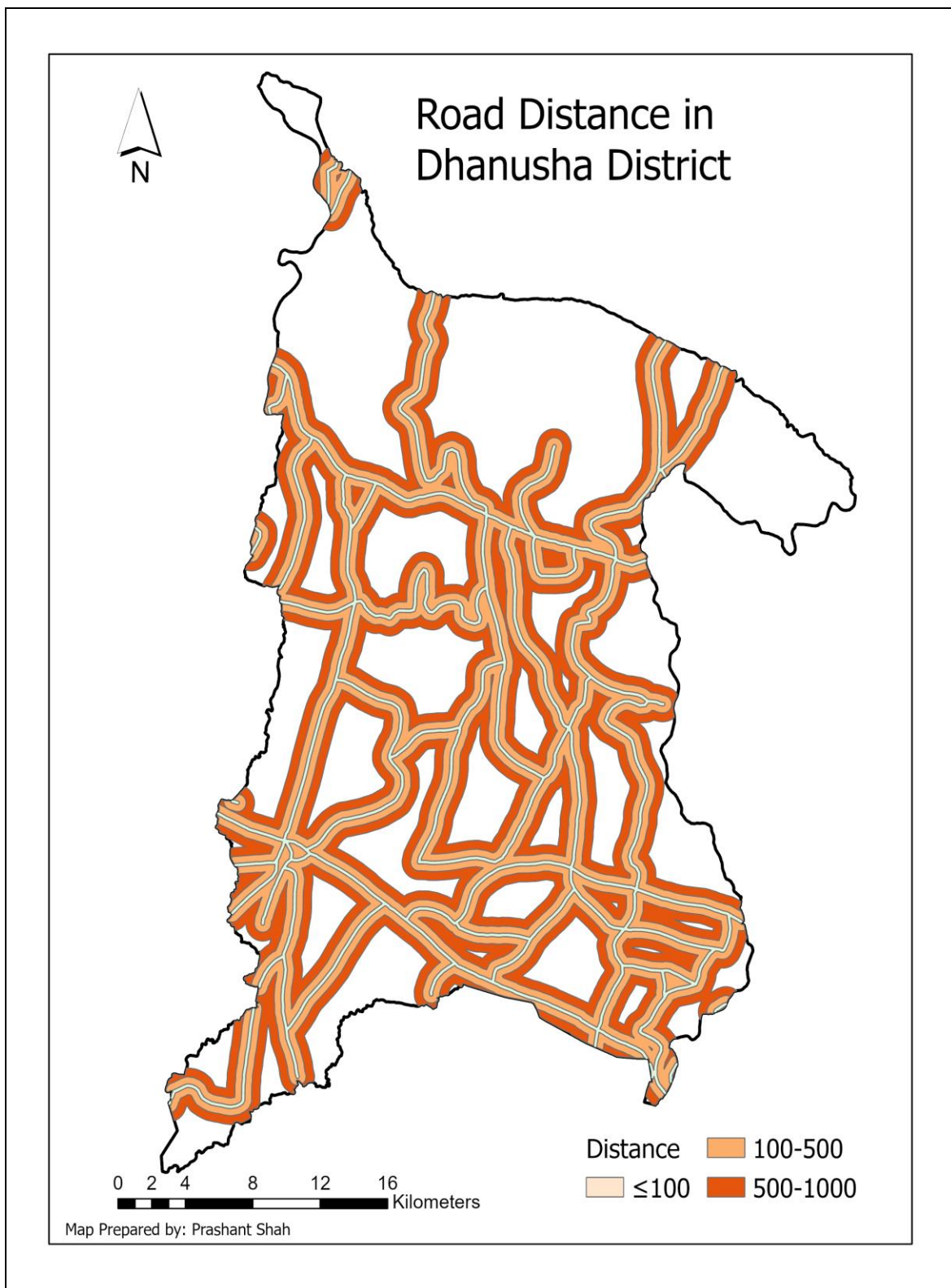
Modeling urban sprawl is the process of creating a trend analysis of historical images and using the trend process for the preparation of future scenarios of urbanization in the area. Modeling of the future urban sprawl was done in QGIS using the MOLUSCE plugin. QGIS is an open-source software used for geographic information analysis. The future prospect of urban sprawl in 2033 and 2043 were analyzed using LULC maps of 1993, 2003, 2013, and 2021. In the first step, the LULC map of 1993 and 2013 was used to analyze the accuracy of modeling the LULC of 2021. In a second step, the LULC map of 2003 and 2013 was used to analyze the accuracy of modeling the LULC of 2021.

The first input was used as the initial map of 1993 and the final map of 2013 was used. The spatial variables of distance to existing roads and DEM. The correlation was evaluated for the first raster distance to roads and the second raster DEM. The correlation of the raster was done using Pearson's Correlation. The DEM was used to consider that the plain areas in the study area will be more developed in the future than the areas which are hilly. In the high elevated regions, hills are less used for housing development when plain lands are available, plain areas are also easy for agricultural use which makes them more available for urban sprawl.

The distance to roads was classified from up to 100 meters, 100 to 500 meters, and 1000 meters. The distance to the road as the spatial variable means that the places that are near the existing roads will have more population growth and sprawl than those places far from the roads. The distance to the road considers development will take place in areas where roads are existing as infrastructure development will be available in areas that already have roads. The road network is on the southern side of the study area, elevation was also higher in the northern side of the area.

