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Identification of Suitable Sites for Built-up Area Expansion in Kamalamai Municipality, Sindhuli District, Nepal

by

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Kathmandu, 22.06.2021

Science Pledge

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

Kathmandu: 22 June 2021

Place and Date | Signature

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Abstract:

Kamalamai Municipality lies in Sindhuli district on the intersection of cities of terai plains and Kathmandu, capital city of Nepal. The municipality became an important travelling route after the construction of BP Highway which is the shortest route to Kathmandu from eastern terai which consist of big cities like Janakpur and Biratnagar. These new connections have increased the movement of people through the municipality increasing business opportunities which have increased migration of people from neighbouring villages to the municipality, subsequently the municipality has witnessed a rapid population growth. The population growth in the municipality has given rise to unplanned infrastructural development.

Unplanned infrastructural development may lead to undesirable development trends without proper consideration of environmental factors and risks associated with natural disasters. Similarly, new development may take place in areas lacking essential facilities and create additional infrastructural demand pressure on local governments. The unplanned urbanisation can be mitigated by proper planning measures and policies that regulate infrastructural development in desirable areas. To make such important planning decisions and to regulate future development, planners and decision makers need to know the developmental trends, the areas suitable for urban development and the areas that would have more development pressure in future to ensure adequate infrastructural development beforehand so to maintain the quality of life of residents.

There have been previous studies on land use in relation to climatic variables but studies specific to built-up change, suitability and future built-up modelling that are crucial in urban and land use planning lags in the study area. Thus, the general aim of this study is to identify the suitable areas for built-up expansion in Kamalamai Municipality, Sindhuli district, Nepal. The specific objectives of the study include; a) Identify the change in Land Use Land Cover (LULC) in Kamalamai Municipality during the period of 2001, 2016 and

2021; b) Identify built-up expansion suitability areas; c) Prepare land change transition model in built-up expansion suitable areas for 2031, 2041 and 2051. This thesis uses Remote Sensing (RS) and Geographic Information System (GIS) technologies for deriving and analysing LULC changes. Analytical Hierarchy Approach (AHP) pair-wise comparison of suitable parameters was used for identification of suitable areas for built-up development. Multi-layer Preceptor (MLP) neural network was used for transition sub-modelling and Markov model was used for modelling future urbanization in combination with constraint/incentive panel to redirect the change in suitable areas.

The study analysed LULC classification based on satellite image analysis. During the period of 2001 and 2021 the bult-up increased from 1.09 Km^2 to 3.95 Km^2. The suitability analysis showed 56.28 Km^2 area of municipality not suitable for built-up expansion. Similarly, 55.50 Km^2 area had very low suitability and 21.44 Km^2 area had low suitability for built-up development. The model predicted the built-up to increase to 5.13 Km^2 by 2031, 6.69 Km^2 by 2041 and 8.25 Km^2 by 2051 when redirecting the expansion in controlled suitable areas. The study can be beneficial for the preservation of natural environment, reduce risk and low-cost development planning. The research can be used by planners, policy makers, government and non-governmental organizations, and other stakeholders to plan sustainable built-up development and expansion.

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Acronyms and Abbreviations

AHP	Analytical Hierarchy Process
ANN	Artificial Neural Network
CA	Cellular Automata
CI	Consistency Index
CR	Consistency Ratio
DEM	Digital Elevation Model
ETM+	Enhanced Thematic Mapper Plus
GIS	Geographic Information System
LCM	Land Change Modeller
LULC	Land Use Land Cover
MLP	Multilayer Perceptron
NIR	Near Infrared
NLCD	National Land Cover Dataset
OLI	Operational Land Imager
RS	Remote Sensing
RI	Random Index
SDG	Sustainable Development Goal
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
SWIR	Short Wave Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
USGS	United States Geological Survey

Chapter-1: Introduction

1.1. Background

Nepal is a landlocked country surrounded by China to the north and India to the East, West and South. Nepal has historically been a rural country with traces of urbanization only dating back to 1960s, mostly in Kathmandu valley and other cities like Pokhara, and Biratnagar. Urbanization scenario in Nepal has been dominated by high growth areas like Kathmandu valley, Pokhara valley and a few large and medium cities, the inner terai valleys, boarder towns and market towns on highways passages (Bakrania, 2019). Nepal has remained one of the least urbanized country but at the same time one of the fastest urbanizing country from 1990-2018 and is projected to urbanize at 2.0 per cent per year until 2050 (UN DESA, 2019).

Kamalamai Municipality is the headquarter of Sindhuli district. It is a trade hub for hinterlands and rural areas in proximity of the municipality and has an important interlinkage between Terai region and Kathmandu Valley. The municipality became one of the most important links to the valley after the construction of BP Highway which stretches from Baribas, a booming town in Terai region of Nepal interconnected to East-West Highway and major cities like Birgunj, Janakpur and Biratnagar to the south, and Dhulikhel, gateway to Kathmandu Valley and an important route to trade with China to the north. This short route to valley has become very popular since 2011 which has resulted in huge business opportunities in the area and consequently it has witnessed rapid built-up development in recent years. Furthermore, the decentralization and federal re-structure of the country in 2015 has influenced rise in rural-urban migration to towns like Kamalamai which have become an important hub. Finally, the earthquake in 2015 which displaced many people from their houses also have migrated to towns. The land price rise in the municipal area is also an indication of this trend.

The municipality is developing in a rapid manner in recent years but this development in not planned nor regulated. The issues of air pollution, water pollution and change in agricultural lands as well as open spaces has already surfaced in the municipality. Kamalamai Municipality has shown a decrease in forest area and riverbank from 1995 to 2014 while an increase in built up area and agricultural land due to the population growth (Neupane and Dhakal, 2017). The pressure of urbanisation without any plan and regulation cannot be limited to the towns core but will eventually spill over to the hinterlands. Moreover, the municipality consists of hills prone to landslides as well as plains which are prone to flooding. The current built-up development trend may expand inconsiderately towards flooding and landslide areas, or areas unsuitable for development because of higher slopes or areas where development is less desirable.

The urbanization though rapid can be regulated in an effective manner by the authorities and policy makers and planned in advanced with proper knowledge of the development trend and identifying suitable areas for development. The use of Remote Sensing (RS) and Geographic Information System (GIS) techniques is an effective method to study urban trends. The use of Land Use Land Cover (LULC) analysis has widely been used in assessing built-up changes. Similarly, suitability analysis to identify areas suitable for development is an important part in future land use planning. Suitability analysis is an initiation towards preservation of natural environment, constraining risk sensitive areas in cities and an efficient way to mitigate unplanned urbanization so to create a healthy environment and ensure effective management of an area.

Despite such importance of urban trend assessment and suitability analysis for assessing areas of future development, there has been very few studies on LULC and none on the assessment of future built-up suitability in the study area. (Neupane and Dhakal, 2017) studied the land use change in relation to climate climatic variability in Kamala watershed including Kamalamai Municipality in the period of 1995 and 2014 which concluded decrease in forest areas and riverbank while settlement area increase. (Portnov, Adhikari and Schwartz, 2007) studied the urban settlement growth in Nepal to however the analysis was at national level between 1952 and 2001 and concluded that areas in major population centre, areas in proximity to highways and those in proximity to Indian border were fastest growing localities. (Basyal and Khanal, 2001) focused on spatial and temporal situation of Nepal in the period of 1952, 1961, 1971, 1981 and 1991 using secondary data sources.

1.1.1. Rationale of the Study

In recent years, Nepal has experienced rapid population growth in urban areas resulting mainly from rural-urban migration. This unprecedented urban growth has put immense pressure on land and other resources. Most of the terrain in Nepal is hilly, these areas have fewer flatlands so the infrastructure development eventually shifts to hillsides. Hillsides often have areas of soil instability, high slopes, and resource rich lands which should be avoided for development. Identification of suitable sites for urban development is a critical issue for settlement planning in hilly areas (Kumar and Shaikh, 2013). Suitability of using land assists in the decision for sustainable development and construction (Ristić et al., 2018).

Recent incidences in the country have shown that poorly planned settlements have suffered even from low level natural calamities (Bhattarai and Conway, 2021). There is an urgent need for an urban development strategy to preserve good-quality agricultural land and help conserve natural resources (Bhattarai and Conway, 2021). Identifying areas suitable for urban development helps in demarcating future development areas so to reduce the risk of natural disasters, preserve the natural environment and sustain the future population growth in a planned manner. Land suitability analysis is the assessment of the suitability of the land to specific land use which provides a basis for land use planning (Karim et al., 2020).

Previous studies have demonstrated the capability of integrating different data sources including land use/cover, RS, and GIS as a method for land suitability analysis (Youssef, Pradhan and Tarabees, 2011). The use of GIS-based multicriteria analysis and Land Use Land Cover (LULC) simulation provides a satisfactory database for solving the problem regarding development works of future. Suitability analysis and land change modelling of future LULC is essential component in settlement planning and infrastructure development planning which will in turn assist in environmental protection and balancing the human induced pressure on the environment of an area thus benefitting by diminishing the pressure on urban environment mitigating flood risk and urban pollution.

Therefore, the purpose of this study is to assess the suitable areas for built-up expansion in Kamalamai Municipality of Sindhuli district, Nepal using RS and GIS tool, Multi-Criteria Decision Making (MCDM), weighted overlay analysis and LULC simulation model. The identification of built-up expansion suitable areas will assist in the sustainable development of the municipality by providing essential information on factors. This study will be beneficial to the local citizens, planners, land developers, local decision-makers, politicians, policymakers, and public authorities responsible for urban development and environmental management.

1.1.2. Research Approach

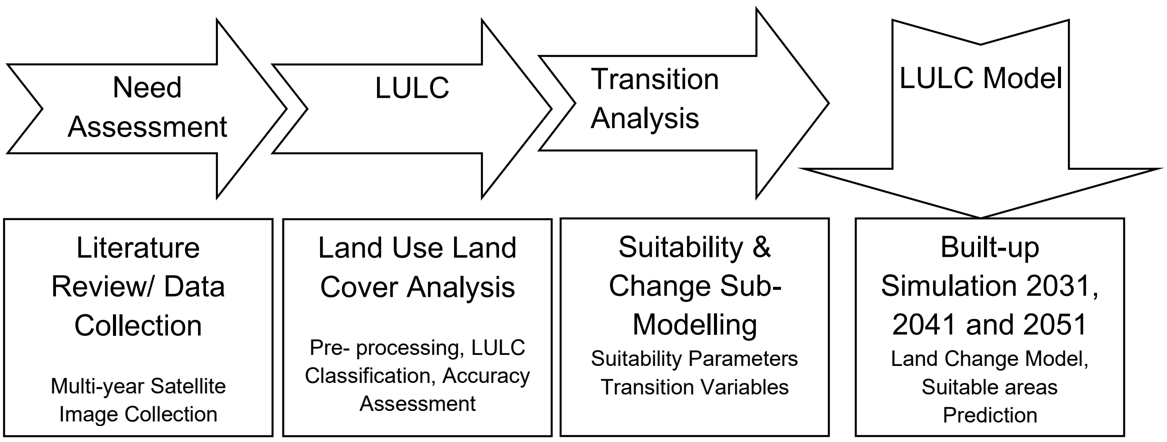


Figure 1. Research Approach

The research approach used in the study is presented in Figure 1. LULC map have been generated from for 2001, 2016 and 2021. Accuracy of the LULC map was assessed so to achieve accuracy within the tolerance level. Analytical hierarchy method was used to give weightage to the LULC classes. The LULC classes used to model the land change along with suitability parameters and transition variables. The model parameters were assigned in Markov model for 2001 and 2016, the LULC map of 2021 was used to verify the model's accuracy. The verified model was used to identify areas of built-up for the year 2031, 2041 and 2051. Detail procedure is shown in Figure 8.

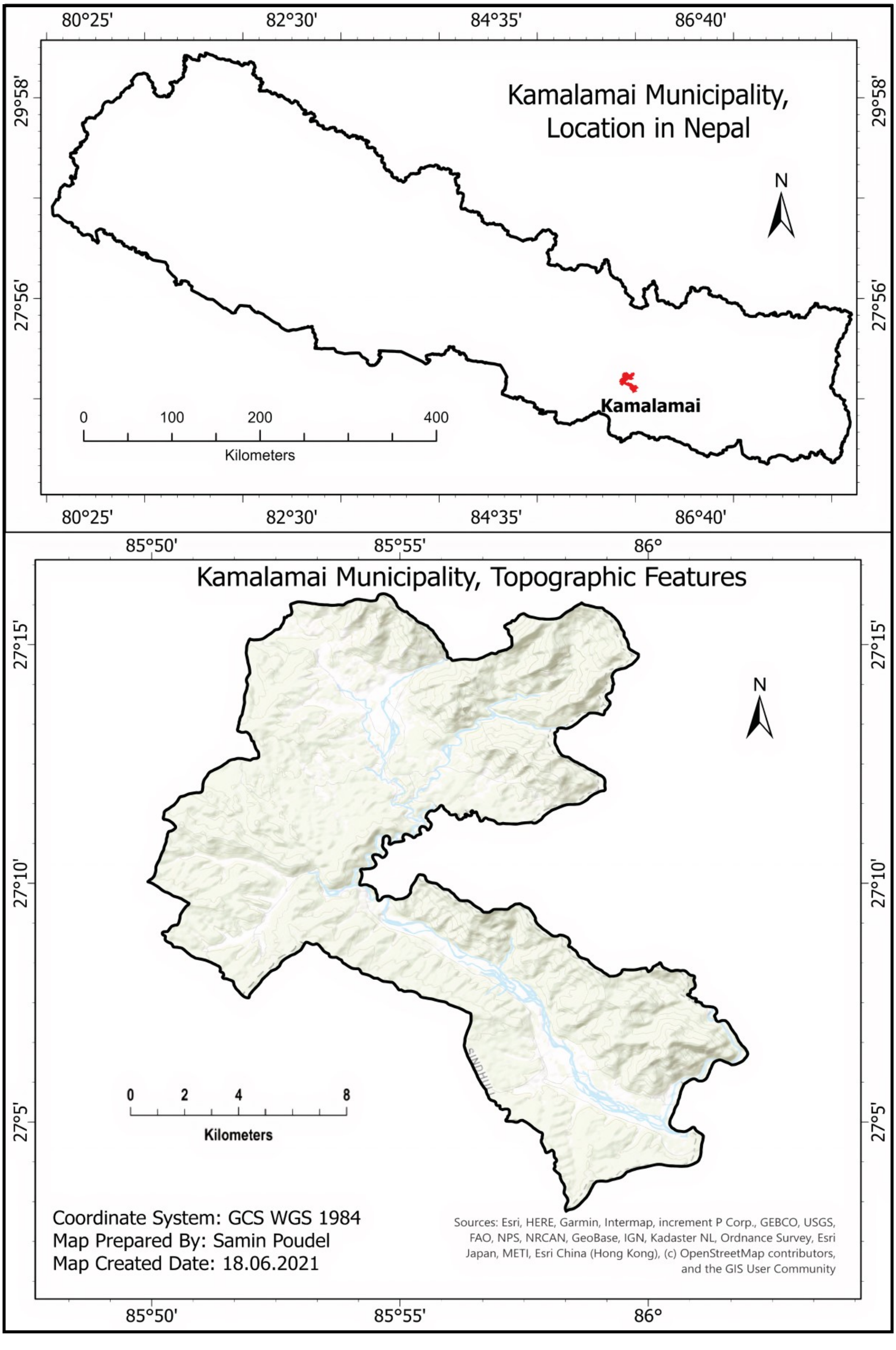
1.2. Objectives

The main objective of the study is to identify suitable sites for built-up development in Kamalamai Municipality are as follows:

- Analyse Land use land cover in Kamalamai municipalities for 2001, 2016 and 2021 (Section 3.2).
- Identify built-up expansion suitability area (Section 3.5 and 3.6).
- Prepare land change transition sub-model and simulation built-up expansion in suitable areas for 2031, 2041 and 2051 (Section 3.7 and 3.8).

1.3. Study Area

Kamalamai Municipality is situated in hilly region of central-eastern Nepal located in Sindhuli District, Bagmati Province of Nepal and is the largest municipality of the country according to the area. The district includes two Municipalities Kamalamai Municipality and Dudhauli Municipality, and seven rural municipalities. Kamalamai Municipality lies between latitude 27˚ 3' 6" N and 27˚ 16' 17" N and latitudes between 85˚ 48' 36" E and 86˚ 01' 52" E. The municipality is surrounded by Ranichauri, Bhimsthan, Belghari and Ranibas in the east, Bhadrakali and Dandi Gurase in the west, Bhadrakali and Ratanchura in the north and Sarlahi, Mahottari and Dhanusha Districts in the south. Kamalamai covers an area of 205 km^2 and is comprised of 14 wards. The location map is presented in Map 1.



Map 1. Location of Kamalamai Municipality

The municipality stretches from Chure to the Mahabharata range with elevation ranging from 400m to 1600m, thus having diverse climatic conditions. The climate ranges from lower tropical to temperate regions. The average rainfall in the district is 2788 millilitres per year which is the second highest rainfall area in Nepal after Pokhara. The summer season falls between April to September and winter between October and March.

Historically, Sindhuli district has played an important role. The battle at Sindhuli Gadhi fort between Gorkha Army and British East India Company when the Gorkha Army became victorious was a historic achievement for the Gorkha Army. This site of major historical and archaeological importance is in the footsteps of Kamalamai Municipality. The major market area of the municipality is Madhi Bazaar which is densely built with shops on both sides of the lanes. The major rivers in the municipality are Kamala, Chadaha, Gadhauli, Bhiman, Gwankhola, Buka, Labdaha and Marin River. The Kamala River which flows through the municipality is worshipped by locals as goddess Kamala.

According to the census in 2001, the district had a population of 32,838 while according to census in 2011 the municipality's population increased to 39,413. The male population as per census 2011 is 18,788 (47.66%) while female population is 20,625 (52.34%). The number household was 9304 in 2011. The ethnic composition of municipality is mostly Chhetri, Tamang and Magar people while the most spoken language is Nepali followed by Tamang language. The religious practice includes Hinduism, Buddhism, Christianity and Muslim in the municipality.

1.4. Area of Focus

This project was aimed to understand built-up change and identify suitable areas for built-up in Kamalamai Municipality of Nepal. The study focuses on Kamalamai Municipality and its associated wards which are a part of Sindhuli district. The study location is one of the rapidly urbanizing areas of the country. The study is based on the use of freely available satellite imagery: Landsat-7 and Landsat-8. The processing of imagery was done using ArcGIS Pro software.

The study focuses on built-up areas which is classified based on LULC classification. The classified image is verified based on the satellite imagery as well as google base map. The transition factors were assigned for the development inducing factors and suitability of built-up was assessed based on available dataset for various parameters that affect the suitability for built-up development. The classified image of 2001 and 2016 was used for developing the model for urban development based on transition variables, and the model was later verified using classified image of 2021. The model was used to create built-up expansion areas for 2031, 2041 and 2051 while directing the change only in suitable areas.

1.5. Literature Review

Literature review is carried out to understand the concept of urbanization, urban sprawl, suitability analysis, methods of modelling urban expansion, LULC simulation, RS, Analytical Hierarchy Process (AHP), image classification and GIS. Literature review was useful in collecting study reports from various scientific journals and publications. The in-depth knowledge of the field was essential to carry out the study and was crucial in preparation of this report.

1.5.1. Urban Development Overview

More than half of the world population are living in urban areas and it is projected to grow by 2.5 billion people between 2018 and 2050, with half of this growth concentrated in Asia and Africa (UN DESA, 2019). Cities are one of the most complex structure created by humans as a society, cities are very different in many aspects but at the same time also have similar characteristics which are dynamism and growth (Barredo et al., 2003). Urban areas are complex structures with various factors influencing this structure, they can be continuous, ribbon-like, clustered, scattered around edges or any combination of such patterns, and likewise can expand or shrunk with time (Wahyudi and Liu, 2015). Urbanization is inevitable and even necessary for growth in current globalized world.

Cities have been in existence since the ancient Mesopotamia, when cities were a pattern of densely packed houses, a central institution closed with a city wall but these cities were not globally significant infact the global population proportion residing in urban areas was only 13% in 1900, it increased to 29% in 1950 (Elmqvist et al., 2013). Humans usually lived in tribes and small villages as hunter gatherers. After settling for agricultural products humans started to have surplus grains which meant more and more population growth and enough leisure for people to carry various activities like making agricultural tools, creating military to protect land and grains. This demanded people to live securely within walls and store grains, have military and central administration which gave rise to cities as we know them. Since then, urbanization has increased with each passage of time and has become more complex as well.

As urbanization continues around the world, sustainable development increasingly depends on management of urban growth, especially in lower income countries where the most rapid urbanization is projected (UN DESA, 2019). Urban areas create a better network for exchange of knowledge and information which has till this day driven human civilization’s progress. Cities are place for innovation which serve as a hub for development (UN DESA, 2019). Urbanization should thus be embraced and urban areas should be planned in such a manner that benefits all its citizens, is efficient, networked and is resilient to natural disasters and other risks. The well-being of human population in future depends on urban areas and their resilience against climate change (Apud et al., 2020).

The study of urban change has received an increased attention from planners and researchers working on urban and environmental issue as urban structure is considered as one of the paradigm for sustainable development (Nouri et al., 2014). There is consensus among researchers that cities have major impact on climate change aspects, and other environmental problems and at the same time with proper planning and implementing natural elements in cities we can create a sustainable environment for development. The Sustainable Development Goals (SDG) set by United Nations (UN) for the year 2030 has also highlighted on the issue by stating the goal no. 11, “Sustainable cities”.

Research over several decades have shown that urbanization has impacted atmospheric conditions, ecosystems, changes in carbon cycle throughout the globe possibly inducing climate change (Foley et al., 2005). Thus, urban land use and environmental planning is vital for sustainable development. One of the pressing issue in land use planning is determining the suitability of locations for development considering various physical, environmental, natural and other factors (Karim et al., 2020). Urban planning has faced difficulty in envisaging the growth of an areas so to anticipate the infrastructure required for future urban population because of the complex nature of spatial planning (Wahyudi and Liu, 2015).

To deal with the difficulty of projecting future urbanization researchers and planners have studied structures of urban areas, trends in cities and factors that affect the expansion or contraction of cities and various other dynamics associated with city growth (Wahyudi and Liu, 2015). The progress in mathematical calculations and statistical model was embraced by planners for studying cities while the invention of computational machines and computers revolutionized urban development studies (Wahyudi and Liu, 2015). The computational capacity that was never before imagined was available for studies which was further improved by artificial intelligence and automated computation.

The spatial-temporal dimensions of the dynamic process of urban development is not preventable but the prediction of future urban structure using modelling and simulation of future urban growth can be applicable planning and policy development tool that can assist in overcoming the problems related to rapid urban growth by understanding the interaction of natural and man-made environments (Nouri et al., 2014). The understanding of such effects can be of benefit for the planners and policy makers to create a sustainable and viable future plan that benefit all in a holistic manner.

1.5.2. Urban Sprawl

"Sprawl", the term itself was coined by Earle Draper, one of the early city planner in United States in 1937, urban sprawl is generally meant the tendency of city towards lower density and expansion of city footprint (Nechyba and Walsh, 2004). Urban sprawl is interpreted differently but in general it is the excessive spatial growth that cities grow to accommodate increasing population (Brueckner, 2000). Urban sprawl is a global phenomenon driven mainly by population growth, increased economy, infrastructure and large scale migration (Sudhira, Ramachandra and Jagadish, 2004). The difference in land prices in city core and areas in proximity can also contribute to urban sprawl.