Road distance is shown by using multiple buffers for different distances from existing

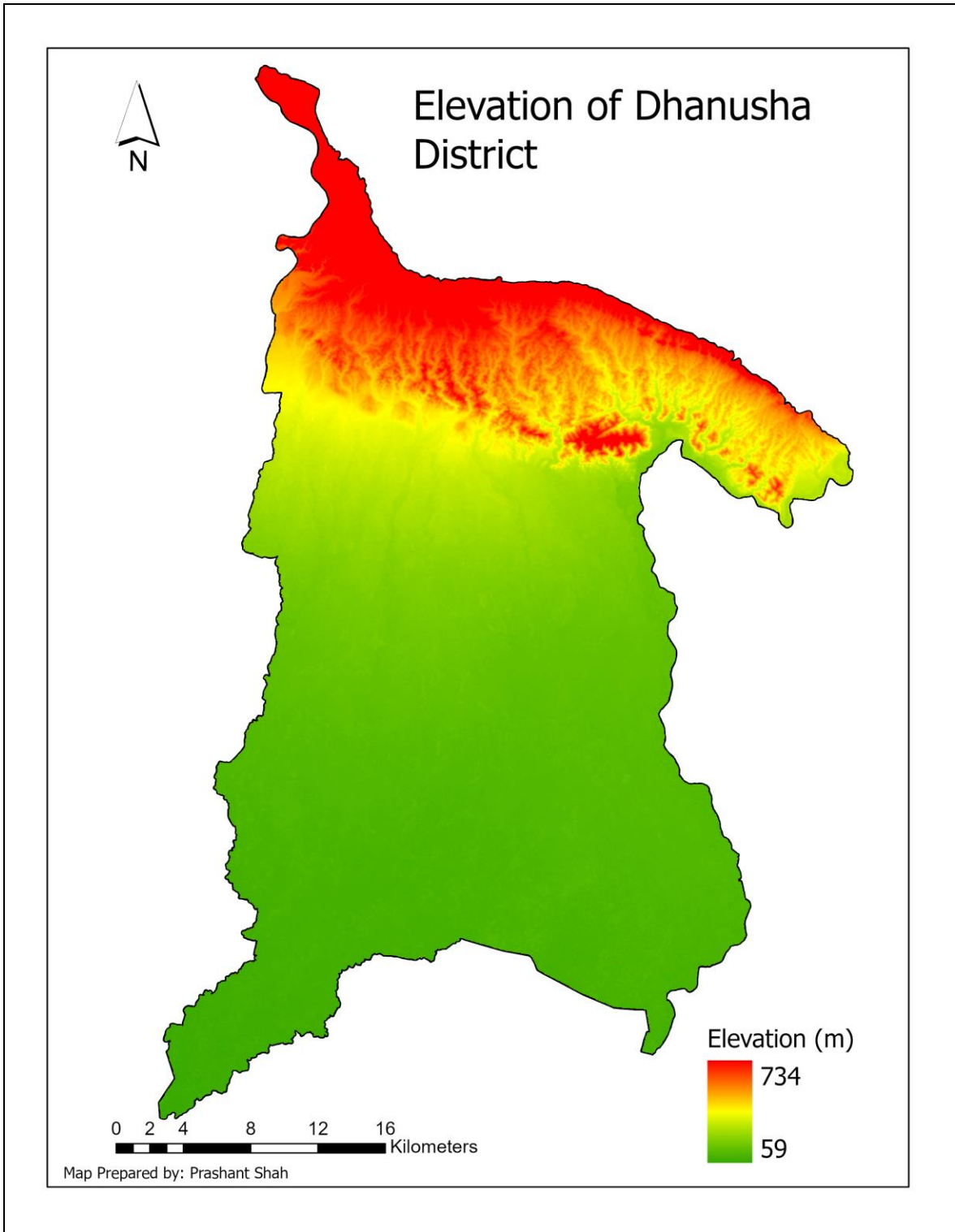
roads. The distance to roads map is shown in Map 7.



Map 7. Road Distance in Dhanusha

The elevation map is shown in Map 8. The elevation of Dhanusha was found under 734

meters and 59 meters.



Map 8. Elevation Map of Dhanusha

The LULC simulation was verified for accuracy assessment with LULC classified image of 2021. First the image of 1993 and 2013 was used for the simulation of LULC 2021. The spatial variables of DEM and road buffers, the geometry was checked for the input and variable images. In the second step the correlation was evaluated for the spatial variables, first raster, DEM, and second raster roads. The Pearson's Correlation was used for the result. The third step was Area changes. The area changes were measured for all the classes of LULC. 1 being water, 2 as developed, 3 as barren, 4 as forest, 5 as shrubland and 6 as agricultural lands. The area changes, class statistics are presented in Figure 23.

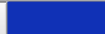


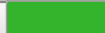


Class statistics							raster units
	Class color	1993	2013	Δ	1993 %	2013 %	Δ %
1		15500700.00 sq. metre	8149500.00 sq. metre	-7351200.00 sq. metre	1.30694304481	0.687125893909	-0.619817150905
2		18415800.00 sq. metre	35417700.00 sq. metre	17001900.00 sq. metre	1.55272998798	2.98624685842	1.43351687044
3		28840500.00 sq. metre	38684700.00 sq. metre	9844200.00 sq. metre	2.43168959363	3.26170428469	0.830014691063
4		324411300.00 sq. metre	370266300.00 sq. metre	45855000.00 sq. metre	27.3527706616	31.2190394959	3.86626883431
5		51824700.00 sq. metre	57375000.00 sq. metre	5550300.00 sq. metre	4.36960467686	4.83757876716	0.467974090308
6		747034200.00 sq. metre	676134000.00 sq. metre	-70900200.00 sq. metre	62.9862620351	57.0083046999	-5.97795733521

Figure 23. Class Statistics 1993-2013

The transition matrix for these classes is shown in Figure 24.

Transition matrix						
	1	2	3	4	5	6
1	0.153806	0.084538	0.073274	0.192824	0.089880	0.405678
2	0.014564	0.151305	0.027514	0.192308	0.067491	0.546818
3	0.030613	0.045592	0.401623	0.029365	0.171946	0.320861
4	0.003418	0.009796	0.002472	0.833018	0.011483	0.139814
5	0.007589	0.033065	0.039734	0.171057	0.095931	0.652623
6	0.004166	0.033619	0.030250	0.112155	0.054995	0.764814

Figure 24. Transition Matrix 1993-2013

The next step is the training of model for the modelling. The artificial neural network (multi-layer perceptron). The artificial neural network (multi-layer perceptron) table is shown in Table 17.

Table 17. Artificial Neural Network 1993-2013

Artificial Neural Network (Multi-layer Perceptron)	
Neighborhood	1 px
Learning Rate	0.100
Maximum Iterations	1000
Hidden Layers	10
Momentum	0.050
Overall Accuracy	-0.00490
Min Validation Overall Error	0.04222
Current Validation Kappa	0.64819

Cellular Automata Simulation was used for the simulation of LULC of 2021. Number of 1 simulation was used for the simulation. The Neural Network learning curve graph is presented in Figure 25.