Urban sprawl drives the change in LULC pattern while sprawl normally extends radially around the city core or linearly along highways (Sudhira, Ramachandra and Jagadish, 2004). The competition for land use normally arises between agricultural uses and urban use, while the outcome generally is in favour of urban use resulting in growth of cities followed by urban sprawl (Brueckner, 2000). These changes are particularly visible in major cities like Kathmandu and Lalitpur, where the agricultural lands have been converting to built-up with high land prices which agricultural products cannot trade off with ever increasing prices.

1.5.3. Impacts of Unplanned Built-up Expansion

Urban areas have been facing ever increasing socio-economic and environmental problems (Apud et al., 2020). The changes as a result of built-up development has been increasingly recognized as critical factor in relation to global change (Kumar, Radhakrishna and Mathew, 2014). In earlier stages of built-up development people tend to migrate inward to the city core but after a certain time urban development when unplanned usually moves outward of city centre mostly because of overcrowding, traffic and increased land prices (Rukhsana and Hasnine, 2020). The uncontrolled changes in spatial structures due to unplanned physical development, population, and economic growth and rural-urban migration has serious implications on environmental and social factors which decreases the quality of life of residents (Nouri et al., 2014).

Urban expansion can result in loss of natural or cultural landscapes, agricultural lands, while affects a wide range of phenomenon such as landscape fragmentation, soil erosion, surface sealing, increase in run-off, and may contributes in decline of biodiversity, so city management needs reliable method for informed decision making for sustainable development (Mohammady and Delavar, 2016). The access to basic facilities critical for quality of life such as drinking water supply, electricity, transportation, sanitation and health facilities are crucial but unplanned urbanization means that amenities are not equally distributed over space while people get caught in struggle to gain access to these facilities (Parry, Ganaie and Bhat, 2018).

1.5.4. Measures to Mitigate Unmanaged Urbanization

The assessment of LULC transformation using RS and GIS analysis is of vital importance for effective management of environmental and land resources (Shen et al., 2020). The modelling and predicting future LULC and urban growth can enable to understand a holistic view so to create a more competent urban management, preservation of natural resources and develop policies for sustainable development (Hasan et al., 2020). Supportive tools such as LULC models can be used to examine the transition among LULC categories and analyse causes and consequences of change (Shen et al., 2020).

Land use simulation assists as a decision support system to explore the anthropogenic interference on natural environment (Liu, Zheng and Wang, 2020). LULC change simulation provides the baseline scenario for predicting future patterns of development and indicate future anthropogenic impact, such as deforestation, and can be used in spatial planning to minimize such impacts (Saputra and Lee, 2019). With the use of model analysis and simulation of land use LULC change and spatial pattern of change can be identified along with the rate of land use change so to analyse possible multiple scenarios and their interactions (Han, Yang and Song, 2015).

Urban simulations are of particular interest to urban and regional planners since the future impacts of actions and policies are critically important (Rocha and Tenedório, 2018). However, urban growth processes are usually difficult to simulate (Barredo et al., 2003). Most of the simulation methods include two aspects, the number of predictions and simulation of the spatial patterns of future while some of the widely used methods for land use change simulation are Markov analysis, CA, multivariate spatial models, neural network based CA, optimization models, empirical-statistical models, and agent-based models (Saputra and Lee, 2019).

1.5.5. Spatial Modelling

Spatial models are developed as decision support tools to balance the environment and the scarce resources by analysing different scenarios of LULC changes and their effects (Mohammady and Delavar, 2016). Spatial modelling has been helpful for planners and decision makers to anticipate the future urban scenario in different stages of planning (Wahyudi and Liu, 2015). A model is broadly defined as a simplification of reality (Barredo et al., 2003). Models simplify the complex spatial patterns (Hasan et al., 2020). Spatial modelling in GIS is used in future scenarios simulation based on historic information of geographical changes, the models are created based on quantification of LULC changes

(Rocha and Tenedório, 2018). In spatial modelling history models aims to understand spaces allocation and mechanisms that shape these spaces (Wahyudi and Liu, 2015).

Since the beginning of 1960 various spatial models have been introduced, Burgess' depicted general features of Chicago city with a multi-ring representation of different functions, Alonso modelled values of lands according to distance, later in 70's and 80's the models shifted to extensive use of mathematical equations, and in 90's and 00's models shifted to computer technology and complex theory (Wahyudi and Liu, 2015). LULC models have been proven to be an effective method for describing and estimating urban development and have thus proven to be an important step for informed development planning decisions (Gharbia et al., 2016). The theory and methods for developing urban models were initiated and has been developed for four decades in United States and Europe (Wahyudi and Liu, 2015).

The rapid development of RS and GIS technologies, followed by their extensive use in urban and environmental planning has resulted in the use of decision support tools using spatial modelling methods like neural network, CA and statistical models (Nouri et al., 2014). The models of LULC change processing are in general based on two groups, regression based; which relates the LULC changes as spatially explicit variables using models of logistics, and spatial-transition based model; which allows future land development prediction such as CA models (Kumar, Radhakrishna and Mathew, 2014).

1.5.5.1. Neural Network

Neural Networks are mathematical models which are like brain neurons that store information using learning algorithms which are often called Artificial Neural Network (ANN), which is often also known as the framework for performing machine learning (Keijsers, 2010). The interconnected units of neural networks are very efficient for computing complex functions (Sajda, 2002). ANN incorporates natural cell based operations for the overall on and off processing with multiple connections in multiple levels and dynamic feedback in temporal sequence (Pagel and Kirshtein, 2017). The land change simulation model is illustrated in Figure 2.

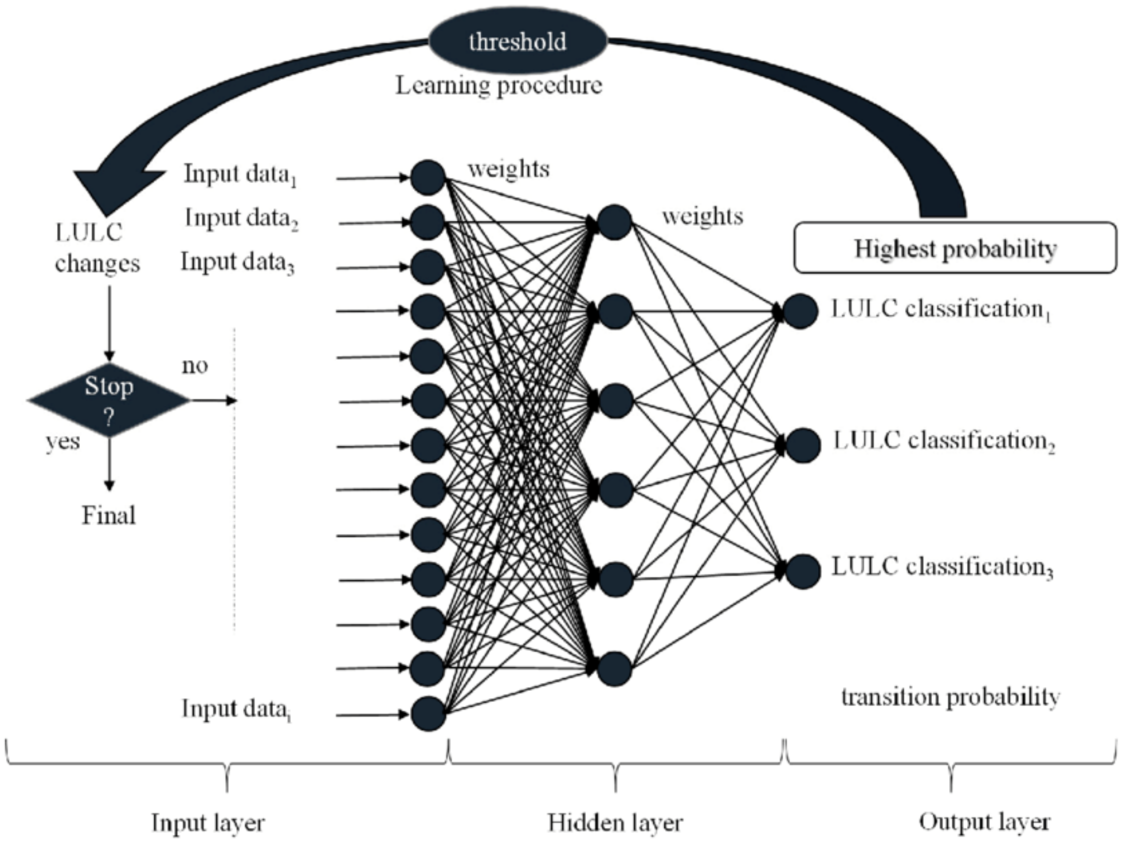


Figure 2. Change Simulation Model Based on Artificial Neural Network-Cellular Automata (ANN-CA). Adapted from:(Saputra and Lee, 2019)

Machine learning and training are important in neural network-based systems as the system only responds to the stimuli to which they have been trained (Pagel and Kirshtein, 2017). The neural network consists of simple processing elements which are interconnected with weights, the network is trained at first using a learning algorithm which estimates the interconnected weights and finally the trained network is used for classification (Udpa and Udpa, 2001). The neural network classes most often used for classification if Multi-layer Perceptron (MLP) network. The variety of neural network architectures are used in simulation like MLP, recurrent networks and self-organizing networks while computer simulation plays an important role with both software and hardware advancement (Sajda, 2002).

MLP consists of three types of layers; input layer, which receives he input signal for processing; hidden layer, which are placed between input and output in arbitrary number that does the computations; output layer, which does the prediction and classification (Abirami and Chitra, 2020). A simple MLP with hidden layer with number of neurons in hidden layer *m,* number of input layer nodes *n* for 1 output neuron, then the number of weights that need to be estimated for learning stage given by Eq. 1 (Dash and Dash, 2017).

$$[m\ (n + 1) + m + 1]$$ …………(Eq. 1) (Dash and Dash, 2017)

1.5.5.2. Cellular Automata (CA)

CA dates back to the beginning of digital computation, one of the pioneers Von Neumann developed the concept that a set of rules or instructions could provide software with reproducibility, later with sets if local rules that generated mathematical patterns Conway developed 'Game of Life' in 1970 while in the same year Tobler introduced CA to geographical sciences (Geertman, Hagoort and Ottens, 2007). CA is a well-known tool for urban modelling, originally developed in computer programming in 1983 by Wolfram and later adopted for urban system study by spatial researchers (Wahyudi and Liu, 2015).

Cellular Automata (CA) is defined as a automated machine that processes information, proceeds on action to action logically and relentlessly by applying data received as input and the instruction programmed within itself (Liu and He, 2009). CA is a commonly used method for simulating LULC changes by estimating the state of a pixel in initial state, neighbourhood effects of surrounding pixels and defined transition rules (Saputra and Lee, 2019). In conventional form CA consists of four basic elements; (i) cell: which represents spatial shape of CA, (ii) state: the possible state cell could have, (iii) transition rules: determine changing state of a cell and (iv) Neighbourhood: adjacent cells surrounding the centre cell (Wahyudi and Liu, 2015). The neighbourhood cells is illustrated in Figure 3.

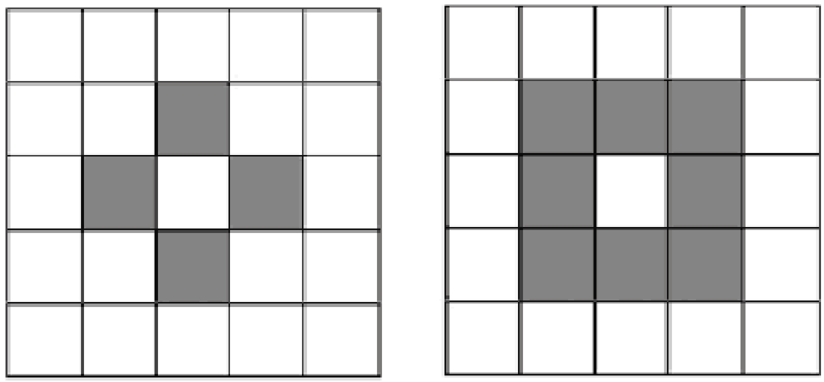


Figure 3. Type of Neighboring Cells in Cellular Automata (CA), Von Neumann 4 cells (left), Moore 8 cells (Right). Adapted from: (Wahyudi and Liu, 2015)

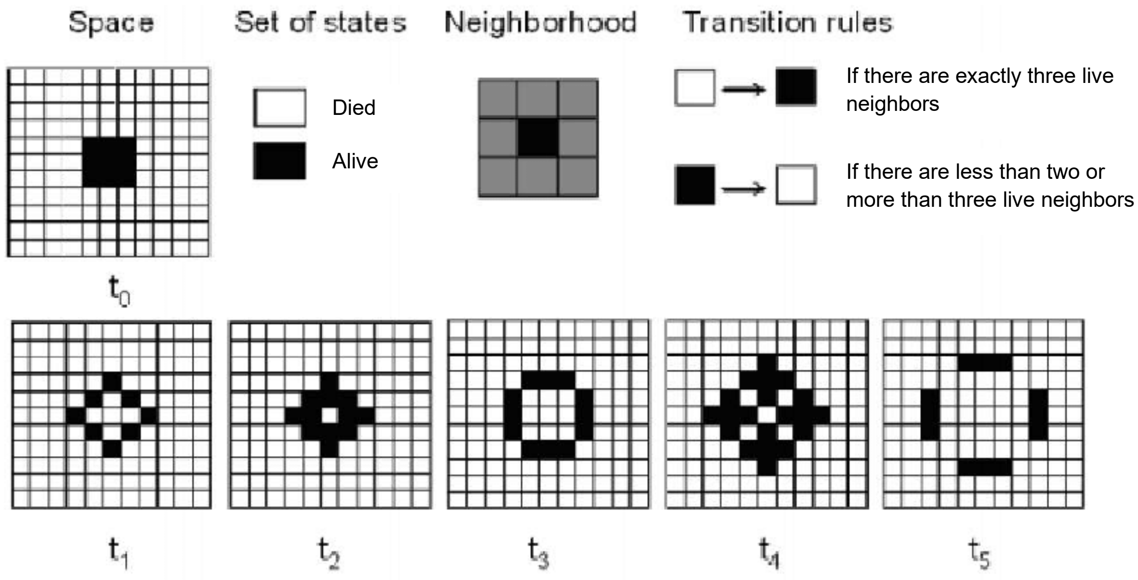


Figure 4. Elements of Cellular Automata (CA). Adapted from: (Wahyudi and Liu, 2015)

The elements of CA are illustrated in Figure 4. The most useful application of CA in terms of spatial planning is its use in simulations of urban growth which is of particular interest to planners for realising future impacts and developing policies (Barredo et al., 2003). CA have been popular modelling tool for urban simulation since the pioneering work of Tobler in 1979, and later have been in wide use for simulating spatial processes due to its simplicity, precision, flexibility and intuitiveness (Gharbia et al., 2016). The ease of CA in simulating urban growth and shrink to explain urban dynamics has prompted its widespread use (Wahyudi and Liu, 2015). The CA models focus on local interactions of cells with distinct spatial-temporal coupling features with powerful computation capability which is suitable for dynamic simulation as well as self-organizing feature systems but they are affected by uncertainties of interaction between model inputs; model structure, elements and quality of data (Sang et al., 2011).

The CA model is expressed as follow:

$$S(t, t+1) = f(S(t), N)$$ ……………(Eq. 2) (Sang et al., 2011)

Where, S is set of limited discrete cellular states, t and $t + 1$ are indication of different times, f is transformation rule of cellular states in local spaces and N is cellular field. The formation of transition rules is at the heart of a CA model which determines how the LULC of cells change form one type to another with time (Lau and Kam, 2005). The state of each cell in CA depends on the previous state of cells in an array within a neighbourhood in accordance with set of transition rules (Gharbia et al., 2016).

1.5.5.3. Cellular Automata (CA) Markov Model

The independent use of CA and Markov model both have advantages for land use change study but have disadvantages as well while CA-Markov model is advantageous with powerful spatial computing for spatial-temporal dynamic modelling with effective incorporation of GIS and RS (Sang et al., 2011). Many studies have revealed the effective match of CA-Markov model, GIS and RS to derive appropriate spatial and temporal model of LULC changes (Nouri et al., 2014).

CA-Markov is a combination of CA, Markov chain, multi-criteria, multi-objective land allocation LULC prediction which adds elements of spatial contiguity and knowledge of spatial distribution of transitions to Markov chain (Sang et al., 2011). The model uses

Markov chain process to control the temporal land use classification changes based on conversion probabilities while local rules determined by suitability maps or CA spatial filters are used to control the spatial changes (Nouri et al., 2014). CA-Markov model has two aspects, Markov chain controls temporal change using transition matrices while CA controls spatial patterns using local rules, neighbourhood configuration and transition potential (Guan et al., 2011). CA-Markov model benefits both from time series and spatial predictions and considers various factors like LULC suitability, effects of natural, economic and societal factors on LULC (Sang et al., 2011).

1.5.5.4. Markov Model

Markov model is convenient tool for simulating difficult to describe landscapes and processes for modelling LULC changes while future state is simulated based on immediate state (Kumar, Radhakrishna and Mathew, 2014). The Markov model theory which is based on the formulation of Markov random process for the prediction and optimal control theory while the model explains the quantified conversion states between land use types as well as the transfer rate among the different LULC (Sang et al., 2011). Markov model uses initial state, transition probabilities for different states to determine the development trend and predict future state (Kumar, Radhakrishna and Mathew, 2014).

The model is related to dynamic distributed lag model which consists of two components; transition matrix and transition probability matrix that represents the number and probability of land changing from one land use class to another in the observed period (Han, Yang and Song, 2015). A Markov model can be specified as having “S” states interconnected with some or all states while each state generates an observation O^{s}_{t} where “s” is the state in time “t” and transition occurs in some specified probability from one state to another (Hosom, 2003).

The LULC change prediction is calculated as (Eq. 3)

$$S(t+1) = Pij * S(t) \ldots\ldots\ldots\ldots \text{(Eq. 3) (Sang et al., 2011)}$$

Where, S (t) and S (t + 1) are system status at time, t and t + 1 and Pij.is transition probability matrix in a state calculated as (Eq. 4).

$$Pij = \begin{pmatrix} P_{11} & P_{12} & \ldots & P_{1n} \\ P_{21} & P_{22} & \ldots & P_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ P_{11} & P_{12} & \ldots & P_{1n} \end{pmatrix}$$

$$\left(0 \leq Pij < 1 \text{ and } \sum_{j=1}^{N} Pij = 1, \ (i, j = 1, 2, \ldots\ldots n)\right) \ldots\ldots\ldots\ldots \text{(Eq. 4) (Sang et al., 2011)}$$

Markov model can depict the direction of LULC shifts and provide a framework for analysing land use demand on future, thus the model is widely in use for the prediction of LULC changes (Han, Yang and Song, 2015). Markov chain model has been incorporated with GIS and RS Technologies for an effective simulation and prediction of LULC change as the model examines the stochastic natured LULC change dataset while forecasting the future land change (Shen et al., 2020). The transition probability maps which are generated through the Multilayer Perceptron (MLP) as Markov change model provides a probability whether pixel will be converted into another land use class in annual time steps (Hasan et al., 2020). A Markov model is a generator of events with initial generation probability and probability of generating subsequent observations dependent on previous state values (Hosom, 2003).

1.5.6. Analytical Hierarchy Process (AHP)

Decision making in crucial in every-day life of people but rather than just making decisions making effective decision is crucial. Decision making are often based on choosing best alternative as per the requirement criteria of the decision maker. When the decisions are based on only one criterion, they are easy to find the best alternative but decisions generally take multiple criteria as variables and choosing the best alternative becomes an arduous task. Decisions making involves analysing multiple criteria factors that have a role in the decision and making effective choice.

AHP is one of the decision-making tools involving multi-criteria analysis. AHP was developed by Saaty as a Multi-Criteria Decision Making (MCDM). It is a widely used tool for decision making across various sectors (Leal, 2020). Satty proposed AHP based on based on pairwise comparison method introduced by Fechner in 1860 and developed by Thurstone in 1927 (Chu and Liu, 2002). This decision-making tool uses various criteria to reach probable comparative alternatives.

The AHP is a measurement theory using pairwise comparisons and recued on experts judgement to derive priority scale (Saaty, 2008). It is designed to work on the basis of rational and intuitive to select best alternative on the evaluation of several criteria (Saaty and Vargas, 2012). The working of AHP is illustrated in Figure 5.

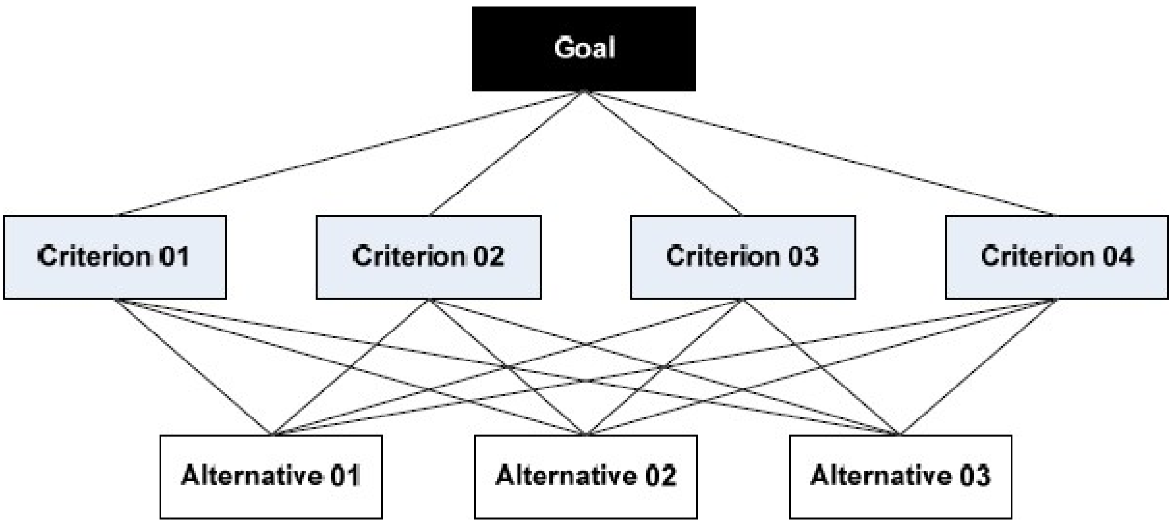


Figure 5. Hierarchy of Criteria and Alternatives. Adapted from: (Vargas, 2010)

The AHP method starts by defining the problem statement that needs the decision-making application. Then the alternatives are assigned a hierarchy based on the judgement of alternatives. This is followed by setting comparison matrices according to the judgment weights such that the expert priorities meet. Pairwise matrix consist pairwise weighted values that signifies the hierarchy of each pair individually. The process is illustrated in Figure 6.

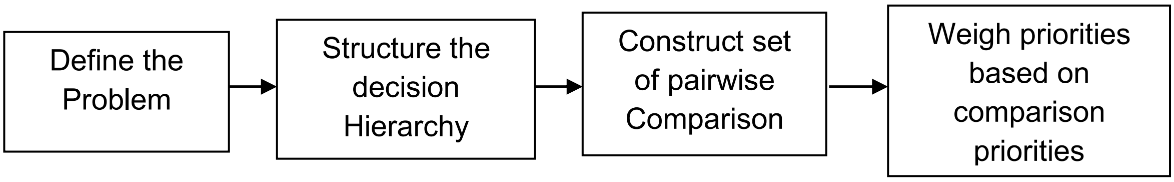


Figure 6. Analytical Hierarchy Process (AHP) (Saaty, 2008)

1.5.7. Weighted Overlay Analysis

Weighted Overlay Analysis is widely used in site suitability assessment but this method can be equally beneficial in other analysis involving two or more factors for integrated analysis. Weighted overlay applies a common measurement scale values or weights for inputs which may not be equally important and output based on the weighted importance (ESRI, 2020).