Neural Network learning curve

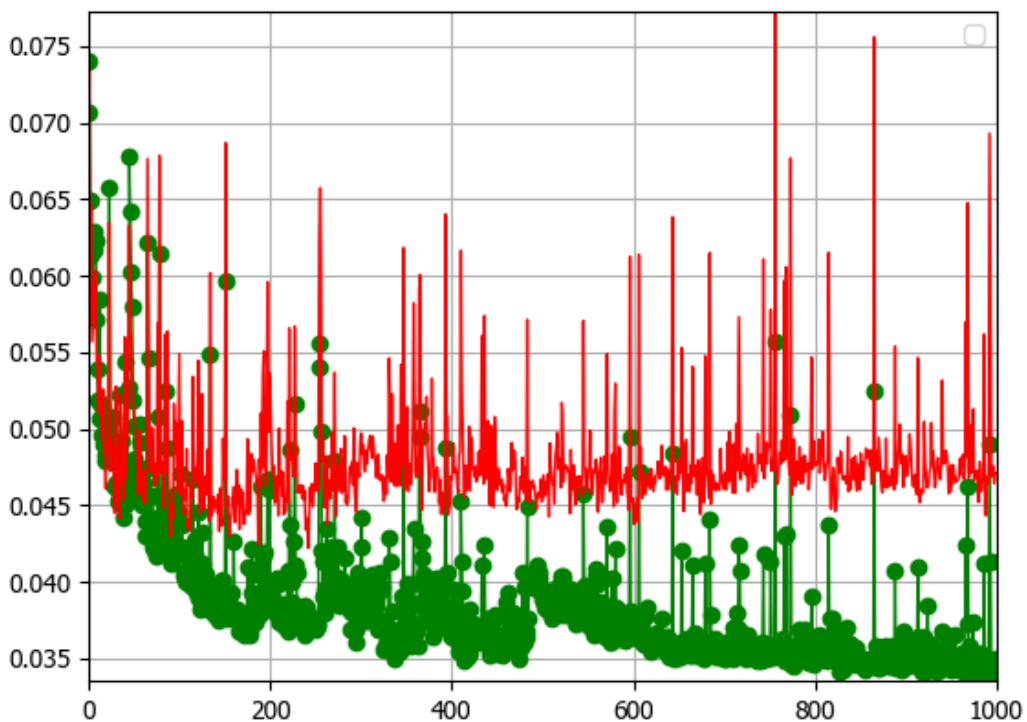


Figure 25. Neural Network learning curve 1993-2013

The accuracy of the simulated map of 2021 and the LULC map of 2021 was done using validation map. The validation details are shown below:

Table 18. Accuracy Assessment 1993-2013

% of correctness	84.82055
Kappa (overall)	0.72862
Kappa (histo)	0.92389
Kappa (loc)	0.78865
Number of validation iterations	5

The accuracy assessment graph between LULC classified image of 2021 and the simulated image of 2021 was analyzed from LULC of 1993 and LULC of 2013. The figure is shown in Figure 26.

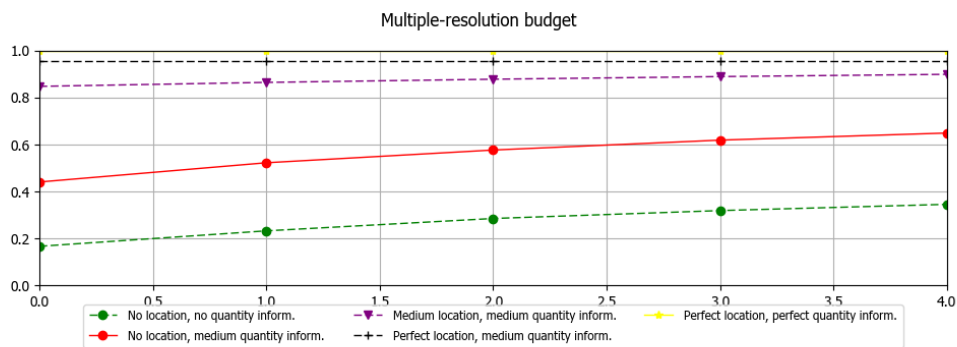


Figure 26. Accuracy assessment 1993-2013

The simulation result of 1993-2013 showed the accuracy of 84.82055. The same process is then again done for the image of 2003 and 2013. The purpose of the simulation of two different time frames is to understand and use the best simulation result from the different timeframes to 2021. So same as before, the LULC simulation of 2003-2013 was verified

for accuracy with the LULC classified image of 2021. The image of 2003 and 2013 was used for the simulation of LULC 2021. The spatial variables of DEM and road buffers, the geometry was checked for the input and variable images. In the second step the correlation was evaluated for the spatial variables, first raster, DEM, and second raster roads. The Pearson's Correlation was used for the result. The third step was Area changes. The area changes were measured for all the classes of LULC. 1 being water, 2 as developed, 3 as barren, 4 as forest, 5 as shrubland and 6 as agricultural lands. The area changes, class statistics are presented in Figure 27.

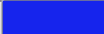





Class statistics		raster units					
	Class color	2003	2013	Δ	2003 %	2013 %	Δ %
1		20746800.00 sq. metre	8223300.00 sq. metre	-12523500.00 sq. metre	1.74596947053	0.692040736258	-1.05392873427
2		25746300.00 sq. metre	35547300.00 sq. metre	9801000.00 sq. metre	2.16670781899	2.99152161103	0.824813792038
3		37311300.00 sq. metre	38835900.00 sq. metre	1524600.00 sq. metre	3.1399729455	3.26827731315	0.12830436765
4		362597400.00 sq. metre	370613700.00 sq. metre	8016300.00 sq. metre	30.5147777244	31.189398151	0.674620426601
5		28065600.00 sq. metre	57559500.00 sq. metre	29493900.00 sq. metre	2.36189102763	4.8439821919	2.48209116427
6		713800800.00 sq. metre	677488500.00 sq. metre	-36312300.00 sq. metre	60.0706810129	57.0147799966	-3.05590101629

Figure 27. Class Statistics 2003-2013

The transition matrix for these classes is shown in Figure 28.

Transition matrix						
	1	2	3	4	5	6
1	0.196859	0.080470	0.165452	0.113005	0.163760	0.280453
2	0.006397	0.292900	0.025448	0.090957	0.083057	0.501241
3	0.023591	0.037967	0.433895	0.013074	0.243192	0.248281
4	0.002743	0.011110	0.002405	0.775480	0.011542	0.196721
5	0.010069	0.030144	0.037872	0.338186	0.112878	0.470850
6	0.002546	0.028083	0.023289	0.104737	0.049869	0.791476

Figure 28. Transition Matrix (2003-2013)

The next step is the training of model for the modelling. The artificial neural network (multi-layer perceptron) table is shown in Table 19.

Table 19. Artificial Neural Network 2003-2013

Artificial Neural Network (Multi-layer Perceptron)	
Neighborhood	1 px
Learning Rate	0.100
Maximum Iterations	1000
Hidden Layers	10
Momentum	0.050
Overall Accuracy	-0.00280
Min Validation Overall Error	0.04121
Current Validation Kappa	0.64289

Cellular Automata Simulation was used for the simulation of LULC of 2021. Number of 1 simulation was used for the simulation. The Neural Network learning curve graph is presented in Figure 29.

Neural Network learning curve

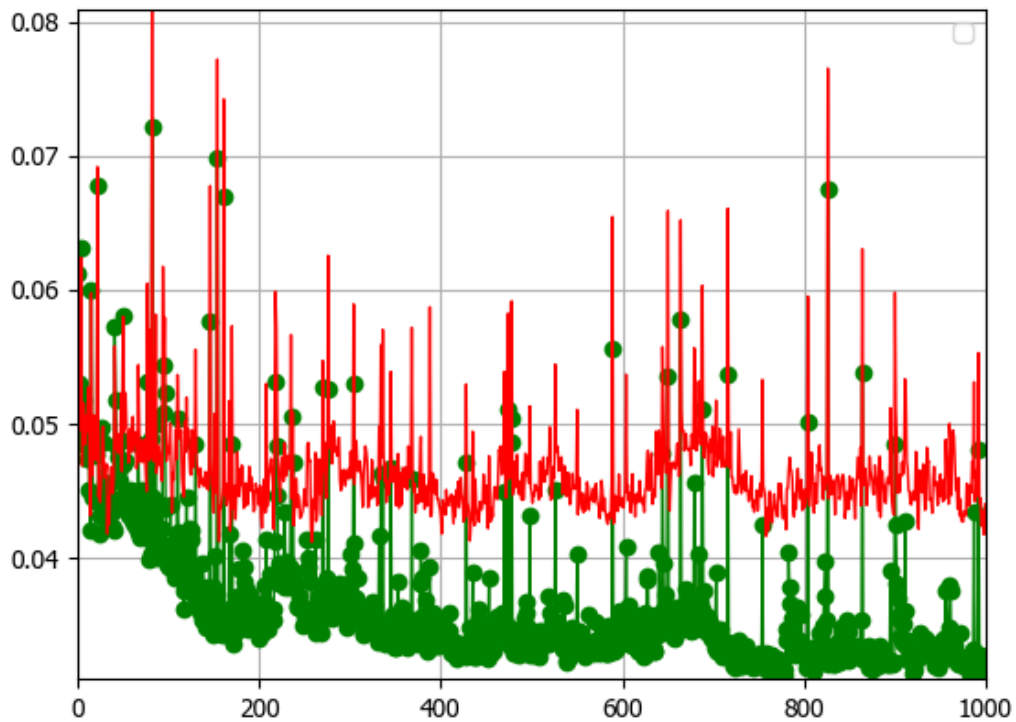


Figure 29. Neural Network Learning Curve 2003-2013

The accuracy of the simulated map of 2021 and the LULC map of 2021 was done using validation map. The validation details are shown below:

Table 20. Accuracy Assessment 2003-2013

% of correctness	89.88433
Kappa (overall)	0.81733
Kappa (histo)	0.90393
Kappa (loc)	0.90420
Number of validation iterations	5

The accuracy assessment graph between LULC classified image of 2021 and the simulated image of 2021 analyzed from LULC of 2003 and LULC of 2013. The figure is shown in Figure 30.

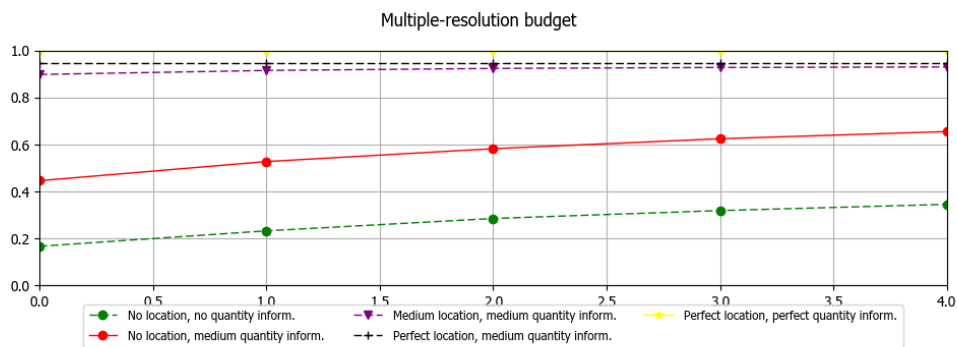


Figure 30. Accuracy Assessment 2003-2013

The accuracy assessment result shows that simulation result of 2003 and 2013 was more accurate than the result shown for the accuracy assessment of 1993 and 2013. The simulated images were checked with the classified image of 2021. The simulation image of 2003 and 2013 was used for the simulation of 2021 at first which was then used for the simulation of 2033 and 2043 as the accuracy of this simulation was more than the

simulation result of 1993 and 2013.

The simulated map of 2021 is analyzed, the land use land cover of Dhanusha district in the year 2021 was similar to the LULC classified image of 2021 with mainly agricultural and forest area dominant. The agricultural areas were shown more than classified image with 51.6% in classified and 56.6% in simulated. The area of 667.55 Sq km. was covered by planted/ cultivated lands in simulated map but 608.64 Sq Km in classified map. The second major land use was forest areas similarly which was calculated as 347.88 Sq km. and was covering 29.5% of Dhanusha. The third main land cover was Shrubland. The data of the simulated LULC in the district is presented in Figure 31.