Weighted overlay analysis is useful in understanding the implication of different measures of layers when combined/overlapped above one another considering various factors. This method is useful when dealing with even very different factors that are significant for an analysis classified with same measurable values.

1.5.8. Suitability Analysis

Land suitability evaluation is a logical basis for LULC planning by predicting the suitability of land to types of land use viable in an area (Karim et al., 2020). The method integrates different factors like slope, risky areas and prime agricultural lands, and determines sites that are more suitable to be used for development or any other land use. Identification of suitable areas for land development is especially relevant in hilly areas and even crucial aspect of planning (Kumar and Shaikh, 2013).

The ease of using criteria and weightage based on importance has contributed in making suitability analysis a very popular tool in planning. Land suitability evaluation has been widely in use since 1960s as main basis for urban planning which has been reinforced later on by the advancement and application of GIS technology for suitability analysis (Karim et al., 2020). Multi criteria evaluation method is used for site selection as well as suitability analysis for selecting most suitable for places for development in many studies in cities of Malaysia, India and Pakistan (Gharaibeh, Shaamala and Ali, 2020).

The method is based on weightage assigned for different parameters and using GIS tools to integrate all weightage of various layers to determine the integrated weightage. GIS techniques in integration with other tools are used for determining the importance of various criteria and their weightage for analytical assessment for evaluating suitable lands for specific land use (Karim et al., 2020). Certain factors are more important than others in case-by-case basis for determining the desirable results so the scoring and weighing of different aspects in consideration for overall suitability can be applied for suitability analysis (Kumar and Shaikh, 2013). AHP is widely used to assign weightage for different layers followed by weighted overlay analysis tool which integrated the weights for each layer to present suitability output. The pairwise comparison method was introduced in 1860 by Fechner and developed by Thurstone in 1927 and based on pairwise comparison, Satty proposed AHP as a method for multi-criteria evaluation (Kumar and Shaikh, 2013). The hierarchy model is used in AHP for solving complex land management problems (Pramanik, 2016).

1.5.9. Remote Sensing (RS)

RS is defined differently across various studies but in general, in geographic context it is the acquisition of physical data of an object without touching it or in contact, image of information of physical world is acquired through sensors like camera or electronic scanning or radiation and derive the information of earth's land and water surface from an overhead perspective (Campbell, 2002). In recent years viewing the earth from space to collect data from earth sensing satellites have become crucial in mapping and understanding earth's features, anthropogenic activities, natural resource and environmental management (Kumar, Radhakrishna and Mathew, 2014).

The increase in availability and improvement in satellite imagery has surged the imagery use in study and research especially using multispectral images and image classification to capture land features (Goldblatt et al., 2016). RS in integration with GIS tools is widely used for LULC research as well as many urban management studies, as these approaches are cost effective and fairly accurate. The use of freely accessible multi spectral images have further eased the use of RS technologies. RS is defined as the practice of deriving earth's land and water surfaces information using overhead perspective images using electromagnetic radiation reflected or emitted from the surfaces (Campbell, 2002).

The use of satellite imagery for LULC classification makes use of multi spectral images for image classification using either pixel-based image classification or object-based classification. GIS tools assist in working with remotely sensed data to analyse imagery for desired output. MSI consists of bands of different ranged electromagnetic radiation that can be interchangeably analysed with GIS tools. The analysis of spatial dataset with detailed landscape layers using GIS is an effective way for evaluation of service supply or the demand of UGS (Lahoti et al., 2019).

1.5.10. Land Use Land Cover (LULC)

Land use is referred as the purpose land serves like recreation, wildlife habitat and agriculture, while land cover is referred as the surface cover over the ground such as vegetation, infrastructures and bare soil, the meaning of the terms are distinct but are often used interchangeably (Saputra and Lee, 2019). Land use activities like converting natural landscapes or changing management practices on land used by humans have transformed the large portions of earth land surface (Foley et al., 2005).

LULC is a widely used method for analysing anthropogenic activities on built environment as well as environmental features on earth's surface. LULC is considered a fundamental variable that links parts of human and physical environments and is considered most important variable in ecological systems affected by global change (Foody, 2002). LULC data is crucial for environment protection and spatial planning (Rwanga and Ndambuki, 2017). LULC provides useful information in environmental and land use planning. LULC change and transformation have importance in displaying socioeconomic phenomenon around the world. LULC changes have been an important measure for urban and regional planning for centuries (Saputra and Lee, 2019).

Digital image classification is the process where pixels or objects are assigned a value respective to classification classes (Campbell, 2002). The application of image classification to depict LULC is one of the most common application of RS (Foody, 2002). LULC models are core in LULC change analysis and in recent years has produced a large set of different models that are useful in exploring and predicting LULC change trajectories (Guan et al., 2011). Image classification is the technique of deriving LULC information using the remotely sensed satellite imagery. The classification techniques are widely used for extracting spatial information from satellite imagery.

The technique utilizes the spatial and spectral characteristics of satellite imagery for deriving LULC maps. Besides spectral and spatial characteristics, the radiometric and temporal properties of satellite imagery are also important on a case-by-case basis for image analysis. The classification techniques are broadly classified into three classes, Automated, Manual and Hybrid classification techniques (Abburu and Golla, 2015). The automated classification uses various methods for classification and is widely used in image classification. The methods are illustrated in Figure 7.

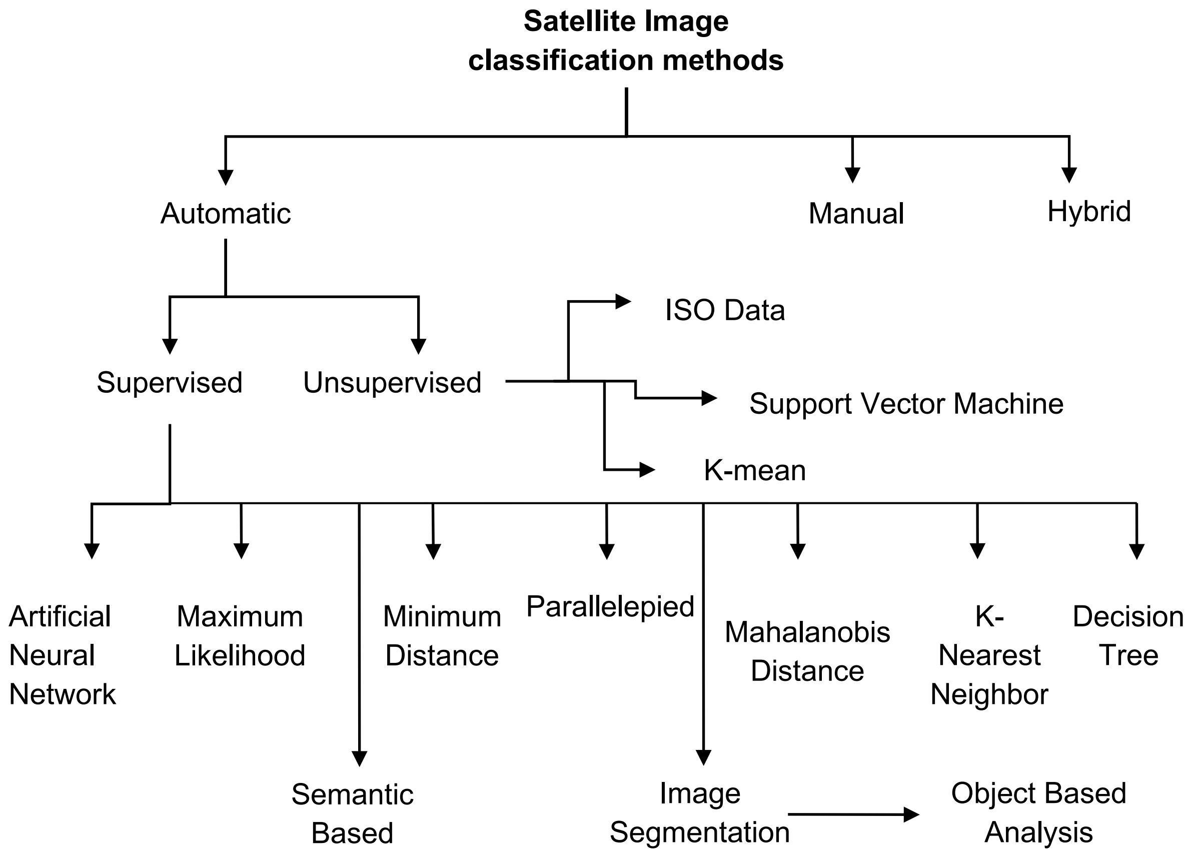


Figure 7. Satellite Image Classification Methods (Abburu and Golla, 2015)

1.6. Concluding Remarks

This project was based on the location of study area, area of focus, need assessment, research approach and literature reviews. LULC change can be mapped and analysed effectively using RS and GIS methods. There are several modelling methods to use for land change modelling. Similarly, AHP is appropriate for determining suitability weights for site suitability analysis. The land use change simulation model based on Markov model and MLP neural network along with suitability parameters based on AHP was used for determining the built-up expansion suitability area for Kamalamai Municipality and model of suitable areas for built-up expansion in Kamalamai Municipality for 2031, 2041 and 2051.

Chapter-2: Methodology

This chapter deals with the workflow of the study, data used for the study and method of work. The Landsat imagery was classified using supervised image classification technique. The classified image of 2001 and 2016 was used to create transition models based on five parameters; water to built-up, barren to built-up, shrub to built-up, agriculture to built-up and forest to built-up. The major software's used in the study for GIS and RS techniques processing were ArcGIS Pro and Terr-set Land Change Modeller (LCM). AHP pair-wise comparison followed by weighted overlay method was used to overlay parameters for suitability analysis using ArcGIS Pro. Detail of the process is presented in the following sections.

2.1. Workflow

Overall methodology for Identifying the suitable sites for built-up expansion in Kamalamai Municipality with the application of RS and GIS techniques composed of the following procedures.

- Landsat 7 image of January 2001 path 140 and row 041, Landsat 8 image of January 2016 path 140 and row 041 and Landsat 8 image of January 2021 path 140 and row 041 were downloaded from United States Geological Survey (USGS) website in 'Tiff' file format for each individual band. Similarly, DEM was downloaded as Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global data from same website, SRTM section under digital elevation. Two elevation models were downloaded to cover the entire study area both consequent images dated 2014.

- The data of municipal boundary, landslide susceptibility, flood susceptibility, roadway and settlements were collected from Department of Urban Development and Building Construction municipal database for Kamalamai Municipality.

- Downloaded image bands 7-bands were composited to a single image using “Composite Bands” tool in ArcGIS Pro for all three imagery of 2001, 2016 and 2021. This was followed by, image clipping using “Clip” ArcGIS Pro tool to the area of Kamalamai Municipality.

- The DEM was mosaiced by using “Mosaic” tool in ArcGIS Pro to cover the entire study area. The process was followed by image clipping using “Clip” to the study area.

- Imagery of year 2001, 2016 and 2021 January was classified using supervised image classification technique, the classified image was checked and “Reclassified” pixels that were assigned wrong LULC class in ArcGIS Pro using “Classification Wizard”.

- Accuracy assessment done using stratified random points assignment over the classified image and using confusion matrix which was verified using the image itself and Google Earth base map.

- The DEM was used to derive slope and aspect of the study area using analyse “Slope” and “Aspect” tools in ArcGIS pro and defining the parameters required for the tool.

- AHP was used to assign weights to the LULC classes and same method was used to derive values form suitability analysis using flood and landslide susceptibility, LULC, aspect, slope, road proximity, settlement proximity and elevation.

- “Reclassify” tool in ArcGIS Pro was used to categorize the parameters into required classes for each layer.

- Each weighted class were reclassified between the values of 1 and 0 using “Reclassify” tool in ArcGIS Pro till each reclassified layer were obtained based on same weightage. The weighted overlay method was used for analysing the weighted overlay values of all layers to find suitable areas for built-up expansion using raster calculator tool.

- The images were exported from ArcGIS pro using "Export Raster" tool in TIFF format. All required images were imported to Terr-set in .rst format using "Import" tab. LCM Change Analysis was first used to analyse changes in LULC from 2001 and 2016.

- Transition variables were used to calculate transition potential maps using multi-layer perceptron (MLP) neural network for water to built-up, barren to built-up, shrub to built-up, agricultural to built-up and forest to built-up.

- The change prediction was done using Markov module analyser, Markov Chain prediction process with prediction date 2021 and potential transitions previously calculated for all five possible transition per classes, then model was run to obtain hard and soft prediction map.

- The classified LULC map of 2021 was later used in change validation panel to analyse the model. The model was then used for transition of 2016 to 2021, 2031, 2041 and 2051.

- The planning tab constraints and incentives regions were assigned in accordance to suitability map which was used to predict future built-up expansion areas suitable for development in future.

- The maps and models created in Terr-set were added as layers in ArcGIS pro. The map data were calculated in ArcGIS pro and exported for further data analysis in Excel and maps were prepared in ArcGIS pro.

- The flowchart of methodology is illustrated in Figure 8.

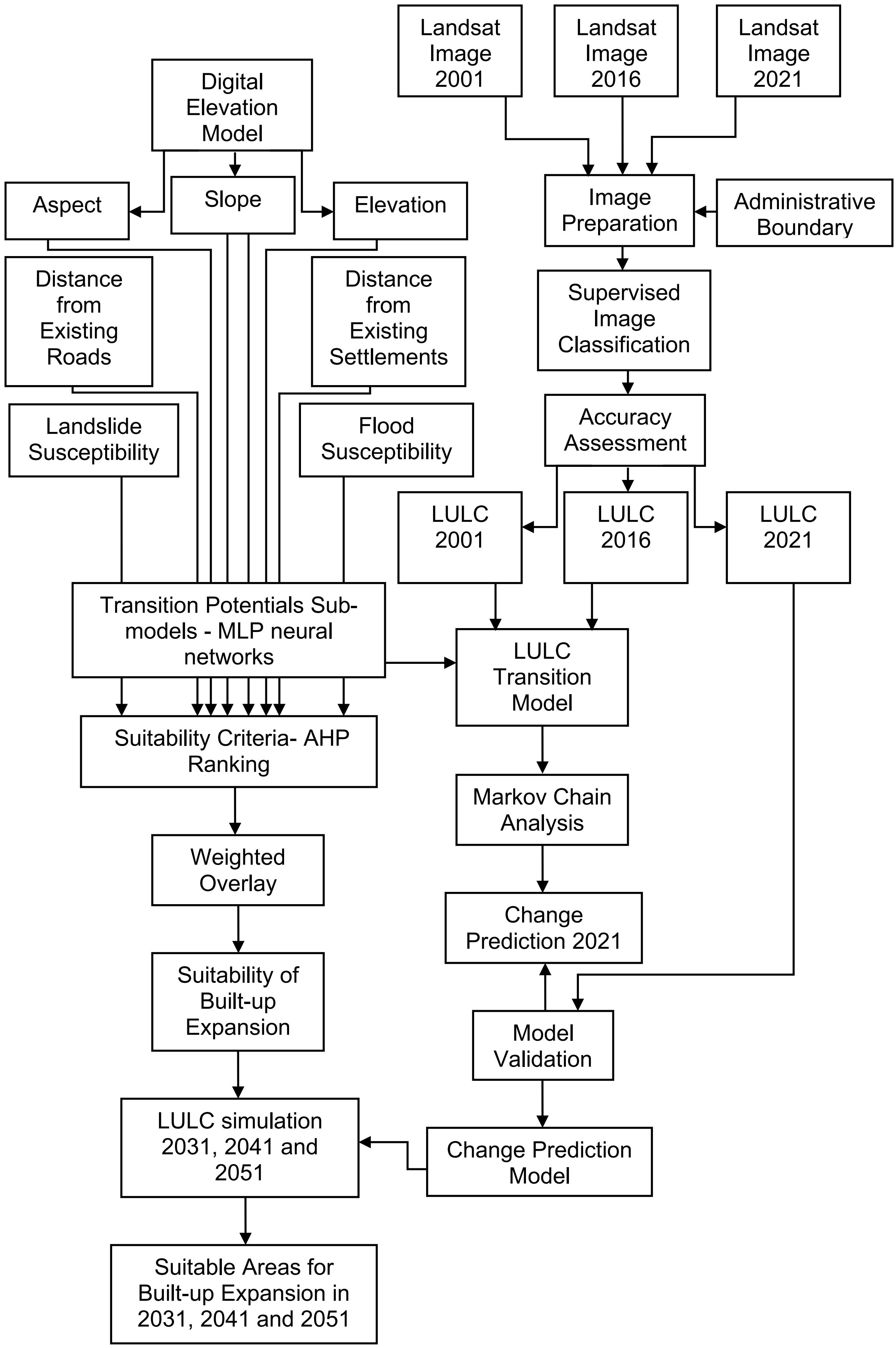


Figure 8. Flowchart of Methodology

2.2. Data

This study is based on Landsat 7 and Landsat 8 imagery as main dataset freely available at USGS website. Other data include slope, aspect and elevation derived from SRTM DEM which is also freely available through the aforementioned website. Finally, administrative boundary of Kamalamai Municipality, road network, existing settlement points, land slide susceptibility, flood susceptibility data were available from Department of Urban Development and Building Construction municipal database while google imagery was used for assistance in image classification and accuracy assessment.

2.2.1. Landsat 7 and Landsat 8 Imagery

The Landsat 7 and Landsat 8 Imagery was downloaded from Earth Explorer provided by USGS Landsat mission. The image acquisition dates and bands specification is presented in Table 1 and 2.

Table 1. Landsat 7 Images Specification (USGS, 2021)

Landsat 7		
Acquisition Date: 18-01-2001		
Bands	**Wavelength (μm)**	**Resolution (m)**
Band 1 – Blue	0.45-0.52	30
Band 2 – Green	0.52-0.60	30
Band 3 – Red	0.60-0.69	30
Band 4 – Near Infrared (NIR)	0.77-0.90	30
Band 5 – Short Wave 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	.52-.90	15

Landsat 7 images Enhanced Thematic Mapper Plus (ETM+) was launched in April 15, 1999, it consists of 8 spectral bands having a spatial resolution of 30 m for bands 1 to 7 and 15m for band 8 and the scene size is 170 Km north-south and 183 Km east-west, it orbits in a sun-synchronous and near polar orbit at an altitude of 705 Km, inclined at 98.2

degrees while circling around the earth every 99 minutes with a 16 day repeat cycle (USGS, 2021).

Table 2. Landsat 8 Images Specifications (USGS, 2021)

Landsat 8		
Acquisition Dates: -01-2016		
00-01-2021		
Bands	Wavelength (μm)	Resolution (m)
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 – 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 Sensor (TIRS) 1	10.6-11.19	100
Band 11 – TIRS 2	11.50-12.51	100

Landsat 8 with Operational Land Imager (OLI) and TIRS instruments was launched in February 11, 2013, it consists of 8 spectral bands having a spatial resolution of 30 m for bands 1 to 9 and 15m for band 8 and the scene size is 185 Km north-south and 180 Km east-west, it orbits the earth in a sun-synchronous and near-polar orbit at an altitude of 705 km with and inclination of 98.2 degrees while completing an earth orbit in 99 minutes and repeating cycle every 16 days (USGS, 2016).

The Level 2 output products are enhanced products available for free download along with level 1 products for the same imagery. Level 2 images don’t contain the panchromatic band but other bands are available for analysis. Panchromatic band if required can be downloaded from the package of level 1 image with same name. The level 2 products are corrected and made available for the download by USGS as illustrated in Table 3.

Table 3. Level-2A Surface Reflectance Products. Adapted from: (Vuolo, Mattiuzzi and Atzberger, 2015)

	Level-1 input data	Atmospheric correction approach	Output surface reflectance Level-2 products	Key features of the two datasets
Landsat CDR	• **Landsat TM/ETM+** Level-1T • 30m pixel size • 6 spectral bands (bands 1-5 and 7)	**LEDAPS** (automatic atmospheric correction for Landsat 4-5 TM for data from August 1982 to May 2012 and Landsat 7 ETM+ scenes acquired from 1999) Algorithm based on 65 and use of Dense Dark Vegetation targets	**Data set 1** "Landsat CDR" No. of scenes (2010-2014): • Landsat 5 TM: 41 • Landsat 7 ETM+: 121 Data source: Data were obtained through the USGS-ESPA On Demand Interface	• Ready-to-use surface reflectance product • Globally available • Free of charge • Accuracy might depend on the quality and quality of DDV targets present in each scene • Limited to Landsat data (it will include Landsat 8 from 2015)
Landsat BOKU	• **Landsat TM/ETM+/OLI** Level-1T • 30m pixel size • **DEIMOS-1** • 22m pixel size • 3 spectral bands equivalent to Landsat TM/ETM+ bands 2-4	**ATCOR- 2** (commercial software package for atmospheric correction of most of the multi-spectral data available from satellite sensors) Algorithm based on MODTRAN version 4 with manual fine tuning of model atmospheric parameters	**Data set 2** "Landsat BOKU" No. of scenes (2010,2012-2014): • Landsat 5 TM: 4 • Landsat 7 ETM+: 6 • Landsat 8 OLI: 11 • DEIMOS-1: 18 Data source: Images were processed within an operational crop monitoring project and made available for this work	• The correction procedure is well-established and used in an operational context • Require dedicated software and high technical skills • Not suitable for global data processing • Can incorporate site-specific data to improve accuracy • Can be applied to almost any satellite sensor data

2.2.2. Digital Elevation Model (DEM)

The Digital Elevation, SRTM model was used for the study. The freely available enhanced void filled elevation model with 1 arc-second, 30m resolution was downloaded from USGS website. The DEM is used in deriving slope and aspect of the study area using ArcGIS pro tool. The specification of DEM is presented in Table 4.

Table 4. Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) Specifications

Projection	Geographic
Horizontal Datum	WGS84
Vertical Datum	ECM96 (Earth Gravitational Model 1996)
Vertical Units	Meters
Spatial Resolution	30 Meters
Raster Size	1-degree tiles
C-band Wavelength	5.6cm

Source: USGS, Earth Explorer-SRTM

2.3. Method

The purpose of the study is to identify the suitable areas for built-up expansion in Kamalamai Municipality, Sindhuli district, Nepal using suitability analysis, transition sub-models and LULC change simulation. Landsat 7 image of 2001 and Landsat 8 images of 2016 and 2021 were used for Image classification to derive LULC. DEM was used to derive slope, aspect and elevation maps. Suitability analysis was used to identify suitable areas for built-up expansion in the municipality. The verified change model along with suitability map was used to identify suitable areas for built-up expansion in Kamalamai Municipality for 2031, 2041 and 2051. The methodology of the study is shown in Figure 9.

2.3.1. Image Preprocessing

Typical image processing uses radiometric pre-processing, to adjust digital values for the effect of atmosphere and geometric pre-processing, to bring an image into registration with another image or a map (Campbell, 2002). The ready to use surface reflectance level 2 was used as the primary imagery for the study which are corrected for operational procedure. The process is shown in Figure 9.