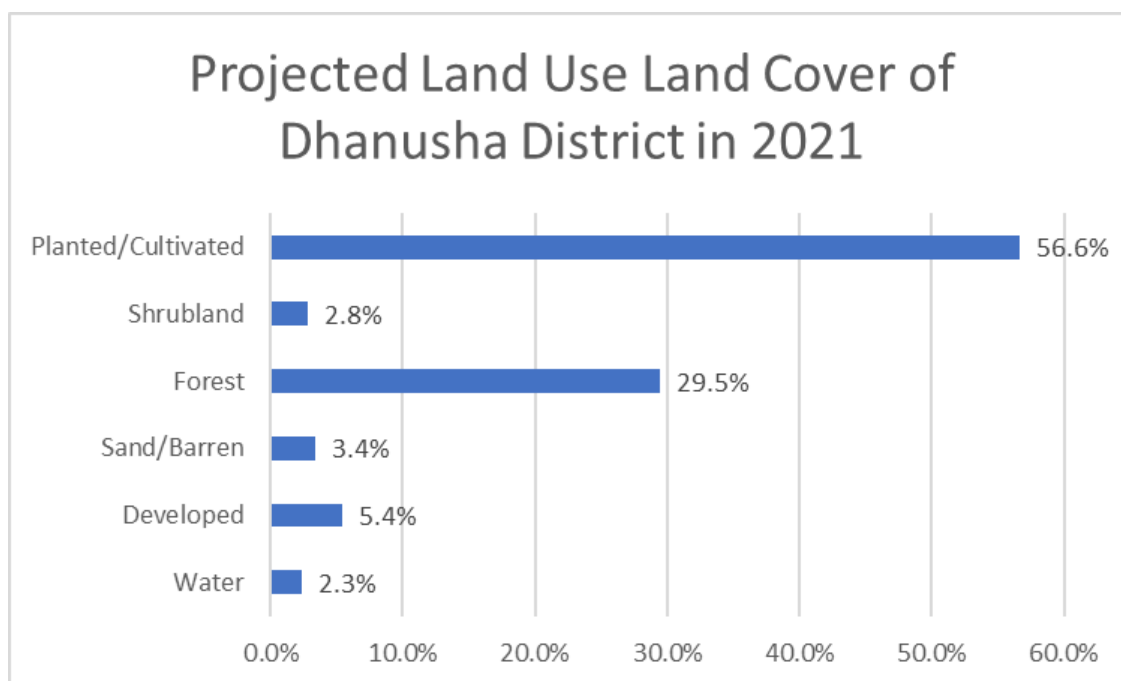
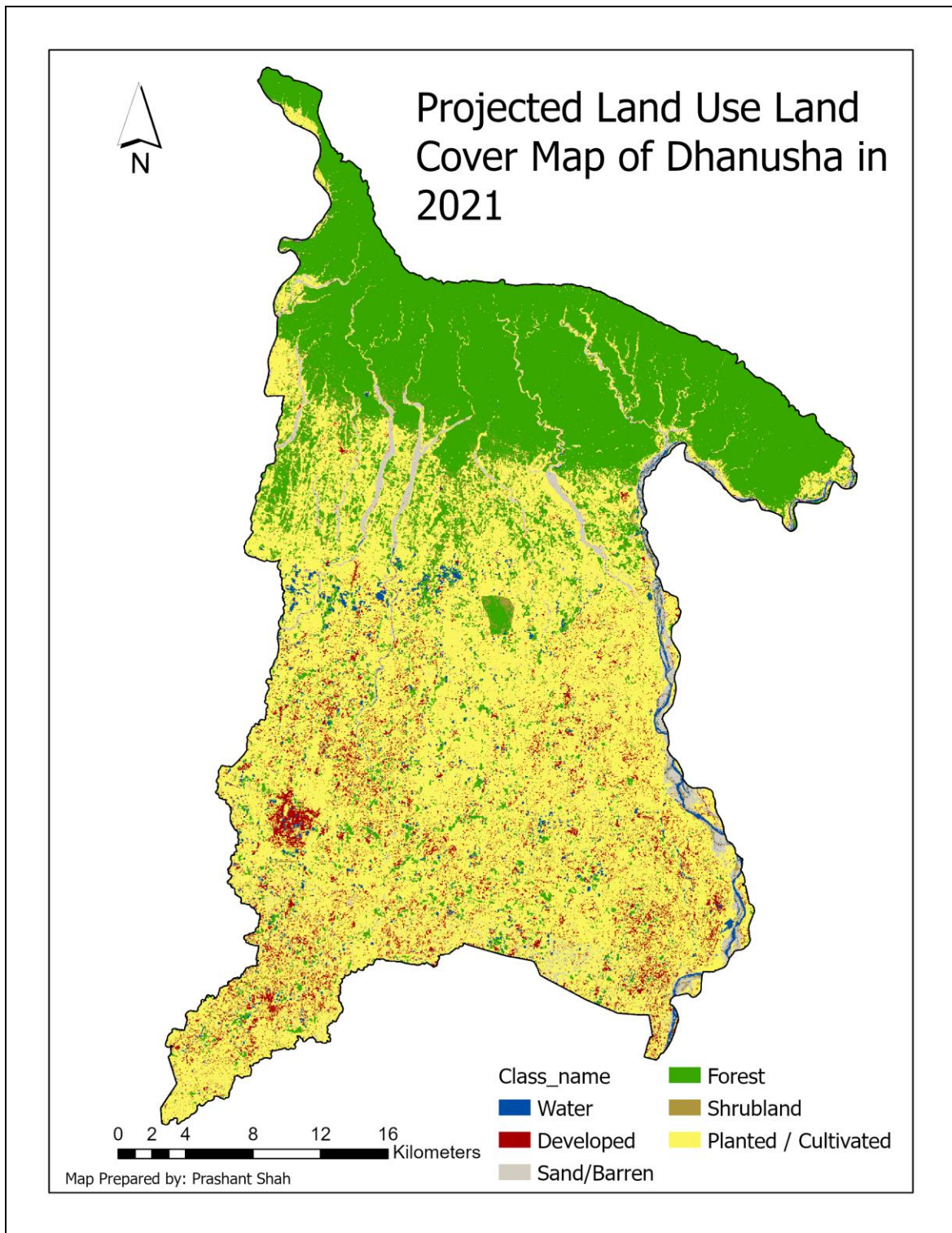


Figure 31. Projected LULC 2021

The least amount of study area was covered by water bodies which are 27.51 Sq km. which covered an area of 2.3%. The simulated developed area which covered an area of 63.77 Sq km. in the district and had a 5.4% coverage in the area but classified developed area which covered an area of 76.56 Sq km. in the district and had a 6.5 % coverage in the area. The Barren/ Sandy areas had a total area of 39.85 Sq km. and covered an area of 3.4% of the Dhanusha district. The developed areas showed a difference of 0.9 % and

in classified image had an increase in coverage of 12.79 Sq km.