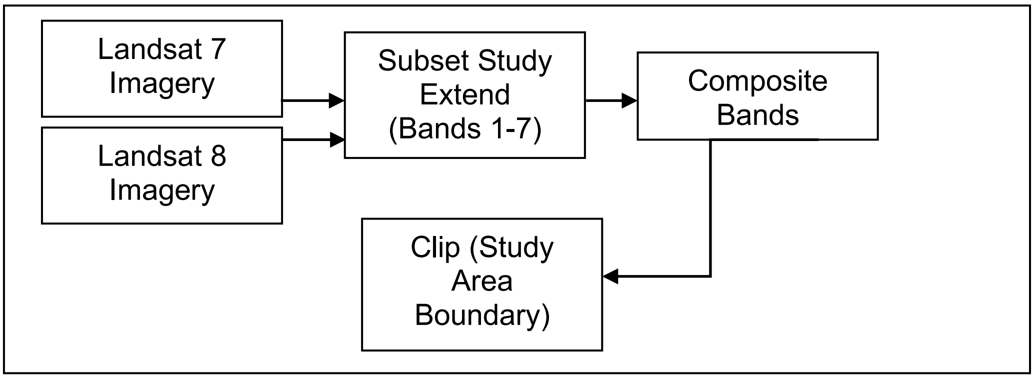


Figure 9. Image Processing Flow Chart

2.3.3. Land Use Land Cover (LULC) Classification

The LULC was derived from Landsat 7 and Landsat 8 images using supervised image classification technique. The LULC classification process is illustrated in Figure 10.

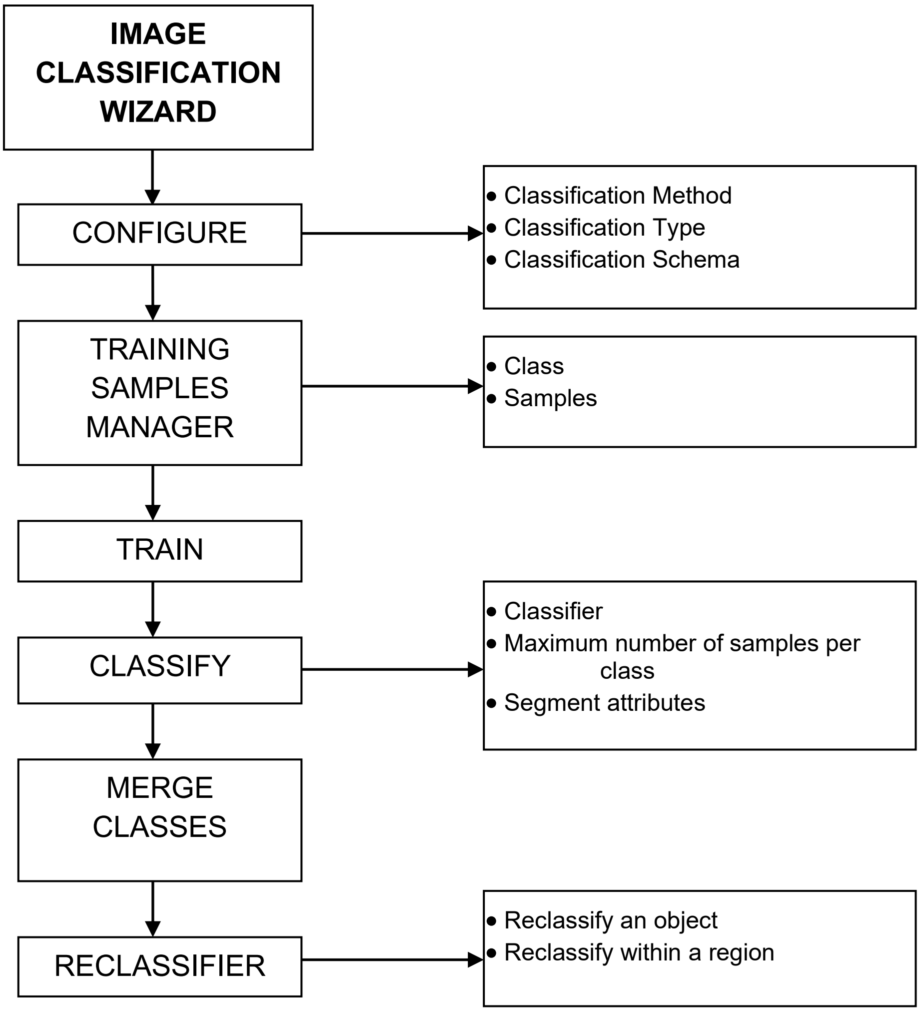


Figure 10. LULC Classification in Classification Wizard

ArcGIS Pro software was used for the LULC classification. The Classification wizard raster tool is a follow through classification provided by ArcGIS pro. The first step in classification is to configure the method to be used for classification whether supervised, unsupervised or object-based technique. The supervised technique is used for this assignment. The second step is to train samples for different LULC classes, the trained samples are then used to classify LULC. The merge class is used to merge any two classes to one if required and finally reclassify tool is used to reclassify any mis classified pixels to desired class.

2.3.4. Accuracy Assessment

Accuracy assessment in mapping projects related to RS data is an integral part of the study (Lunetta and Lyon, 2004). Classification error is when pixels belonging to one category and assigned to another category (Campbell, 2002). The classification errors can result from image quality, mapping units which can be quantified using accuracy assessment to know the quantified error of result (Lahoti et al., 2019). The standard form of assessing accuracy errors is error matrix/ confusion matrix which identifies overall errors for each category as well as errors misclassified by category (Campbell, 2002).

User’s accuracy is computed as number of correct pixels category to total number of pixels classified to specific category which is percentage of right classification for all categories while producer’s accuracy is the number of pixels correctly classified in specific category as percentage of total number of pixels actually belonging to that category (Schuckman and Dunne, 2020). Kappa coefficient is measured as the difference between the observed agreement two maps that are observed by the diagonal entries in error matrix as well as the agreement that might by attained by chance matching of two maps (Campbell, 2002).

The equations determining accuracy of classification are presented using equations (Eq. (5)-(8)) (Lahoti et al., 2019).

$$\text{User's Accuracy in class i} = \frac{n_{ij}}{n_{i.}} \quad \text{.............. (Eq. 5)}$$

$$\text{Producer's Accuracy in class j} = \frac{n_{ij}}{n_{.j}} \quad \text{.............. (Eq. 6)}$$

$$\text{Overall Accuracy} = \frac{\Sigma\, k\^{}i = 1\; n_{ii}}{n} \quad \text{.............. (Eq. 7)}$$

$$\text{Kappa Coefficient} = \frac{n\, \Sigma\, k\^{}i = 1\; n_{ij} - \Sigma\, k\^{}i = 1\; n_{i.}n_{.j}}{n_2 - \Sigma\, k\^{}i = 1\; n_{i.}n_{.j}} \quad \text{.............. (Eq. 8)}$$

where *K* represents number map to be 1,2,….,*k*;

n_{ij} = number of sample units belonging to class i in reference to class j;

$n_{i.}$ = sum of elements in row;

$n_{.j}$ = sum of elements in column;

n = total unit number of samples

Kappa coefficient can also be understood on the basis of observed and expected classification result (Eq. 9).

K is expressed as $\hat{k}$ (“k hat”):

$$\hat{k} = \frac{\text{Observed} - \text{expected}}{1 - \text{expected}} \quad \text{.............. (Eq. 9) (Campbell, 2002).}$$

2.3.5. Analytical Hierarchy Process (AHP) Method

AHP is a multi-criteria decision-making method developed by Prof. Thomas L. Saaty in 1970s which has been extensively used for pair-wise comparison since. The multi-criteria programming with AHP helps to make decisions in complex scenarios where many variables or criteria’s are considered and the prioritization of these variables are different from one another furthermore, the nature of variables are different as well in cases (Vargas, 2010). The fundamental comparison scale is presented in Table 5.

Table 5. Fundamental Comparison Scale (Source: Saaty and Vargas, 2012)

1	Equal importance	Two activities contribute equally to the objective
2	Weak	
3	Moderate importance	Experience and judgment slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very Strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation

The fundamental scale of values is used to make the judgement of paired comparison as shown in Table 5. The scale is validated for its effectiveness in many applications (Saaty and Vargas, 2012). The steps of measuring inconsistencies; consistency index (CI) and Consistency Ratio (CR) are used to improve the consistency of judgements (Saaty and Vargas, 2012). CI is given by (Eq. 10) and CR (Eq. 11)

$$CI = \frac{(\lambda max - n)}{(n - 1)} \quad \text{…………… (Eq.10)}$$

$$CR = \frac{CI}{RI} \quad \text{…………… (Eq. 11)}$$

where, Random Index (RI) is the average value of CI and CR has to be < 0.1 (Saaty and Vargas, 2012) for correct decision.

2.3.6. Weighted Overlay Analysis

Weighted overlay analysis is used as a GIS analysis procedure mostly for site selection or suitability analysis (Ade, 2015). The technique is used to apply a common measurement scale of values to diverse and unsimilar inputs to achieve an integrated analysis (ESRI,

2020) and is an effective method for multi criteria decision making (Kaliraj, Chandrasekar and Magesh, 2015).

The values for each layer can be set by user based on the importance which is done by using AHP method and these factors add up to display the result. The pixel cells of each input raster is assigned with a numeric weightage based on developed common scale then these numeric weight values are combined mathematically to produce new pixel value (Kaliraj, Chandrasekar and Magesh, 2015).

2.3.7. Land Change Modeler (LCM)

Land change modeler is an application in Terr-set which is used for land conversion analysis, future change modelling, land change planning and other change analysis.

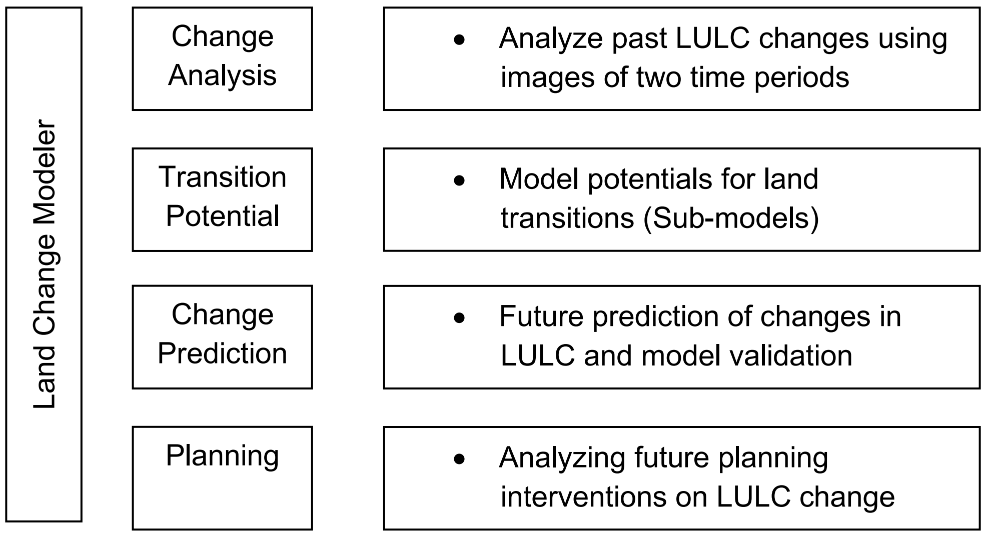


Figure 11. Land Change Modeler Interface. Adapted from: (Eastman, 2016)

The model interface is shown in Figure 11. The land change modeler provides users various application tools for the analysis of LULC change. The Change Analysis option takes into account LULC images of two dates for analysis, then the tool analyses the land cover change of these dates class wise. The analysis can be created into maps. The changes from one class to another can be analysed in this section. The transition potential tab is used to analyse changes from each class to another class using sub-models, which are validated using transition variables like distance from roads, settlements, and accuracy is determined within useable limits.

The change prediction section uses all the sub-models of change created in transition section and analyses the future LULC as for the user defined date. The section has validation option to check the model using actual LULC map which gives, hits, misses and false alarm of predicted image. Planning section provides analysis of constraints and incentives which can be used for defining areas that can be changed and areas which cannot be changed. The REDD project was not used in this study.

2.4. Software Used

ArcGIS Pro software was used for pre-processing of satellite image, LULC classification, weighted analysis, generating elevation, slope and aspect layers, and other geographic analysis as well as map creation. Terr-set LCM was used for change analysis, transition potential creation, change analysis and LULC planning in suitable areas. Microsoft Word 2016 was used for preparing the report, creating tables and flowcharts in the report. Microsoft Excel was used for numeric data, chart and table creation and calculating weightage based on AHP. Finally, Google Earth, Zotero and Adobe Reader were used during the study period.

2.5. Concluding remarks

The methodology described in this chapter was followed for achieving the objectives of this study. The administrative data, municipal data, DEM and satellite imagery were the primary data used. The land change model was used to predict and change for 2031, 2041 and 2051, and suitability map was used as constraint and incentive to identify suitable areas for built-up expansion area for respective years.

Chapter-3: Processes and Results

This chapter discusses the processes and results of LULC classification of the satellite images of 2001, 2016 and 2021, suitability analysis, LULC change, transition and change prediction analysis using ArcGIS Pro and Terr-Set Geospatial Monitoring and Modelling System, LCM. The chapter analyses types of transition variables for changes from other LULC classes to built-up, changes in built-up model validation and the future simulation of built-up suitable areas in Kamalamai Municipality.

3.1. Land Use Land Cover (LULC) Classification Process

The Landsat imagery with 7 bands including bands 1 to 7 were downloaded for the year 2001-landsat 7, 2016-landsat 8 and 2021-landsat 8, the images were from the month of January for all images. The images were used for the same month to diminish the climatic effects that result in different months of the year and get a consistent imagery profile for different years. The bands were composited as single image with band spectral properties using "Composite Bands" tool in ArcGIS Pro. The downloaded satellite image was covering a large area beyond the study area. The boundary of the study area was assigned using "Clip" tool over the satellite image then the area with only the study area was derived. The same process was repeated for other two satellite images. The training samples were marked as polygons for each class. The samples were collected as evenly as possible throughout the study area so to decrease discrepancy in sampled pixels.

The basic classes identified were forest, shrub, water, agricultural, barren and built-up derived from National Land Cover Dataset (NLCD, 2016). For the image of 2001 a total of 217 training samples were collected including 68 agricultural land, 13 water body, 5 shrubland, 76 forest area, 7 built-up area and 48 barren land samples with a pixel percentage of 6.31%, 0.26%, 0.25%, 91.39%, 0.20 % and 1.59%. The classification samples trained per class are shown in the figure below for satellite images of 2001 (Figure 12).

Figure 12. Training Samples 2001

For the image of 2016 a total of 260 training samples were collected including 90 agricultural land, 31 water body, 7 shrubland, 67 forest area, 20 built-up area and 45 barren land samples with a pixel percentage of 12.56%, 0.90%, 0.83%, 83.16%, 0.69 % and 1.86%. The classification samples trained per class are shown in the figure below for satellite images of 2016 (Figure 13).

Figure 13. Training Samples 2016

The image of 2021 a total of 272 training samples were collected including 97 agricultural land, 34 water body, 9 shrubland, 44 forest area, 44 built-up area and 44 barren land samples with a pixel percentage of 10.87%, 1.04%, 1.03%, 82.92%, 2.00% and 2.15%. The classification samples trained per class are shown in the figure below for satellite images of 2021 (Figure 14).

Figure 14. Training Samples, 2021

Support Vector Machine (SVM) was used for the classification with maximum number of Samples per class 500. SVMs have provided better classification results than classification methods like maximum likelihood and neural network classifiers while a very small training set can provide good classification result for Landsat Thematic Mapper (TM) images as well (Tzotsos and Argialas, 2008). After using classification tool, adjustments were done to correct the misclassified classes using Reclassify tool in ArcGIS Pro for a better classification result. Reclassification was done in image classification wizard. This step was used for increasing the accuracy of classified image by reclassifying misclassified pixels. Two edit types for reclassification were used “Reclassify an object” and “Reclassify within a region”. The reclassify an object was used on small pixels reclassification (Figure 15) and reclassify in region was used on fairly large region reclassification.

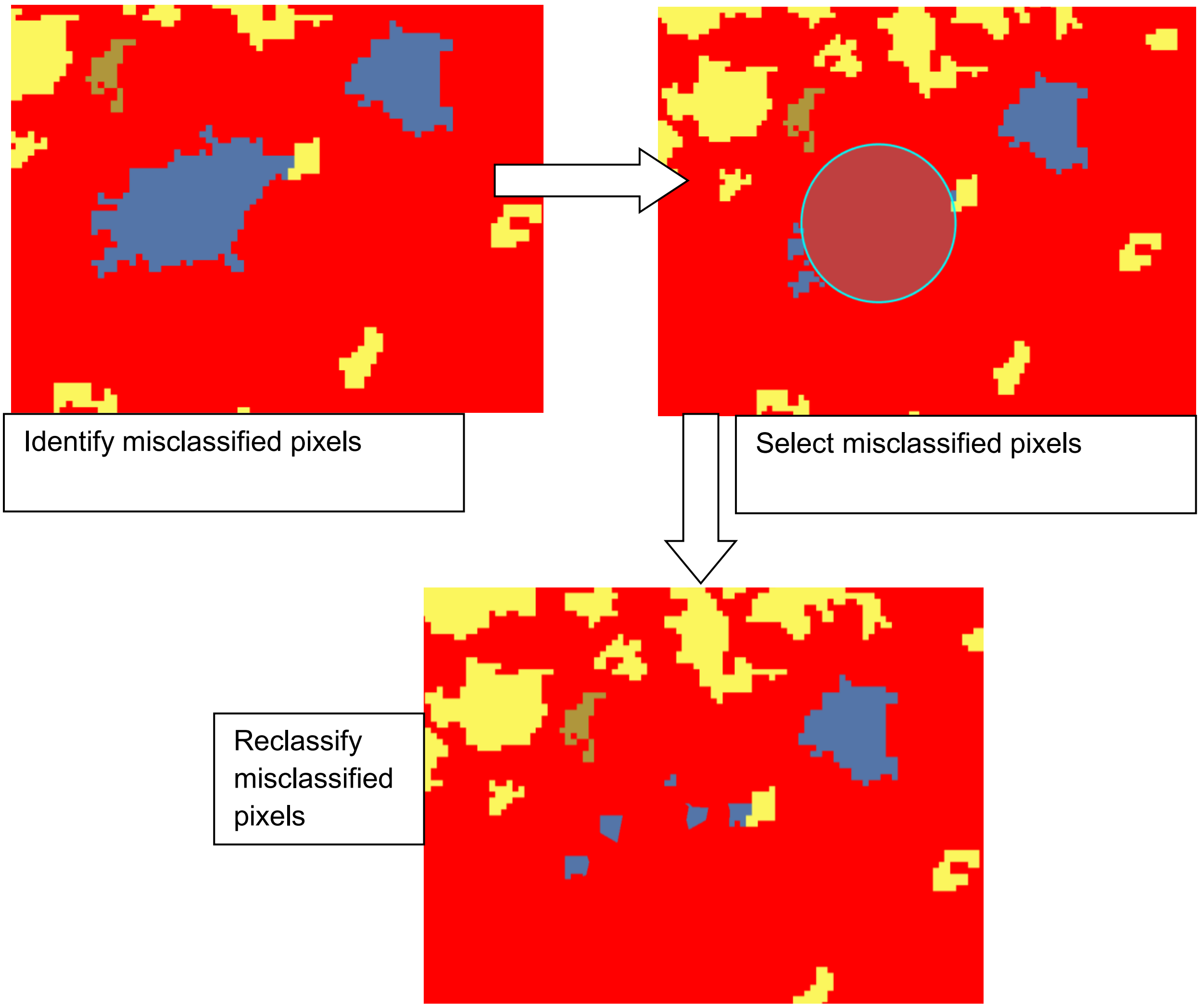


Figure 15. Reclassify Object

The method was repeated for misclassified pixels on case-by-case basis. The method for regional reclassification of pixels was used by freehand drawing polygons of misclassified areas and whole regions were reclassified to new class. The two replacement methods were used until a fairly accurate classification of misclassified pixels were reached for each imagery.

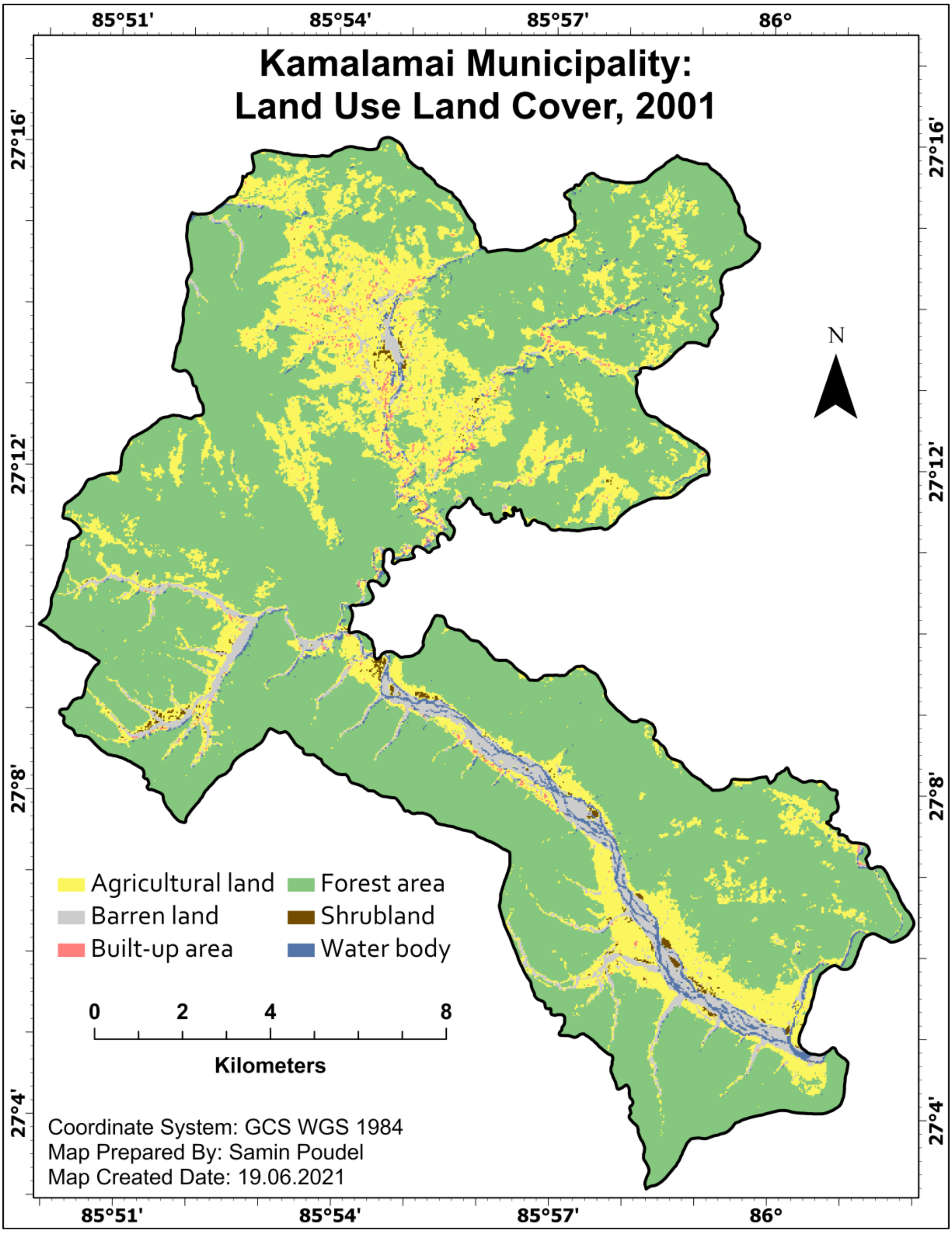
LULC were classified with six different categories; 1. Agricultural land 2. Barren land 3. Built-up area 4. Forest area 5. Shrubland and 6. Water body. The definition of each class is presented in the following Table 6. The classes were based on available land use land cover identified in the municipality satellite imagery.

Table 6. Land Use Land Cover Classification Definition

S.N.	Classes	Definition
1	Agricultural land	Areas consisting cultivated land
2	Barren land	Areas consisting bare land without any vegetation
3	Built-up area	Areas consisting buildings, roads and built-up area
4	Forest area	Areas consisting forests and trees
5	Shrubland	Areas consisting grass, shrubs and bushes
6	Water body	Areas consisting water bodies, river and ponds

3.2. Land Use Land Cover (LULC) Result

The classified LULC-2001 is shown in Map 2. Most of the area in Kamalamai Municipality is found to have forest land use followed by agricultural land use. The map shows that there are very few built-up areas in the municipality in 2001 with built-up mainly concentrated in the central part of the municipality which is the market town and very few scattered settlements. The agricultural lands were identified as mainly concentrated in the plain region of Kamalamai mostly around the built-up area and along the river banks of the municipality. The barren areas identified were river bed sands along the rivers and other barren areas.



Map 2. Kamalamai Municipality: Land Use Land Cover, 2001

The area and percentage of LULC in 2001 was calculated (Figure 16) based on the LULC map (Map 2). The municipality consisted largest area of forest with 73.1% coverage of the municipality and accounting for an area of 149.89 Km². Similarly agricultural land accounts for 20.4% of the municipality with an area of 41.93 Km². The municipality can be considered of a very rural nature in 2001 with only 0.5% built-up area accounting 1.09 Km² area. Remaining area of the municipality is covered by water bodies 1.6% with an area of 3.28 Km², barren land consisted of 4% of municipality with an area of 8.24 Km², and shrubland 0.3% with an area of 0.69 Km². The large barren area in municipality may be because of the seasonal rivers which remain dry most of the year.

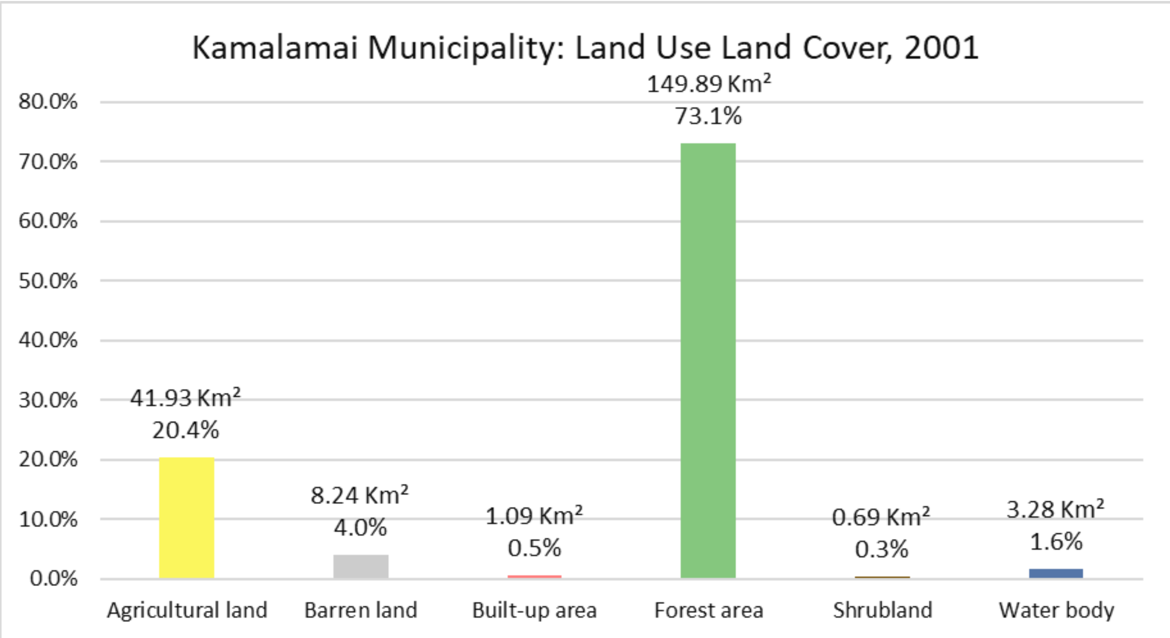
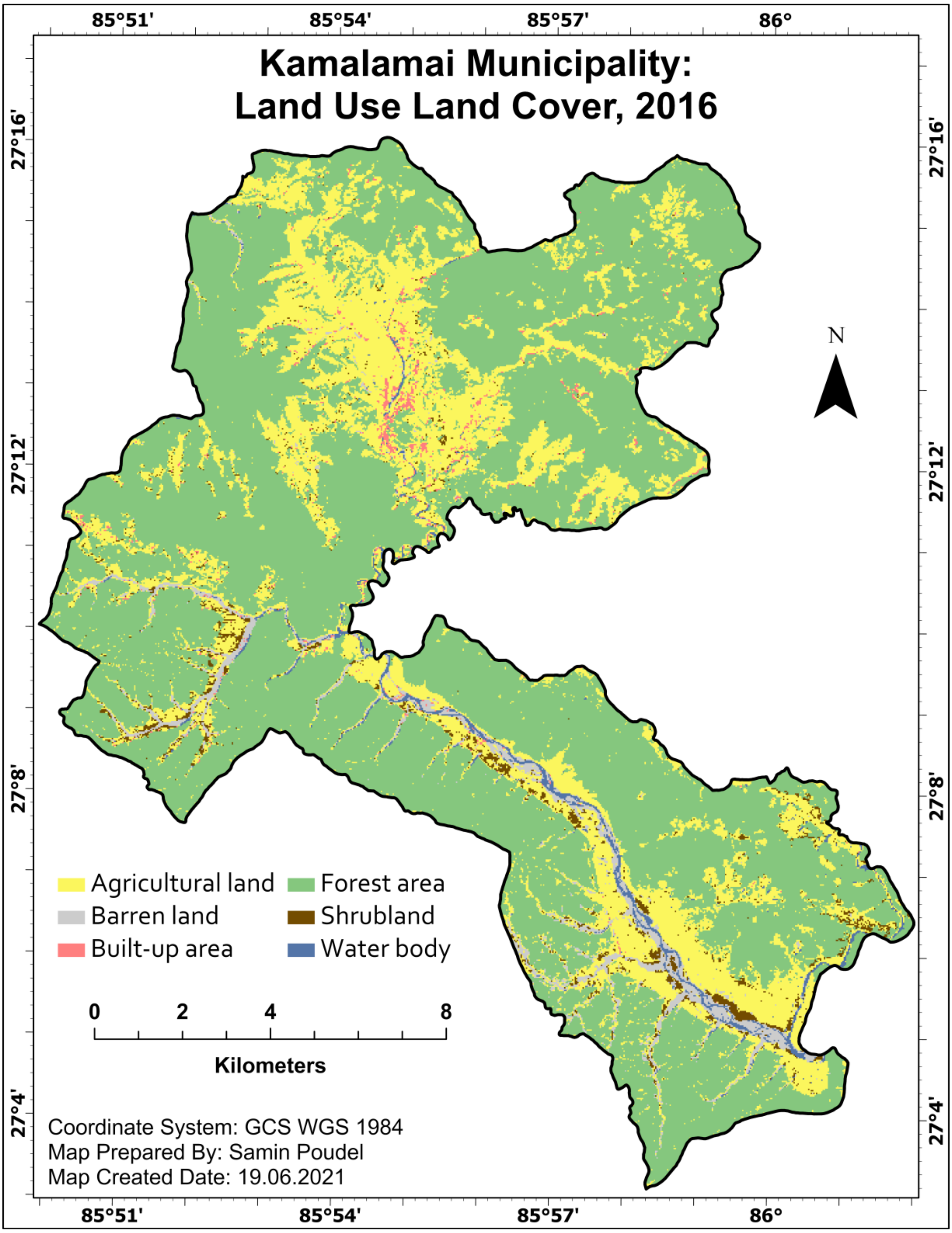


Figure 16. Kamalamai Municipality: Land Use Land Cover, 2001

The classified LULC-2016 is shown in Map 3. Most of the area in Kamalamai Municipality is found to have forest land use as in 2001 followed by agricultural land use. The map shows that the built-up areas in the municipality has increased from 2001 with expansion of built-up in the central part of the municipality and new settlements development around the municipality. There was considerable increase in Shrublands which may be because of outmigration of people from the municipality as well as change in peoples occupation out of farming, resulting in barren lands transformation from previously agricultural lands while the earthquake in 2015 may also have contributed in changing the land use land cover of the municipality.



Map 3. Kamalamai Municipality: Land Use Land Cover, 2016

The area and percentage of LULC in 2016 was calculated (Figure 17) based on the LULC map (Map 3). The municipality still consisted largest area of forest with 70.1% accounting for an area of 143.81 Km² similarly agricultural area accounts for 23.7% of the municipality with an area of 48.51 Km². The forest area has decreased and agriculture areas have increased from 2001. The municipality has increased built-up from 2001 with 0.8% built-up area accounting 1.64 Km² area.

Remaining area of the municipality is covered by water bodies 1.1% with an area of 2.29 Km², barren land 2.7% with an area of 5.46 Km², and shrubland 1.7% with an area of 3.4 Km². The barren and water areas may have changed because of the seasonal rivers flow change, similarly the shrubland has increased which may be because of forest areas degradation and river flow change. The built-up has not increased much which may be because of the earthquake in Nepal.

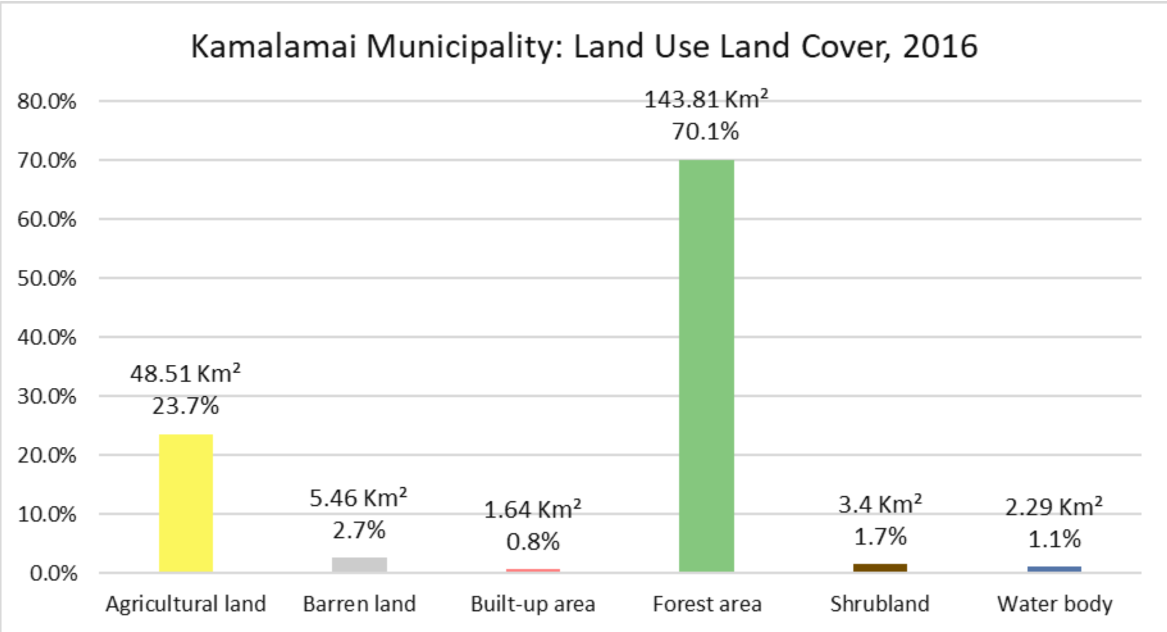
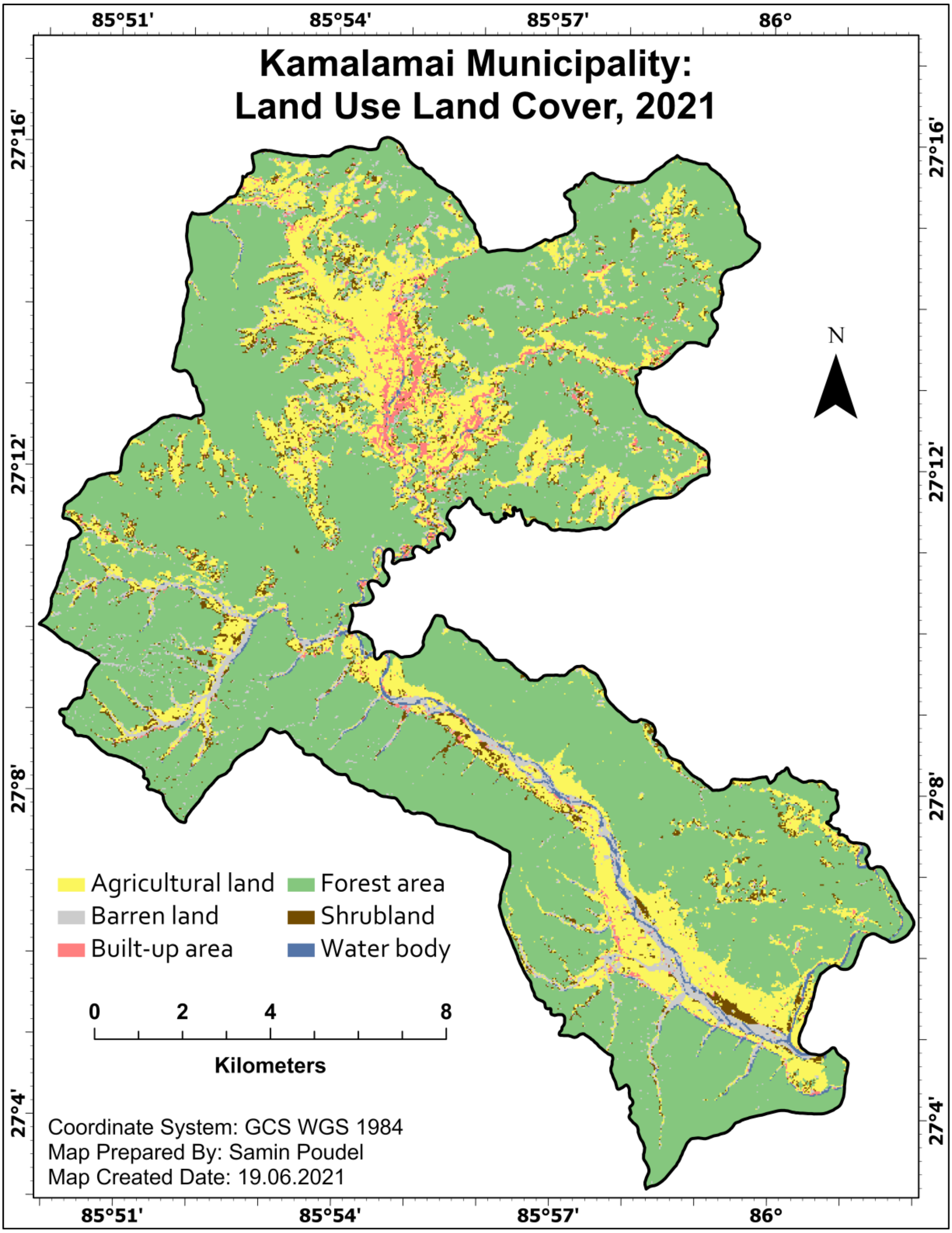


Figure 17. Kamalamai Municipality: Land Use Land Cover, 2016

The classified LULC-2021 is shown in Map 4. Most of the area in Kamalamai Municipality is found to have forest land use as in 2016 followed by agricultural land use. The map shows that the built-up areas in the municipality has increased considerably from 2016 with expansion of built-up expansion in the central part of the municipality. The built-up increase in the central market town of the municipality has been considerable for the year 2021.



Map 4. Land Use Land Cover of Kamalamai Municipality, 2021

The area and percentage of LULC in 2021 was calculated (Figure 18) based on the LULC map (Map 4). The municipality still consisted largest area of forest with 70.9% accounting for an area of 145.46 Km² which increased from 2016 while agricultural area decreased from 2016 accounting for 17.3% of the municipality with an area of 35.40 Km². The municipality has increased built-up considerably from 2016 with 1.9% built-up area accounting 3.95 Km² area, the increase in built-up may be because of new construction of buildings after earthquake in 2015 and the increase in commercial areas along the BP Highway.

Remaining area of the municipality is covered by water bodies 1.1% with an area of 2.16 Km², barren land 5.5% with an area of 11.22 Km², and shrubland 3.4% with an area of 6.93 Km². The barren and water areas may have changed because of the seasonal rivers flow change, similarly the shrubland has increased which may be because of forest areas degradation, uncultivated agricultural lands which maybe because of changing occupation of people from agricultural to other sector, and river flow changes.

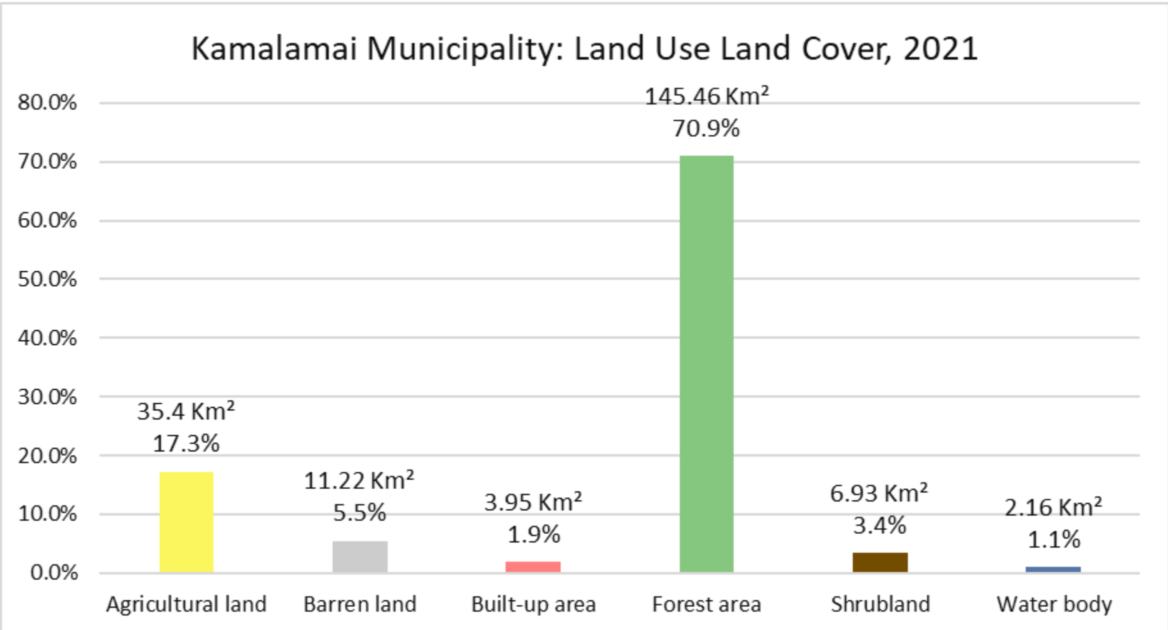


Figure 18. Kamalamai Municipality: Land Use Land Cover, 2021

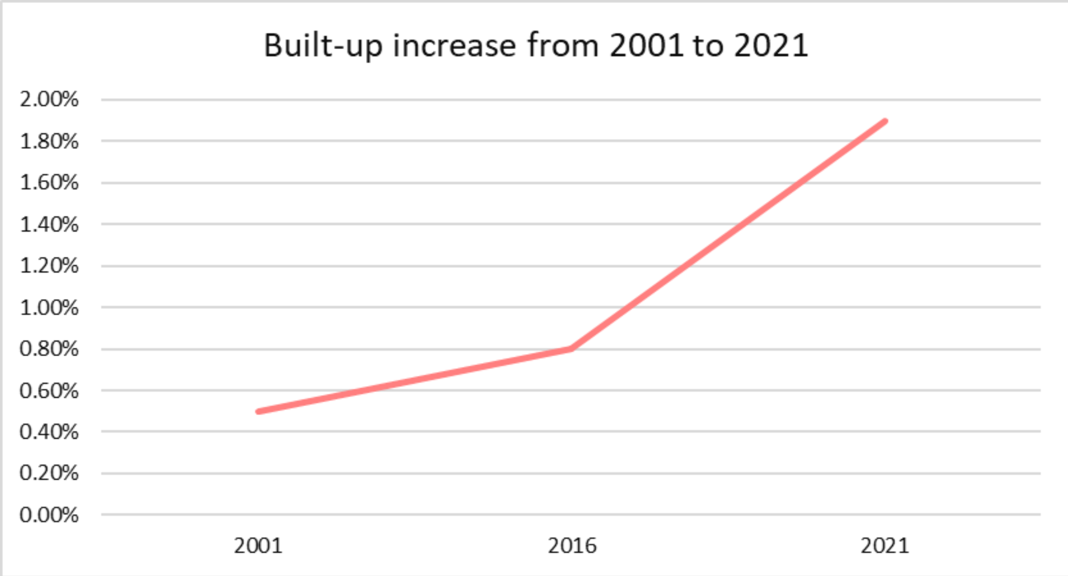


Figure 19. Kamalamai Municipality: Built-up Change (2001-2021)

The built-up increase from 2001 to 2021 is illustrated in Figure 19.

3.3. Accuracy Assessment

The use of error matrix has been accepted as a standard descriptive reporting tool for accuracy assessment of classified image from remotely sensed imagery data (Lunetta and Lyon, 2004). The user's accuracy is considered more reliable and relevant measure of classification to the user (Rwanga and Ndambuki, 2017). The accuracy of classification is usually measured by using the confusion matrix. The "Create Accuracy Points" for each LULC image of 2001, 2016 and 2021, and was used to create accuracy points over the classified image. "Stratified Random" point overlay method was used for creating the points.

The attributes table consisted of the class in which the points were classified as a result of image classification. The classes were verified using the satellite image itself and google earth base map. The verified classes were specified as points adjacent to the classified class. The "Compute Confusion Matrix" tool was used to get an excel table of confusion matrix which included user's accuracy, producer's accuracy, overall accuracy and Kappa coefficient.

The overall accuracy for the classified image 2001 was found to be 92% as shown in (Table 7) which is an acceptable accuracy limit being more than 85% (ThiLoi, Tuan and Gupta, 2015). User's accuracy ranged from 100% to 40% with highest accuracy for Shrubland and lowest accuracy for built class, while producer's accuracy ranged from 100% to 63% with highest accuracy for water, and built-up and lowest accuracy for Shrubland class. The overall Kappa coefficient was found to be 0.92 which is considered substantial and fit to be used for further study. The accuracy assessment showed that the classification was fairly accurate for further study.

Table 7. Confusion Matrix of Image Classification, 2001

Class Value	Water body	Built-up area	Barren land	Forest area	Agricultural land	Shrubland	Total	User' s Accuracy (%)	Kappa
Water body	9	0	0	0	1	0	10	90%	0
Built-up area	0	4	0	1	3	2	10	40%	0
Barren land	0	0	18	0	1	1	20	90%	0
Forest area	0	0	0	362	3	0	365	99%	0
Agricultural land	0	0	3	1	95	3	102	93%	0
Shrubland	0	0	0	0	0	10	10	100%	0
Total	9	4	21	364	103	16	517	0%	0
Producer's Accuracy (%)	100%	100%	86%	99%	92%	63%	0%	96%	0
Kappa	0	0	0	0	0	0	0	0	0.92

(Source: Calculated from Map)

The same procedure was repeated for the accuracy assessment of the classified image of 2016. Similarly, the overall accuracy for the classified image 2016 was found to be 89% as shown in (Table 8) which is an acceptable accuracy limit being more than 85% (ThiLoi, Tuan and Gupta, 2015). User's accuracy ranged from 100% to 50% with highest accuracy for Water and lowest accuracy for built class, while producer's accuracy ranged from 97% to 64% with highest accuracy for forest and lowest accuracy for Shrubland class. The overall Kappa coefficient was found to be 0.89.