The projected map of 2021 is shown below.



Map 9. Projected LULC 2021

The simulated map of 2033 is analyzed using the simulation of 2003 and 2013, The land use land cover of Dhanusha district in the year 2033 also had the similar result of largest LULC to the LULC image of 2021 with mainly agricultural and forest area dominant. The agricultural areas were shown less than in 2021 with 4.5% decrease and total of 52%. The area of 614.11 Sq km. was covered by planted/ cultivated lands in simulated map. The second major land use was forest areas similarly which was calculated as 358.35 Sq km. and was covering 30.4% of Dhanusha. The third main land cover was Shrubland. The calculations is shown below.

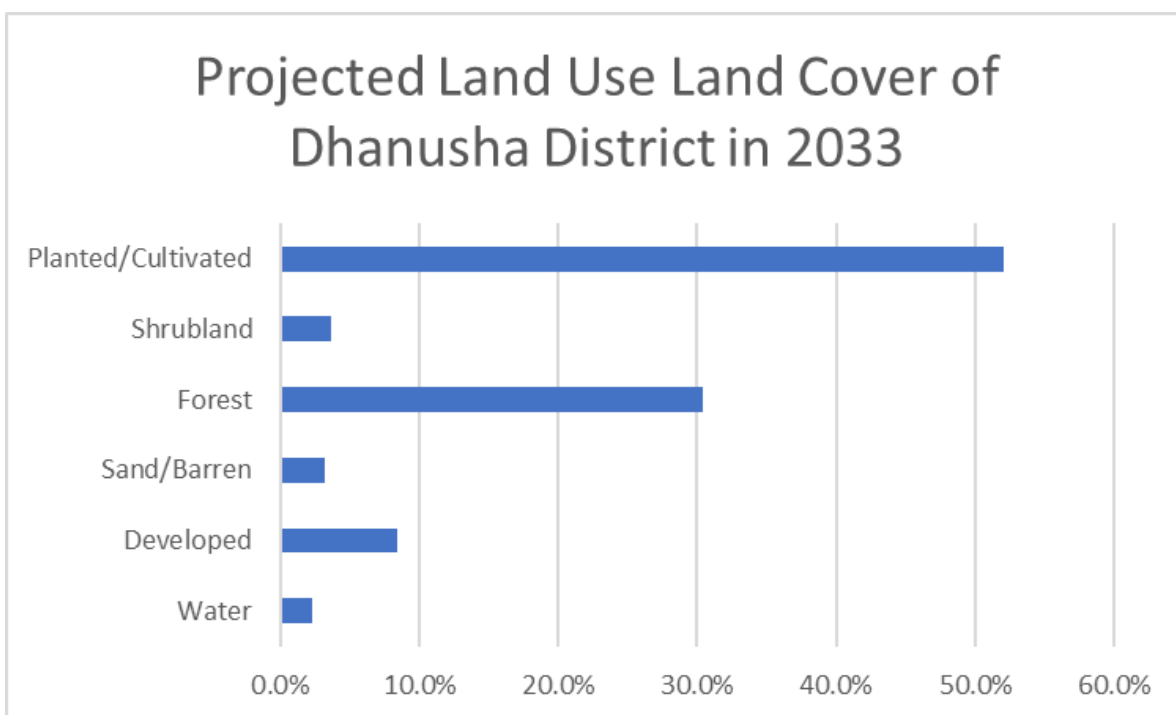
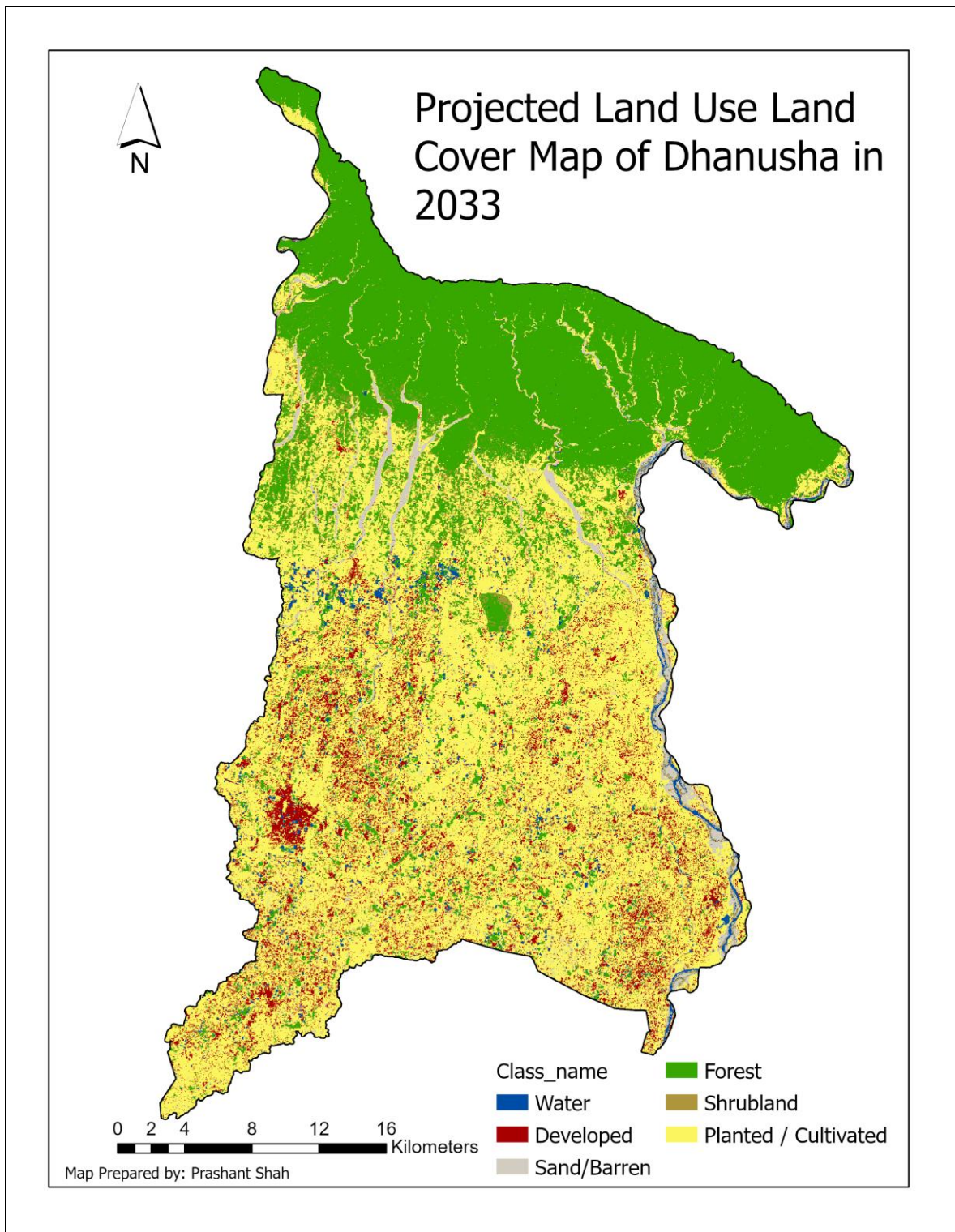