Table 8. Confusion Matrix of Image Classification, 2016

Class Value	Water body	Built-up area	Barren land	Forest area	Agricultural land	Shrub land	Total	User' s Accuracy (%)	Kappa
Water body	10	0	0	0	0	0	10	100%	0
Built-up area	2	5	1	0	2	0	10	50%	0
Barren land	0	0	12	0	1	0	13	92%	0
Forest area	0	0	0	351	0	0	351	100%	0
Agricultural land	0	1	4	10	98	5	118	83%	0
Shrubland	0	0	0	0	1	9	10	90%	0
Total	12	6	17	361	102	14	512	0%	0
Producer's Accuracy (%)	83%	83%	71%	97%	96%	64%	0%	95%	0
Kappa	0	0	0	0	0	0	0	0	0.89

(Source: Calculated from Map)

The overall accuracy for the classified image 2021 was found to be 95% as shown in (Table 9) which is an acceptable accuracy limit being more than 85% (ThiLoi, Tuan and Gupta, 2015). User's accuracy ranged from 99% to 65% with highest accuracy for forest and lowest accuracy for shrubland class, while producer's accuracy ranged from 100% to 65% with highest accuracy for water and lowest accuracy for Shrubland class. The overall Kappa coefficient was found to be 0.90.

Table 9. Confusion Matrix of Image Classification, 2021

Class Value	Water body	Built-up area	Barren land	Forest area	Agricultural land	Shrubland	Total	User' s Accuracy (%)	Kappa
Water body	8	0	0	0	1	1	10	80%	0
Built-up area	0	9	0	0	0	1	10	90%	0
Barren land	0	0	22	2	2	1	27	81%	0
Forest area	0	0	1	353	1	0	355	99%	0
Agricultural land	0	1	1	3	78	3	86	91%	0
Shrubland	0	1	0	2	3	11	17	65%	0
Total	8	11	24	360	85	17	505	0%	0
Producer's Accuracy (%)	100%	82%	92%	98%	92%	65%	0%	95%	0
Kappa	0	0	0	0	0	0	0	0	0.90

(Source: Calculated from Map)

3.4. Pairwise Comparison Matrix

The Saaty's method was used to deal with inconsistencies of the pairwise comparison matrix (ThiLoi, Tuan and Gupta, 2015). The pair wise comparison matrix was used to evaluate the alternatives with combined priority with respect to criteria and goals to achieve the weightage for suitability analysis parameters as well as LULC classes which is derived to the scale of 1 to 0. The values are assigned for every comparative matrix. The first pairwise comparison was carried out for deriving the weightage for LULC classes, Built-up, Barren, Shrubland, Agricultural, Forest and Water (Table 10).

Step 1. A1.

Table 10. Deriving Priorities for Land Use Land Cover Classes

	Built-up area	Barren land	Shrubland	Agricultural area	Forest area	Water body
Built-up area	1	2	3	5	8	9
Barren land	0.50	1	2	3	8	9
Shrubland	0.33	0.50	1	4	5	7
Agricultural area	0.20	0.33	0.25	1	4	6
Forest area	0.13	0.13	0.20	0.25	1	2
Water body	0.11	0.11	0.14	0.17	0.50	1

The product of all the rows of A1 are calculated then each product is calculated for 1/5th power. Furthermore, each product is added to find the sum of products.

Product of Columns of A1		**Power (1/5)**
= 1 * 2 * 3 * 5 * 8 * 9	= 2160	= 3.59536
0.5 * 1 * 2 * 3 * 8 * 9	+ 216	= 2.44949
0.33 * 0.5 * 1 * 4 * 5 * 7	+ 23.33	= 1.69043
0.20 * 0.33 * 0.25 * 1 * 4 * 6	+ 0.4	= 0.85837
0.13 * 0.13 * 0.20 * 0.25 * 1 * 2	+ 0.00156	= 0.34065
0.11 * 0.11 * 0.14 * 0.17 * 0.5 * 1	+ 0.00015	= 0.22972
	Sum of Product =	**9.16402**

The 1/5th of product of each row of A1 is then divided by the sum of product to get A2. A2 is the pairwise compared value for each variable but the authenticity of the paired values should be checked.

Step 2. A2. = Power (1/5)/ Sum of Product	**A2**
= 3.59536 / 9.16402	= 0.4
= 2.44949 / 9.16402	= 0.3
= 1.69043 / 9.16402	= 0.2
= 0.85837 / 9.16402	= 0.1
= 0.34065 / 9.16402	= 0.0
= 0.22972 / 9.16402	= 0.0

The consistency check is used to check the A2 values. The step first involves multiplying matrices A1 and A2.

Step 3. Consistency Check

A3. = A1 x A2 = A3

						A2	A3
1	2	3	5	8	9	x 0.392	= 2.471
0.50	1	2	3	8	9	x 0.267	= 1.636
0.33	0.50	1	4	5	7	x 0.184	= 1.184
0.20	0.33	0.25	1	4	6	x 0.093	= 0.606
0.13	0.13	0.20	0.25	1	2	x 0.037	= 0.230
0.11	0.11	0.14	0.17	0.50	1	x 0.025	= 0.158

The measurement of consistency is done first by dividing A3 by A2 then the average of divided value is calculated.

Step 4.	**A4 = A3/A2**	**A4**
	= 2.471 / 0.392	= 6.299
	= 1.636 / 0.267	= 6.122
	= 1.184 / 0.184	= 6.423
	= 0.606 / 0.093	= 6.474
	= 0.230 / 0.037	= 6.189
	= 0.158 / 0.025	= 6.339
	Average of A4	**= 6.308**

The CI is calculated first which is the average of A4 subtracted by number of variables divided by number of variables subtracted by 1.

CI = (6.308-6) / (6-1)   = 0.06161

The CR is the CI divided by random index whose value is 1.25 for 6 variables. The final value is less than 0.1 so A2 values can be used.

CR = CI / RI

= (0.06161 / 1.25)

= 0.0492< 0.1

Similarly, the pairwise comparison was also done for Suitability classes. The values are assigned for every comparative matrix (Table 11).

Step 1. A1.

Table 11. Deriving Priorities for Suitability Parameters

	Landslide	Flood	LULC	Aspect	Slope	Road	Settle-ment	Elevation
Landslide	1	1	4	5	6	7	8	9
Flood	1.00	1	4	5	6	7	8	9
LULC	0.25	0.25	1	3	4	6	7	8
Aspect	0.20	0.20	0.33	1	2	5	6	7
Slope	0.17	0.17	0.25	0.50	1	4	5	7
Road	0.14	0.14	0.17	0.20	0.25	1	1	3
Settlement	0.13	0.13	0.14	0.17	0.20	1.00	1	3
Elevation	0.11	0.11	0.13	0.14	0.14	0.33	0.33	1

The product of all the rows of A1 are calculated then each product is calculated for 1/5th power. Furthermore, each product is added to find the sum of products.

Product of Columns of A1		**Power (1/5)**
= 1 * 1 * 4 * 5 * 6 * 7 * 8 * 9	= 60480	= 3.960
1 * 1 * 4 * 5 * 6 * 7 * 8 * 9	+60480	= 3.960
0.25 * 0.25 * 1 * 3 * 4 * 6 * 7 * 8	+252	= 1.996
0.20 * 0.20 * 0.33 * 1 * 2 * 5 * 6 * 7	+5.6	= 1.240
0.17 * 0.17 * 0.25 * 0.5 * 1 * 4 * 5 * 7	+0.4861	= 0.913

0.14 * 0.14 * 0.17 * 0.20 * 0.25 * 1 * 1 * 3 +0.00051= 0.387

0.13 * 0.13 * 0.14 * 0.17 * 0.20 * 1 * 1 * 3 +0.00022= 0.349

0.11 * 0.11 * 0.13 * 0.14 * 0.14 * 0.33 * 0.33 * 1 +3.5E-06= 0.207

Sum of Product = 13.0155

The 1/5th of product of each row of A1 is then divided by the sum of product to get A2. A2 is the pairwise compared value for each variable but the authenticity of the paired values should be checked.

Step 2. A2. = Power (1/5)/ Sum of Product **A2**

= 3.960 / 13.0155	= 0.30
= 3.960 / 13.0155	= 0.30
= 1.996 / 13.0155	= 0.15
= 1.240 / 13.0155	= 0.10
= 0.913 / 13.0155	= 0.07
= 0.387 / 13.0155	= 0.03
= 0.349 / 13.0155	= 0.03
= 0.207 / 13.0155	= 0.02

The consistency check is used to check the A2 values. The step first involves multiplying matrices A1 and A2. The matrices are multiplied as arrays. The result of the array matrix is A3.

Step 3. Consistency Check

A3. = A1 x A2 = A3

								A2	A3
1	1	4	5	6	7	8	9	x 0.30	= 2.686
1.00	1	4	5	6	7	8	9	x 0.30	= 2.686
0.25	0.25	1	3	4	6	7	8	x 0.15	= 1.366
0.20	0.20	0.33	1	2	5	6	7	x 0.10	= 0.830
0.17	0.17	0.25	0.50	1	4	5	7	x 0.07	= 0.622
0.14	0.14	0.17	0.20	0.25	1	1	3	x 0.03	= 0.253
0.13	0.13	0.14	0.17	0.20	1.00	1	3	x 0.03	= 0.232
0.11	0.11	0.13	0.14	0.14	0.33	0.33	1	x 0.02	= 0.145

The measurement of consistency is done first by dividing A3 by A2 then the average of divided value is calculated. The average of A4 is used to determine the CI. The CI is calculated first which is the average of A4 subtracted by number of variables divided by number of variables subtracted by 1.

Step 4. A4 = A3/A2 **A4**

= 2.686 / 0.30	= 8.830
= 2.686 / 0.30	= 8.830
= 1.366 / 0.15	= 8.912
= 0.830 / 0.10	= 8.714
= 0.622 / 0.07	= 8.872
= 0.253 / 0.03	= 8.516
= 0.232 / 0.03	= 8.654
= 0.145 / 0.02	= 9.092
Average of A4	**= 8.80321**

(CI) = (8.80321-8) / (8-1)

= 0.11475

The CR is the CI divided by random index whose value is 1.41 for 8 variables. The final value is less than 0.1 so A2 values can be used.

CR = CI/ RI

= (0.11475 / 1.41)

= 0.08138 < 0.1

The CI for both comparison was found to be less than 0.1 thus the weight assigned are correct (Chu and Liu, 2002). The relative weights for each criterion are given below:

a. Landslide Susceptibility: 0.30
b. Flood Susceptibility: 0.30
c. LULC: 0.15
d. Aspect: 0.10
e. Slope: 0.07
f. Distance from Existing Roads: 0.03
g. Distance from Existing Settlements: 0.03
h. Elevation: 0.02

The CR for weights per LULC categories was 0.08138. The relative weights for each type of green are given below:

a. Built-up area: 0.4
d. Agricultural land: 0.1

b. Barren land: 0.3 e. Forest area: 0.0

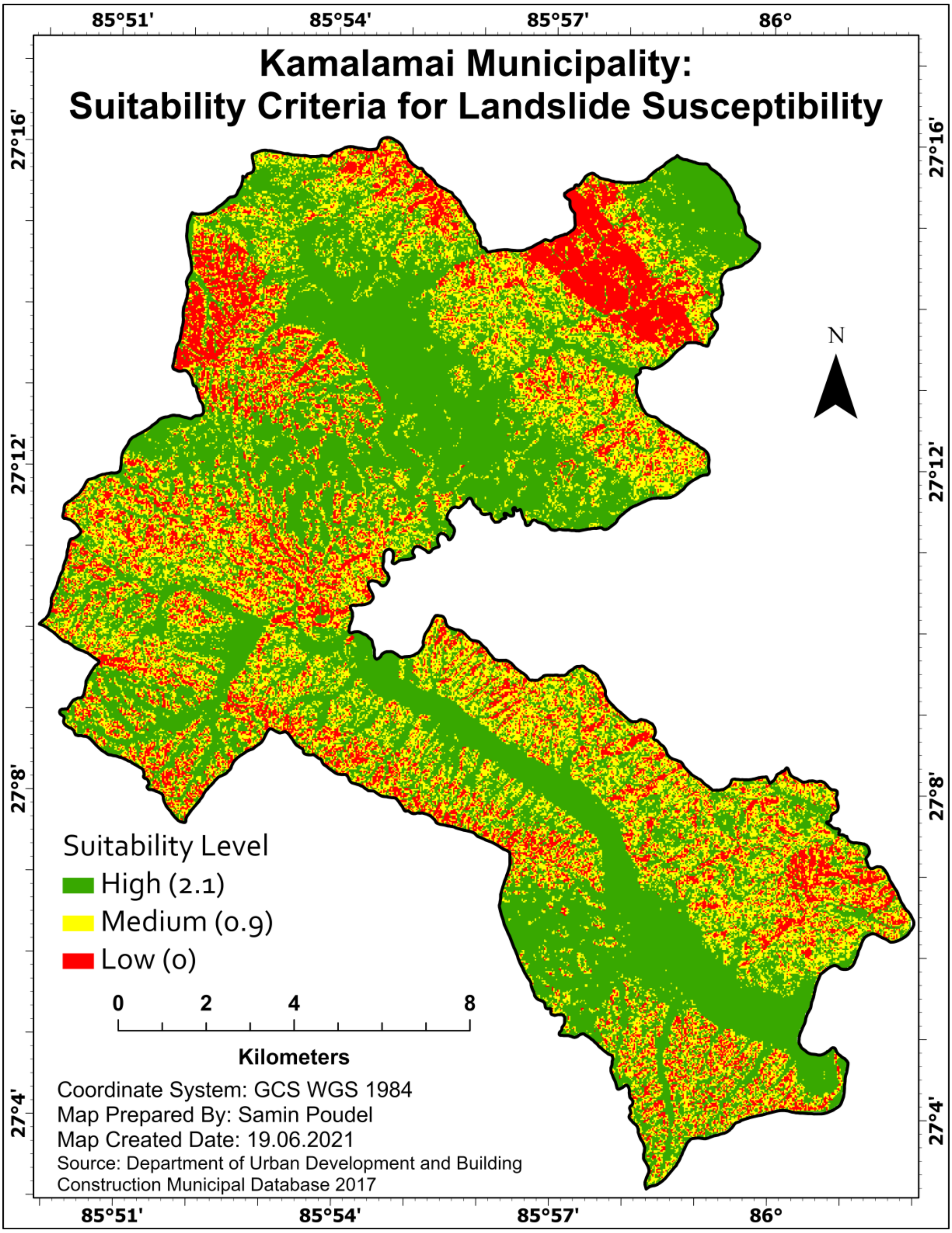
c. Shrubland: 0.2 f. Water body: 0.0

3.5. Suitability Parameters

The parameters used for suitability analysis were landslide susceptibility, flood susceptibility, existing LULC of 2021, aspect, slope, distance from existing roadway, distance from existing settlements and elevation. The data of Landslide susceptibility, flood susceptibility, roadway line and settlement points were collected from Department of Urban Development and Building Construction, Nepal and were used for further analysis. The elevation, slope and aspect were derived from DEM. The SRTM DEM single scene did not cover the whole study area so two adjacent DEM were downloaded for the study "n27_e085_1arc_v3" and "n27_e086_1arc_v3" as Tiff file.

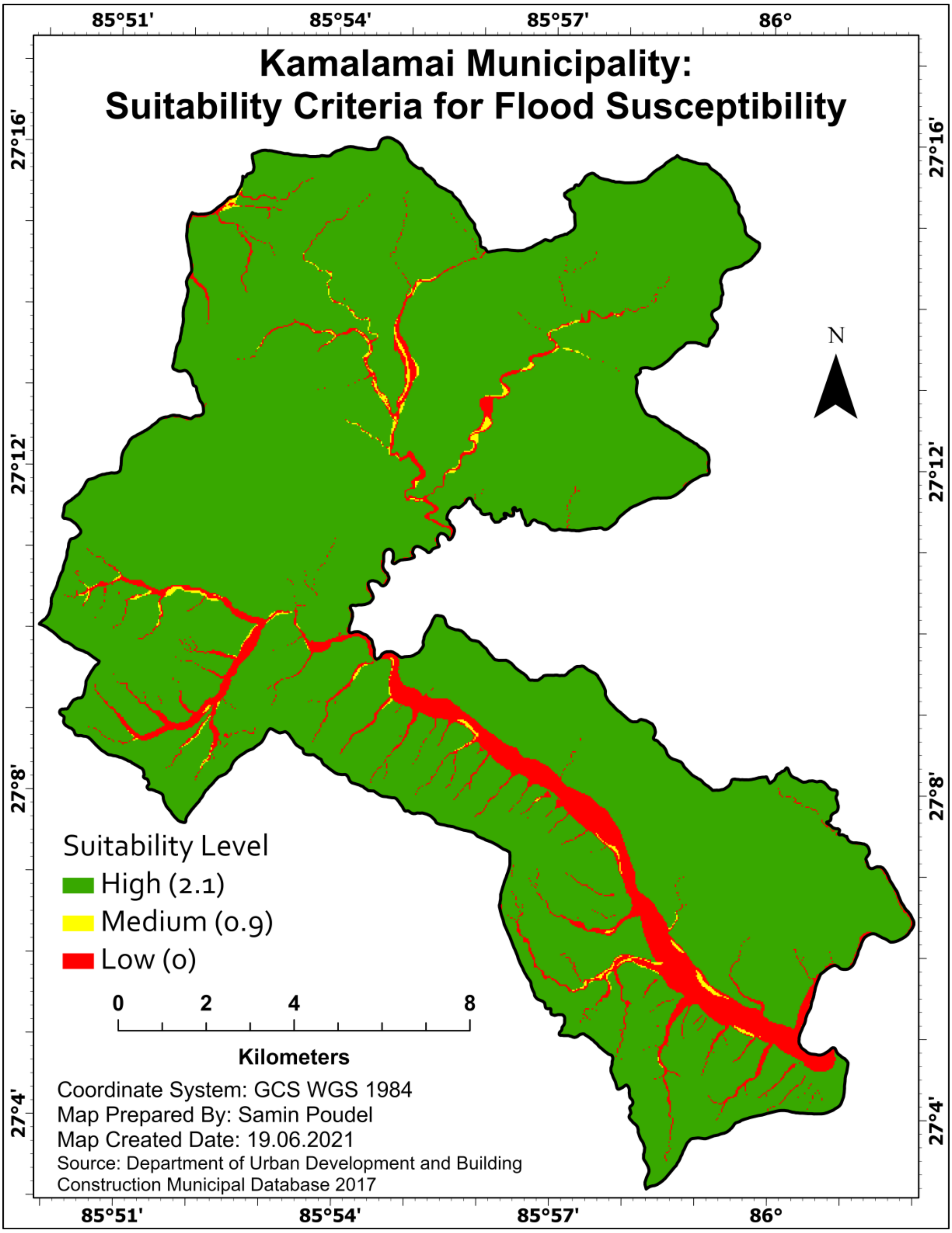
The "Mosaic Raster" tool under raster functions in data management was used to blend the two DEM Tiff files for creating elevation model with the coverage of whole study area. The DEM was then processed with "Clip Raster" tool to define and extract the DEM for study area boundary. The landslide susceptibility data indicated areas prone to landslide as highly susceptible, areas where landslide would rarely occur as medium prone areas and areas where it was unlikely to be affected by landslides as low susceptible. Similarly, the flood susceptibility data indicated places prone to flooding as high flooding areas, places near river banks as medium flooding areas and areas where flood was unlikely to occur as low susceptible area.

The LULC suitable areas for existing LULC map was categorized to classify forest areas and water bodies as unsuitable for development, while existing built-up area where infill development could still happen as suitable, similarly, agricultural areas, shrubland and barren areas as suitable areas for built-up expansion while the values were determined such that to have less impact on agricultural land. The landslide susceptible areas were categorized as low, medium and high susceptibility. The landslide susceptibility is illustrated in Map 5.



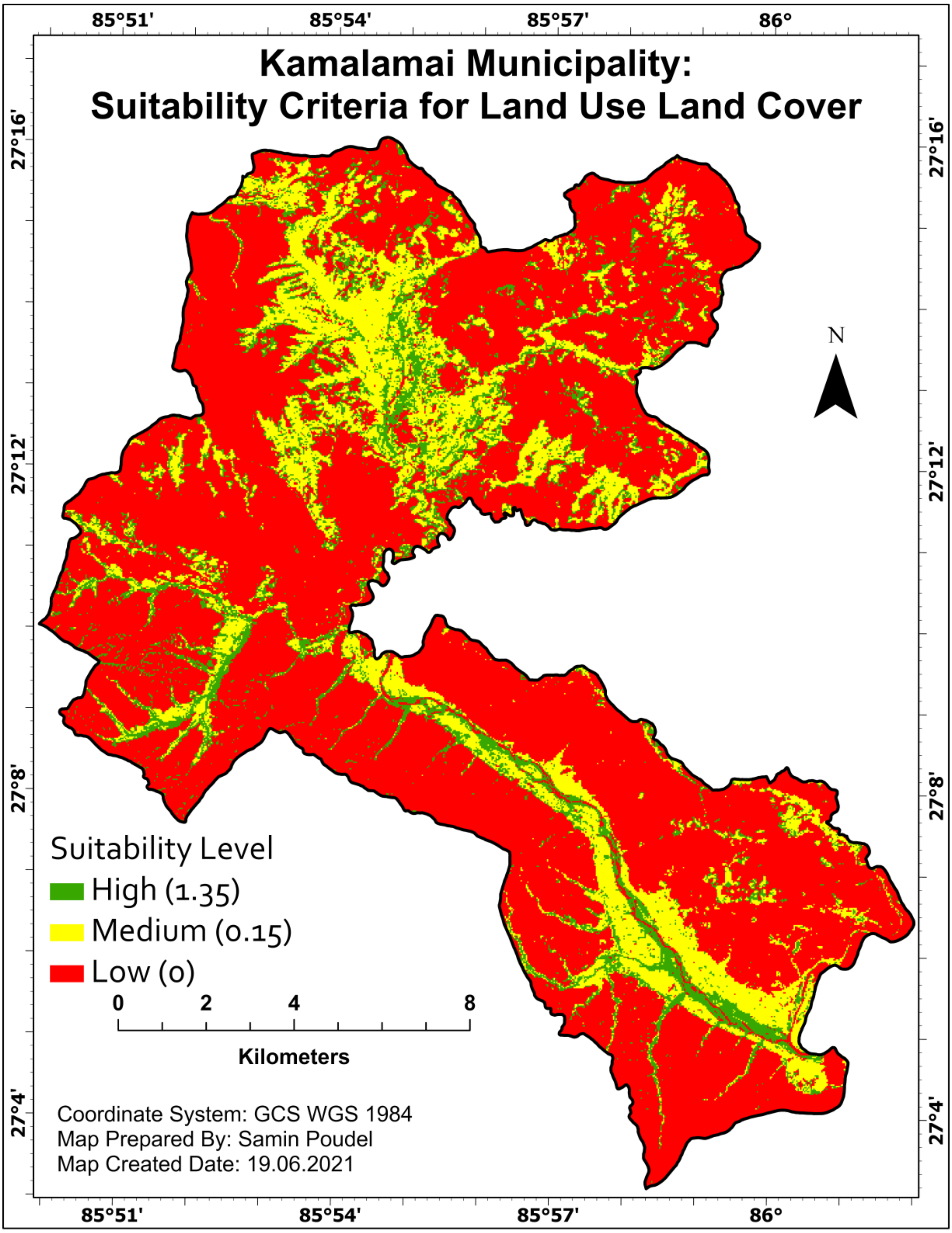
Map 5. Kamalamai Municipality: Suitability Criteria for Landslide Susceptibility

The values assigned were 2.1 for high, 0.9 for medium and 0 for low suitable landslide prone area for reclassification. The flood susceptibility is illustrated in Map 6.



Map 6. Kamalamai Municipality: Suitability Criteria for Flood Susceptibility

Similarly, the values assigned were 2.1 high, 0.9 moderate and 0 low. The values for LULC were assigned according to AHP weightage. The suitability is shown in Map 7.



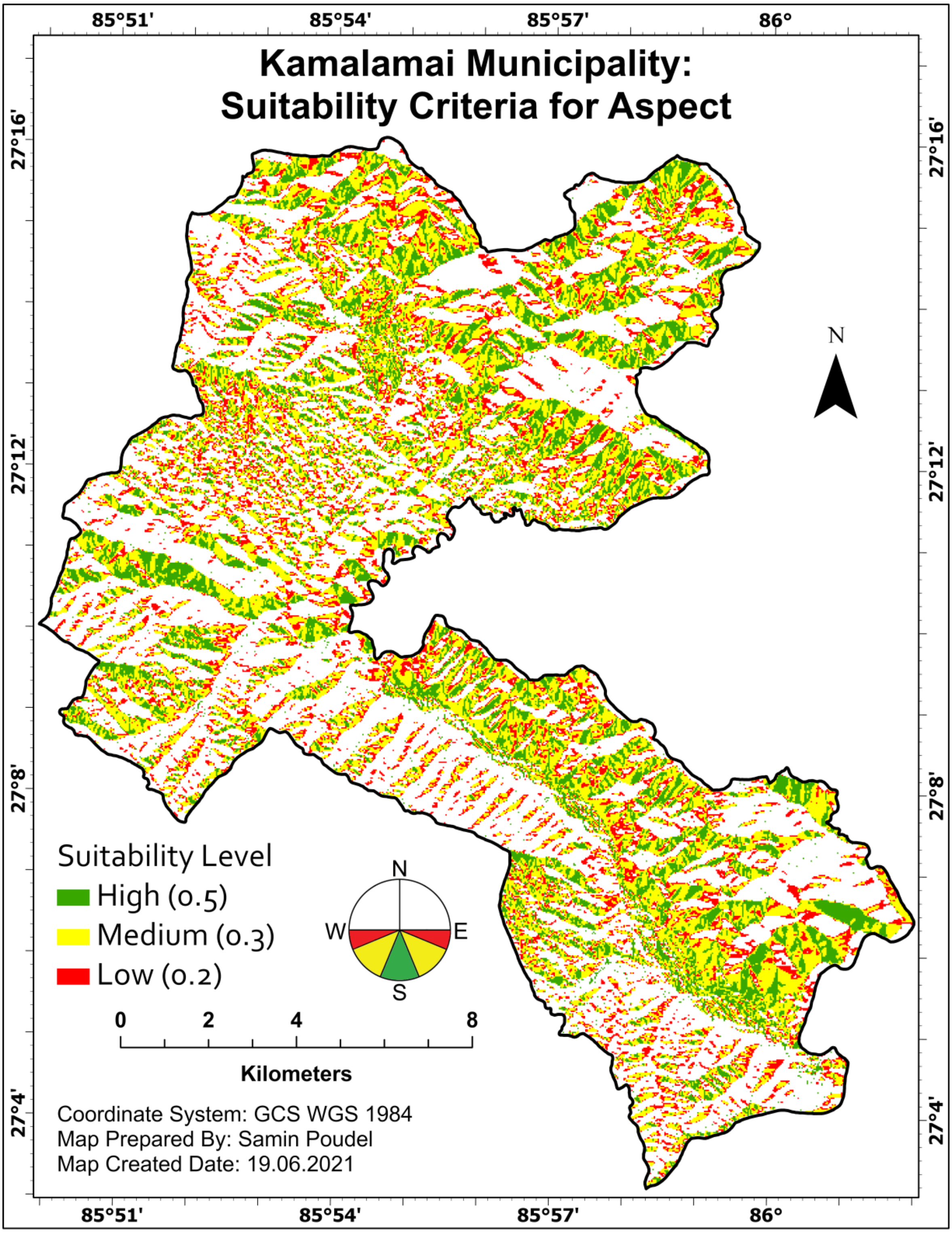
Map 7. Kamalamai Municipality: Suitability Criteria for Existing Land Use Land Cover

The suitable areas for LULC categories were identified as existing built-up area where infill built-up can be developed, similarly barren lands were identified as suitable within the non-flood zones. There were many barren areas around the river flood zones which were supposed to be eliminated from the flood susceptibility category later during suitability analysis. The values assigned were 0.4 for built-up, 0.3 for barren, 0.2 for Shrub, altogether 1.35 as high suitability, 0.15 as medium for agriculture and finally 0 values were assigned for forest and water as not favourable for built-up development.

The Slope and Aspect maps were derived from the elevation map in ArcGIS Pro using "Slope" and "Aspect" tool. The values of these variables were as well set from 0 to 1, 0 being least suitable and 1 highly suitable. Slope is an important criteria for development site suitability as steeper slopes means an increase in cost for development (Santosh, Krishnaiah and Deshbhandari, 2018). The geography of Nepal is comprised of rugged hilly terrain with high sloped areas so site suitable areas are categorised as most suitable for less slope area and not suitable for very high slopes.

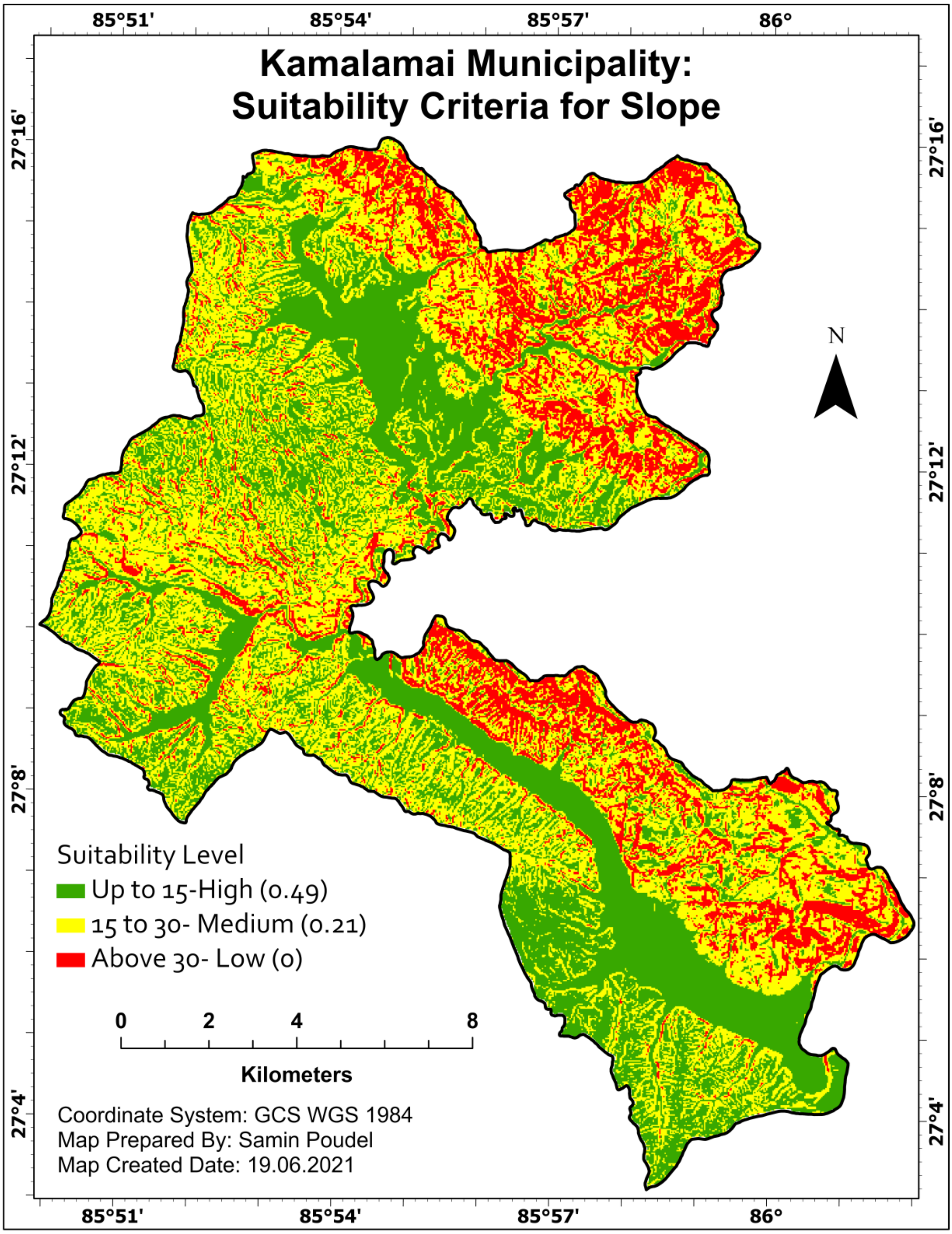
Aspect in also an important variable in hilly areas. The aspect map indicates the direction of hill slopes which are derived as compass direction, in northern hemisphere, northern slopes receive less sunlight because of the angular movement of sun while the southern slopes receive more amount of sunlight (Santosh, Krishnaiah and Deshbhandari, 2018). Elevation has less significant directly on built-up development elevation often plays a factor in development of agriculture and encourage movement of people thus encouraging development areas are suitable for agriculture. The higher elevation areas are important for horticulture, medicinal plantation is to be preserved.

Similarly, the distance from existing roadway and distance from existing settlements determine existing infrastructures which are cost effective and decreases the demand for new development. The proximity to existing infrastructures also ensures that most of the facilities such as market access and shops are also already available for the new development. The proximity to infrastructures is more relevant in poor countries like Nepal where infrastructure funds are scarce. The aspect of the study area is illustrated in Map 8.



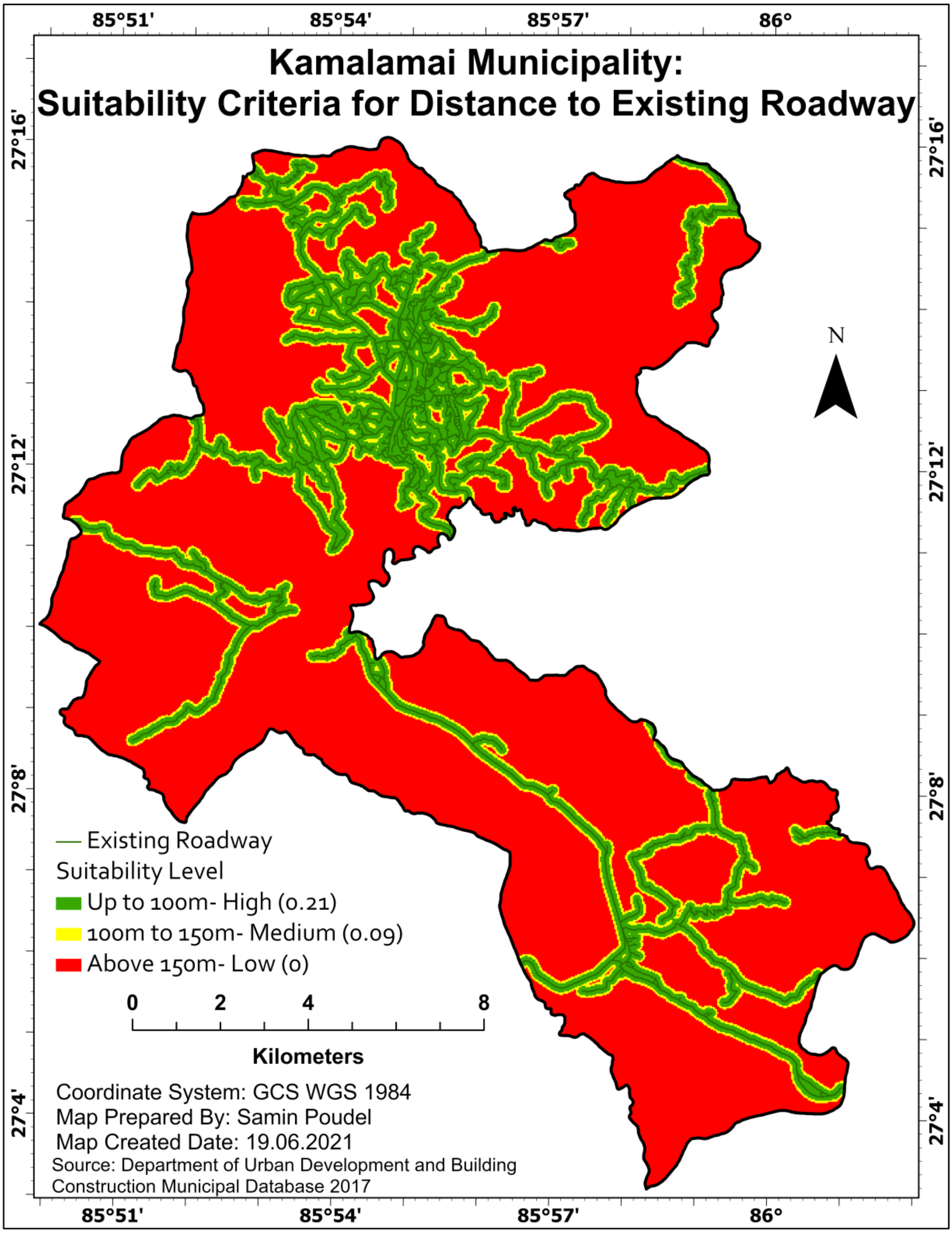
Map 8. Kamalamai Municipality: Suitability Criteria for Aspect

The slope was assigned such that higher slopes more than 30˚ were least favourable and lower slopes 15˚ to 20˚ as medium and less than 15˚ as favourable (Map 9).



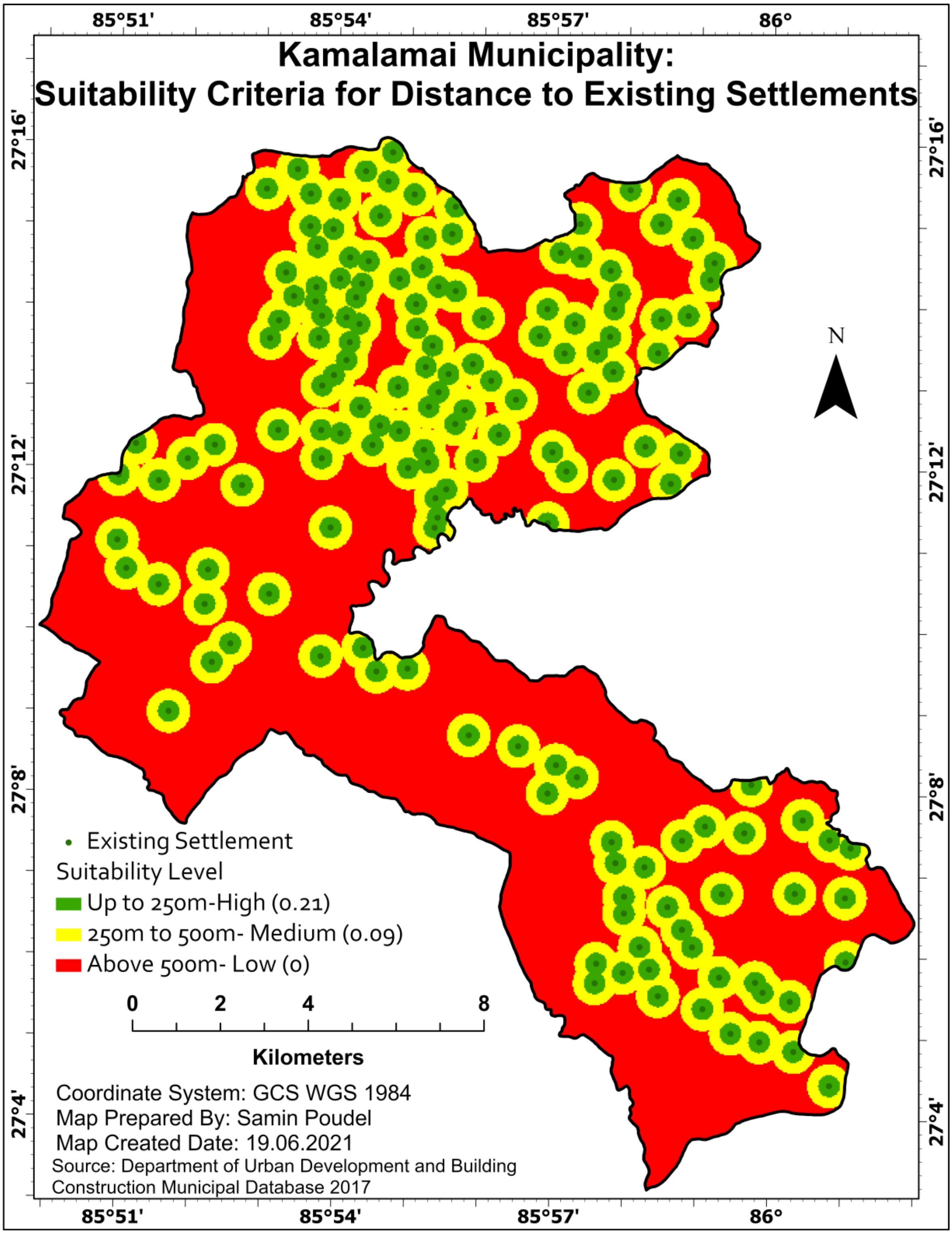
Map 9. Kamalamai Municipality: Suitability Criteria for Slope

The existing roads were multi-buffered in ArcGIS Pro to produce distance to existing roadway map (Map 10).



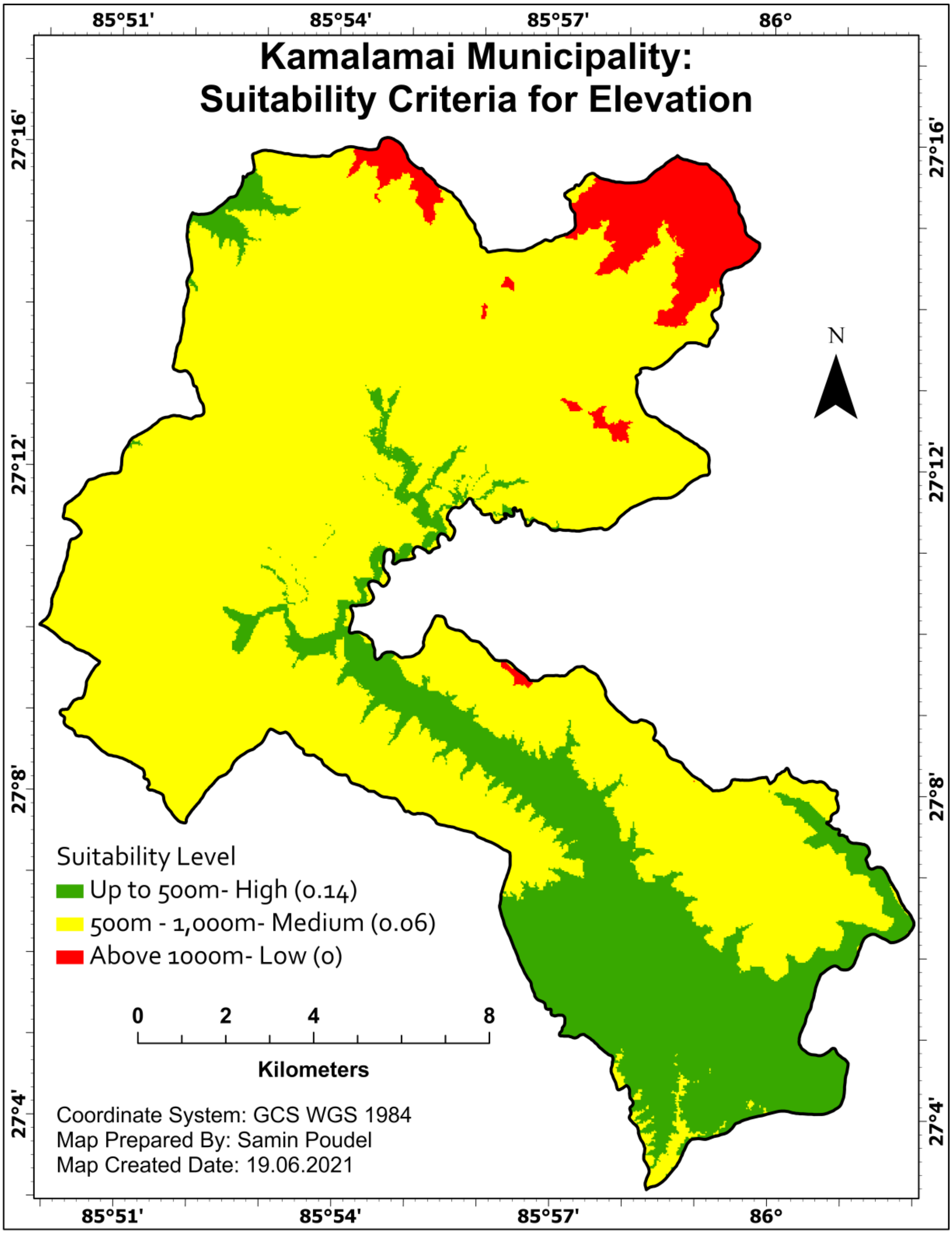
Map 10. Kamalamai Municipality: Suitability Criteria for Distance to Existing Roadway

The distance less than 100m of roadway was assigned value of 0.21, 100m to 150m as 0.09, and more than 150m as 0.



Map 11. Kamalamai Municipality: Suitability Criteria for Distance to Existing Settlements

The settlement areas were multi-buffered as less than 250m as highly suitable, 250m to 500m as medium suitable and more than 500 was least suitable (Map 11).



Map 12. Kamalamai Municipality: Suitability Criteria for Elevation

The elevation of less than 500m was assigned as highest suitable, 500m to 1000m as Medium suitable and more than 1000m was assigned as least suitable (Map 12).