Figure 32. Projected LULC 2033

The least amount of study area was covered by water body which is 27.00 Sq km. which covered an area of 2.3%. The simulated developed area which covered an area of 99.52 Sq km. in the district and had an 8.4% coverage in the area but simulated 2021 developed area which covered an area of 63.77 Sq km. in the district and had a 5.4 % coverage in the area. The Barren/ Sandy areas had a total area of 38.21 Sq km. and covered an area of 3.2% of the Dhanusha district. The developed areas showed a difference of 3.0 % and in 2033 had an increase in coverage of 35.75 Sq km. The projected map of 2033 is

shown below.



Map 10. LULC of 2033

Again, the simulated map of 2043 is analyzed using the simulation of 2003 and 2013, The land use land cover of Dhanusha district in the year 2043 also had the similar result of largest LULC to the LULC image of 2033 with mainly agricultural and forest area dominant. The agricultural areas were shown less than in 2033 with 1.8% decrease and total of 50.3%. The area of 593.22 Sq km. was covered by planted/ cultivated lands in simulated map. The second major land use was forest areas similarly which was calculated as 344.13 Sq km. and was covering 29.2% of Dhanusha. The third main land cover was Shrubland. The calculations is shown below.

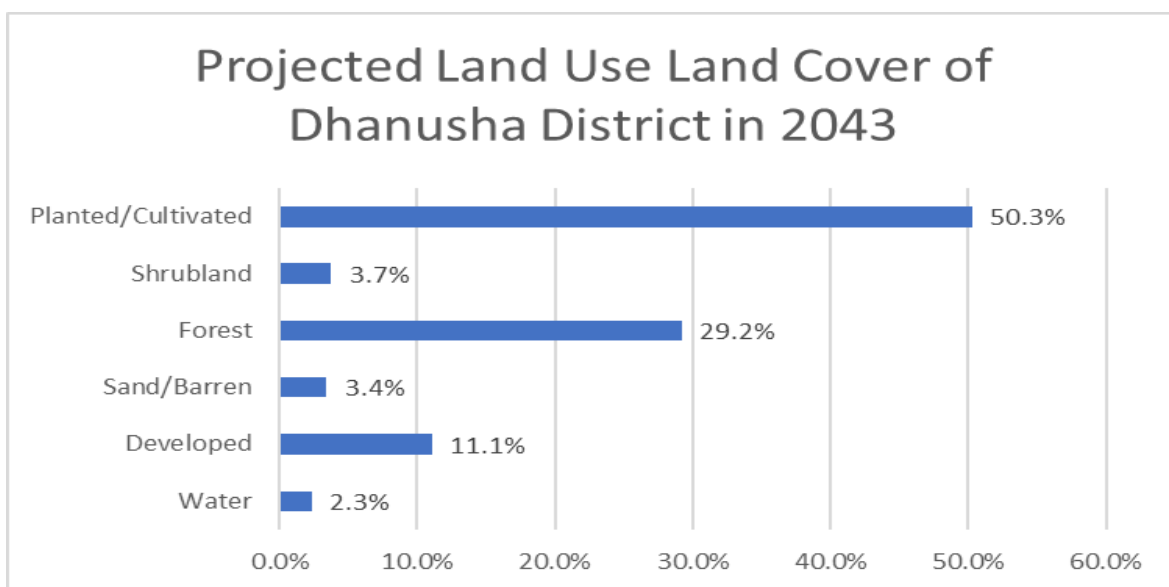
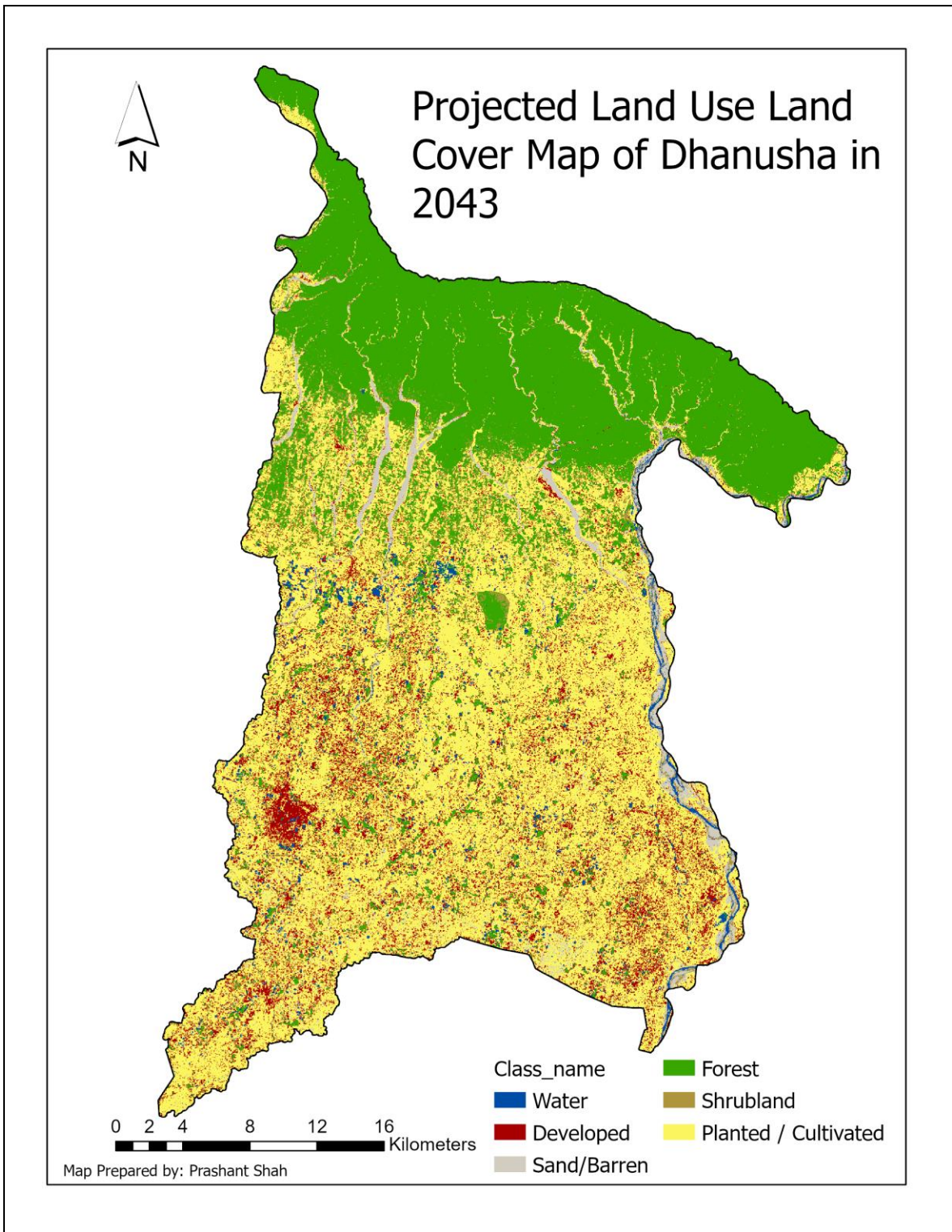


Figure 33. LULC Graph 2043

The least amount of study area was covered by water bodies which are 27.48 sq km. which covered an area of 2.3%. The simulated developed area which covered an area of 130.58 Sq km. in the district and had a 11.1% coverage in the area but simulated 2033 developed area which covered an area of 99.52 Sq km. in the district and had a 8.4 % coverage in the area. The Barren/ Sandy areas had a total area of 40.35 Sq km. and covered an area of 3.4% of the Dhanusha district. The developed areas showed a difference of 2.6 % and in 2043 had an increase in coverage of 31.06 Sq km.

The projected map of 2043 is shown below.



Map 11. LULC 2043

Chapter-4: Conclusion and Recommendation

This chapter discusses and concludes the results of this study. The result showed an increase in the developed areas of the district from 1993 to 2021 and is predicted to increase in 2033 and 2043. In 1993 the developed area was 18.33 sq. Km. which increased to 25.57 Sq. Km. in 2003 and same as that increased to 35.30 Sq. Km. in 2013 and also increased in 2021 to 76.56 Sq. Km. The maps of 2003 and 2013 were more accurate for the simulation of 2021 LULC than the maps of 1993 and 2013. The projected LULC of 2021 showed similar results as the classified LULC of 2021. The projected LULC increased to 99.52 Sq. Km. in 2033 and again increased in 2043 with an increase of 130.58 sq. Km.

The conclusion from this study is that the simulation of LULC give a fairly accurate representation of future urban sprawl trend. The trend study can help in various sectors of urban planning. The study showed results of years near to the forecast years gives better result than past years. The difference can be because of factors that create population increase in recent years. The same was observed as the developed areas had increased in recent years than in past years which can be because of the popularity of the migration in the area from other areas in recent years. This study will be useful in land use planning in Dhanusha district.

The use of classification methods, simulation methods, RS and GIS was useful through the study. The use of open-source software made the work comparatively easy for analysis of various parts of the study. The open-source software provided an easy operation of the simulation process. MOLUSCE plugin in QGIS was easily available from the plugin section of the application and download was very easy in little time. The direction for using the application and plugin was easily available in google and YouTube which eased the task.

In future the study should be done using high resolution images with better computers and available images. The analysis can also be checked with this result. The use of satellite images for the study is recommended as its ease of use in land use planning. The data should be used by the district and its municipalities as a reference for land use planning in their areas but because of the limitations of the study more accurate study should be performed for practical use in the area. The study can be used along with another suitability study with many spatial factors influencing the urban sprawl in the area.

Chapter-5: Limitation and Future prospective

The limitation of the study includes the checking of accuracy with other relevant studies in the area. The study was done in 30m resolution satellite imagery which could have affected the accuracy of the classified images of all the years used in the study. The use of high-resolution images would have given a better accurate result. The processing power of personal computers also was low for high-resolution images and the availability of free satellite imagery for this resolution meant the use of such images for analysis. The accuracy of the images was analyzed using google earth historical images and the satellite images and the ground data could not be used for the study due to its limitations in part of the study. The factors that influenced the urban sprawl were examined using DEM and roads only as other factors were not available for the study area.

The study of land use land cover is important and examination of past and future trends can be important in land use planning. There may be high-functioning computerized systems which can handle huge amounts of data. The large high-resolution real-time data will be more accurate in analyzing the process of land use changes and simulation in the future.

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