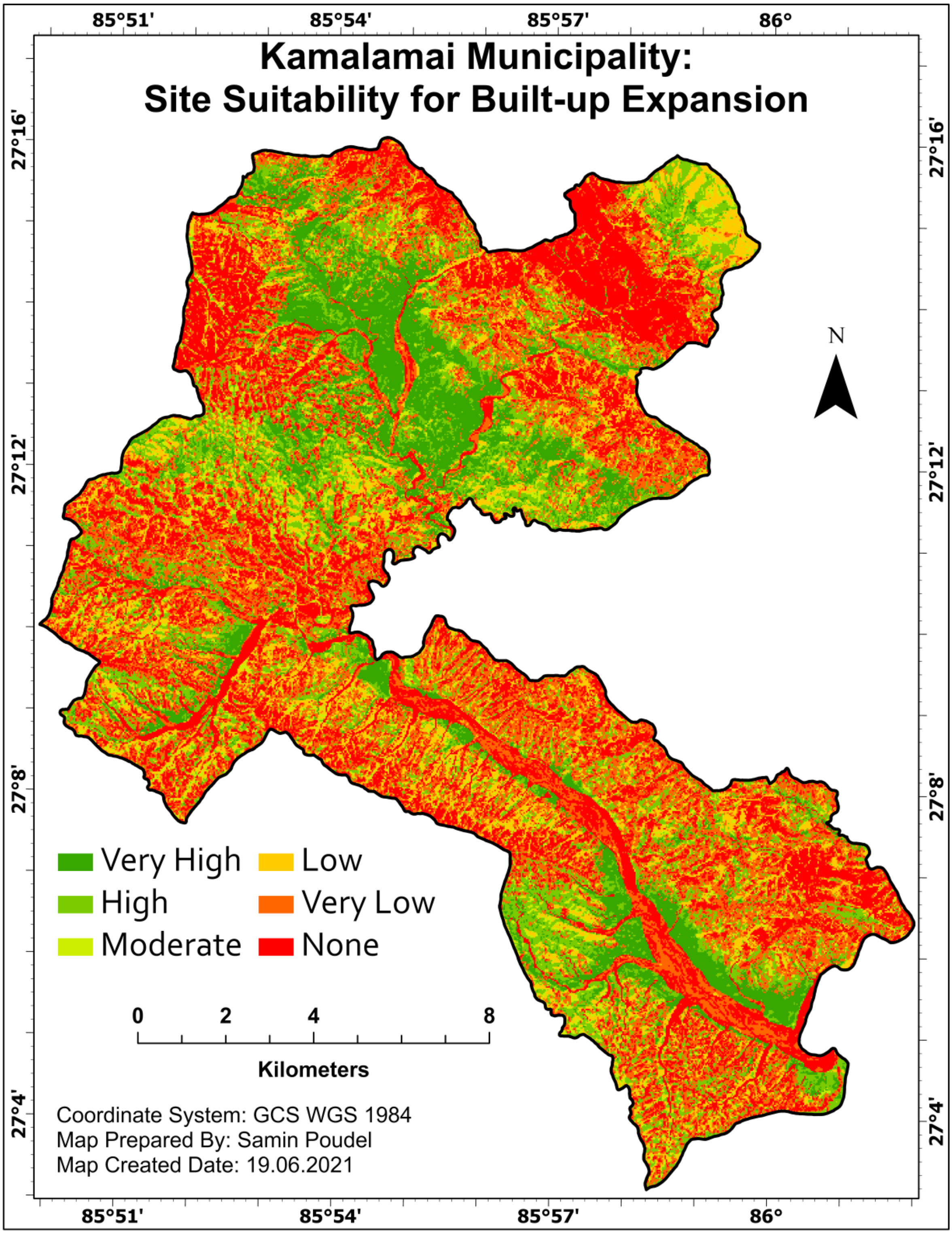
3.6. Site Suitability for Built-up Expansion

The site suitability map was obtained by weighted analysis of all the aforementioned layers according to the weightage derived for each layer using AHP Process. The six classes of site suitability are based on the scale from highly suitable areas to non-suitable areas. The weights per classes are summarized in Table 12.

Table 12. Weightage for Each Suitability Parameters

Suitability Level: Landslide		**Aspect**	
High	2.1	High- (157.5 to 202.5)	0.5
Medium	0.9	Medium (112.5-157.5 and 202.5-247.5)	0.3
Low	0	Low (90-112.5 and 247.5-270	0.2
Suitability Level: Flood		None (0-89.5 and 271-360)	0
High	2.1	**Distance from Existing Road**	
Medium	0.9	High- Up to 100m	0.21
Low	0	Medium- 100m to 150m	0.09
LULC-2021		Low- Above 150m	0
High- Built-up, Barren, Shrub	1.35	**Distance from Existing Settlement**	
Medium- Agriculture	0.15	High - Up to 250m	0.21
Low- Forest, Water	0	Medium -250m to 500m	0.09
Slope		Low - Above 500m	0
High- Up to 15˚	0.49	**Elevation**	
Medium- 15˚ to 30˚	0.21	High- Up to 500m	0.14
Low- Above 30˚	0	Medium- 500m to 1000m	0.06
		High- Above 1000m	0

The aforementioned values were assigned to each category for each layer using "Reclassify" tool in ArcGIS Pro. The reclassified values were then assigned weightage in "Raster calculator" tool as: ("Reclass_Landslide" * 0.3) + ("Reclass_Flood" * 0.3) + ("Reclass_LULC2021" * 0.15) + ("Reclass_Aspect" * 0.1) + ("Reclass_Slope" * 0.07) + ("Reclass_Road" * 0.03) + ("Reclass_Settlement" * 0.03) + ("Reclass_Elevation" * 0.02). The suitability map was thus obtained presented in Map 13. The very high suitable areas represent very suitable areas and None represents are not suitable for built-up.



Map 13. Kamalamai Municipality Site Suitability for Built-up Expansion, 2021

The suitable expansion areas were classified using geometric interval classification method in ArcGIS Pro, which gives mathematically defined class-width in accordance to geometric interval. The built-up expansion suitability map of Kamalamai Municipality shows that the municipality has 27.4% of area which is not suitable for development which accounts for 56.28 Km². Similarly, the 27.1% of the municipality has very low development potential which accounts for and area of 55.50 Km² and 10.5% of the municipality had a low suitability for development with an area of 21.44 Km², altogether the lower values for suitability accounted for 64.9% with an area of 133.21 Km².

The moderately suitable area for development accounted for 5.9% of the municipality with an area of 12.18 Km². The highly suitable area for the development accounted for 16.3% with an area of 33.54 Km² which is the highest among the classified area and finally the area having very high suitability was 12.8% with an area of 26.20 Km². The overall moderate and high areas suitable for development accounted for 35.1% covering an area of 71.91 Km². The suitability analysis showed that more areas in the municipality had a low suitability for built-up expansion as 64.9%.

The suitability map was later used for determining the future built-up growth model to expand towards suitable areas and constraint the development towards less suitable areas. The layer was classified from 0 to 1 data value using “Raster Calculator” in ArcGIS Pro. The file was then exported using “Export Raster” tool was Tiff file, then it was imported to LCM as .rst IDRISI file type.

3.7. Transition Potential Modelling

The land change transition model was used to model transitions potential from other classes to built-up class. The “MLP Neural Network” was used for developing sub-models that was later used for predicting future development. The sub-models of transition were selected ‘no’ for parameters other than water, shrub, barren, forest and agriculture to built-up so that only built-up change can be modelled. The sub-models for these five transitions were evaluated independently for each of them. The transition models were run using automatic training and using dynamic learning rate training parameters. The accuracy and skill measure for each sub models with modelling parameters are presented as model result.

Land Change Modeler MLP Model result for change from forest to built-up is presented below. The general information of the model includes the input files that were used for analysing areas potential for development. The parameters and performance include the data used for modelling the transition. The accuracy of the model was 78.17% which is acceptable as the accuracy should be near 80% according to Terr-set Manual. Similarly, the skill measure of the model was 0.5634. The input layers define the number of variables used in the model, the hidden layer determine the mathematical computation required for the model and the output layer are responsible for the prediction of the simulation of model (Table 13).

Table 13. Parameters and Performance (Transition Forest to Built-up)

Input layer neurons	6
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	146
Final learning rate	0.0005
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3740
Testing RMS	0.4041
Accuracy rate	78.17%
Skill measure	0.5634

The samples per classes were chosen to have standard value in the model while selecting the variables, and similarly other parameters were also left to have a standard value. The sensitivity model details out the accuracy of independent variables along with the most influential variable and least influential variable. This shows the independent accuracies of variables, their skill measure and influence status of each variable in creating the model. The most influential variable determines higher accuracy of the model. The second variable, Existing Roadway is most influential this transition while variable 4 is the least influential for determining the model accuracy (Table 14).

Table 14. Forcing Single Independent Variable to be Constant (Forest to Built-up)

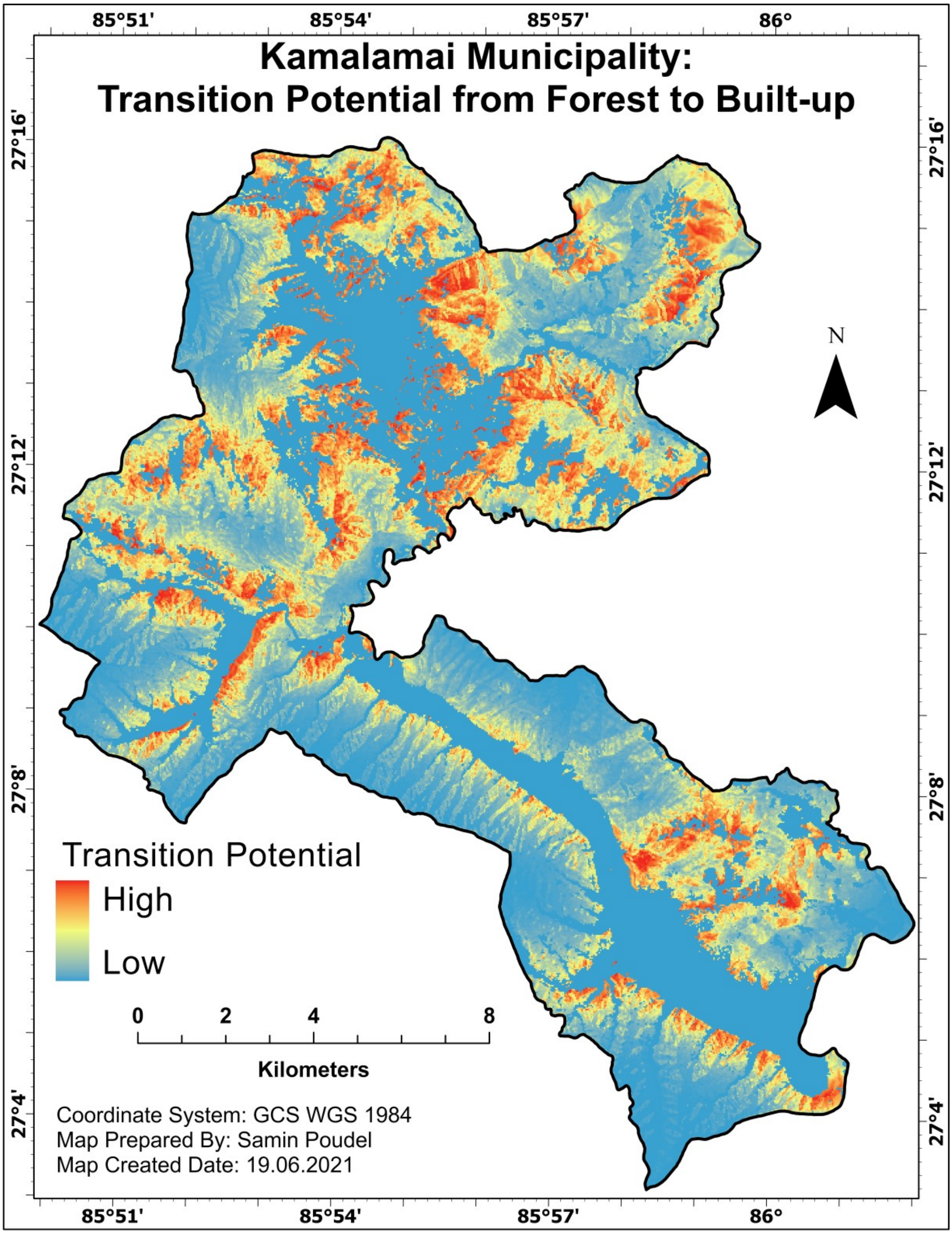
Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.17	0.5634	N/A
Var. 1 constant	77.46	0.5493	5
Var. 2 constant	66.20	0.3239	1 (most influential)
Var. 3 constant	76.76	0.5352	3
Var. 4 constant	78.17	0.5634	6 (least influential)
Var. 5 constant	76.76	0.5352	4
Var. 6 constant	75.35	0.5070	2

Similarly, the backwards stepwise shows accuracy when variables are kept constant to run the model. This process assists in eliminating the variables that are not required to determine the same accuracy of the model. Accordingly, the model would give the same accuracy, with variable 4 and 1 as constant (Table 15).

Table 15. Backward Stepwise Constant Forcing (Transition Forest to Built-up)

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	78.17	0.5634
Step 1: var.[4] constant	[1,2,3,5,6]	78.17	0.5634
Step 2: var.[4,1] constant	[2,3,5,6]	78.17	0.5634
Step 3: var.[4,1,3] constant	[2,5,6]	78.87	0.5775
Step 4: var.[4,1,3,6] constant	[2,5]	80.99	0.6197
Step 5: var.[4,1,3,6,5] constant	[2]	74.65	0.4930

The map is generated from the model for transition from Forest to Built-up. The high values show higher potential and low values show low potential for transition (Map 14).



Map 14. Transition Potential from Forest to Built-up

Similarly, the model was generated for transition potential from Shrubland to Built-up. The accuracy of the model was 72.73% and the skill measure was 0.4545 (Table 16).

Table 16. Parameters and Performance (Transition Shrub to Built-up)

Input layer neurons	6
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	10
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.4866
Testing RMS	0.4544
Accuracy rate	72.73%
Skill measure	0.4545

The third variable, is the most influential for this transition while variable 6 is the least influential for determining the model accuracy (Table 17).

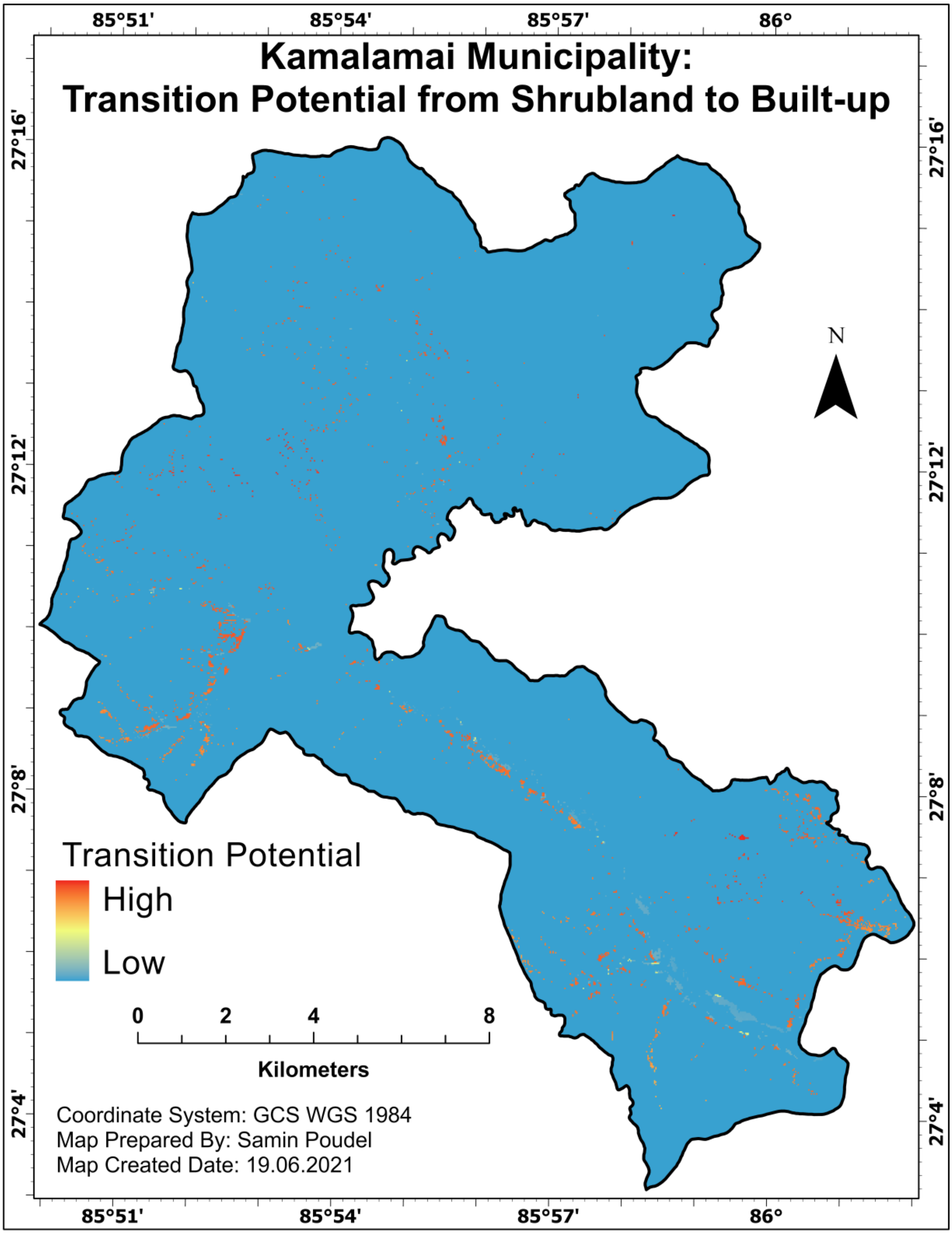
Table 17. Forcing Single Independent Variable to be Constant (Shrub to Built-up)

Model	Accuracy (%)	Skill measure	Influence order
With all variables	72.73	0.4545	N/A
Var. 1 constant	72.73	0.4545	2
Var. 2 constant	72.73	0.4545	3
Var. 3 constant	54.55	0.0909	1 (most influential)
Var. 4 constant	72.73	0.4545	4
Var. 5 constant	72.73	0.4545	5
Var. 6 constant	72.73	0.4545	6 (least influential)

Table 18. Backward Stepwise Constant Forcing (Transition Shrub to Built-up)

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	72.73	0.4545
Step 1: var.[1] constant	[2,3,4,5,6]	72.73	0.4545
Step 2: var.[1,2] constant	[3,4,5,6]	72.73	0.4545
Step 3: var.[1,2,4] constant	[3,5,6]	72.73	0.4545
Step 4: var.[1,2,4,5] constant	[3,6]	72.73	0.4545
Step 5: var.[1,2,4,5,6] constant	[3]	72.73	0.4545

The backward stepwise constant is presented in Table 18. The map generated for transition from Shrubland to Built-up is presented in Map 15.



Map 15. Transition Potential from Shrubland to Built-up

Similarly, the transition potential from Water to Built-up model accuracy was 76.67%. The table for the parameters and performances of the transition model is presented in Table 19.

Table 19. Parameters and Performance (Transition Water to Built-up)

Input layer neurons	7
Hidden layer neurons	4
Output layer neurons	2
Requested samples per class	114
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3748
Testing RMS	0.4019
Accuracy rate	76.67%
Skill measure	0.5333

The first variable, is the most influential for this transition while variable 2 is the least influential for determining the model accuracy (Table 20).

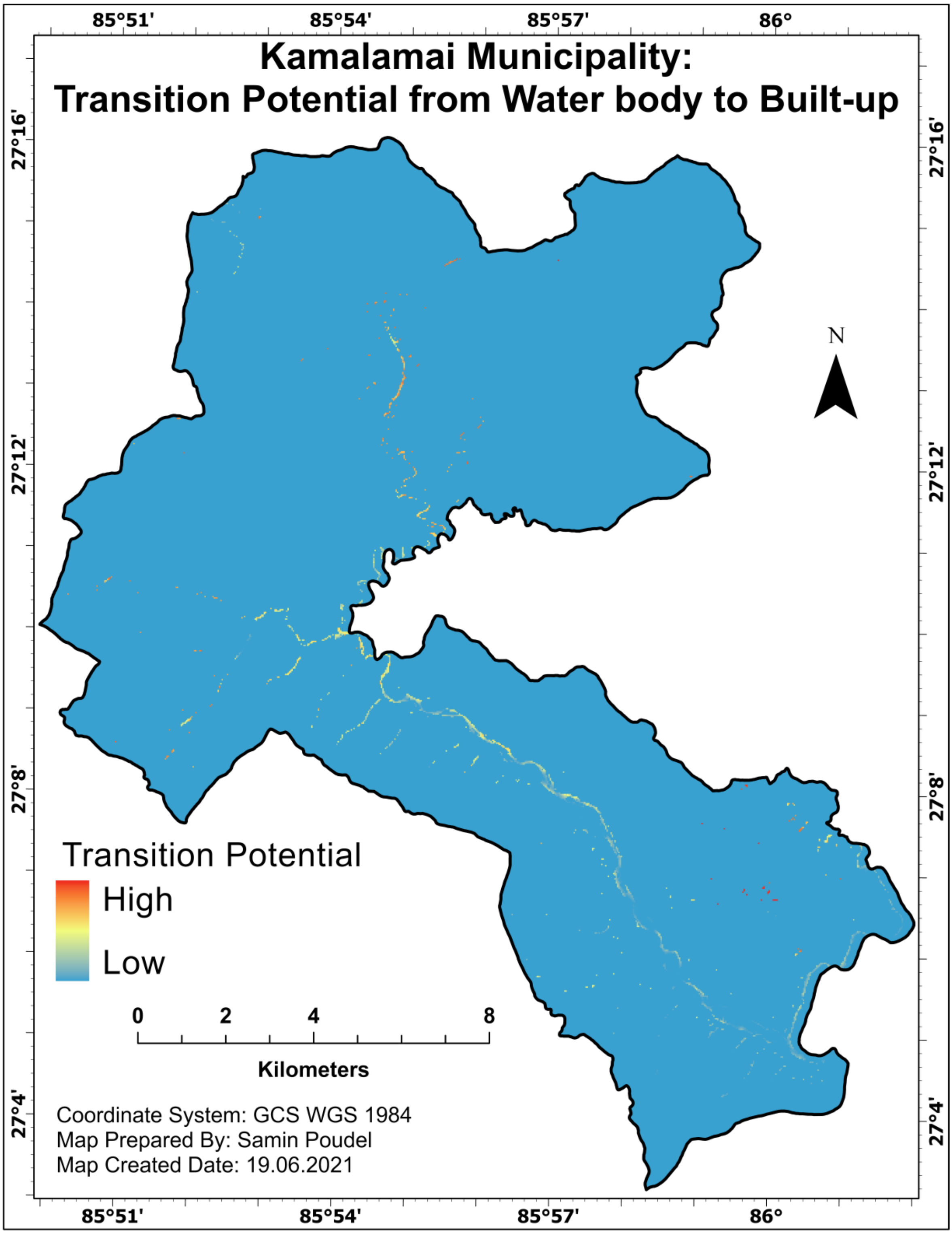
Table 20. Forcing Single Independent Variable to be Constant (Water to Built-up)

Model	Accuracy (%)	Skill measure	Influence order
With all variables	76.67	0.5333	N/A
Var. 1 constant	69.17	0.3833	1 (most influential)
Var. 2 constant	77.50	0.5500	7 (least influential)
Var. 3 constant	76.67	0.5333	5
Var. 4 constant	76.67	0.5333	4
Var. 5 constant	76.67	0.5333	3
Var. 6 constant	76.67	0.5333	2
Var. 7 constant	77.50	0.5500	6

Table 21. Backward Stepwise Constant Forcing (Transition Water to Built-up)

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	76.67	0.5333
Step 1: var.[2] constant	[1,3,4,5,6,7]	77.50	0.5500
Step 2: var.[2,3] constant	[1,4,5,6,7]	78.33	0.5667
Step 3: var.[2,3,4] constant	[1,5,6,7]	78.33	0.5667
Step 4: var.[2,3,4,6] constant	[1,5,7]	80.00	0.6000
Step 5: var.[2,3,4,6,5] constant	[1,7]	80.00	0.6000
Step 6: var.[2,3,4,6,5,7] constant	[1]	71.67	0.4333

The backward stepwise constant is presented in Table 21. The map thus generated from the model for transition from water to Built-up is presented in Map 16.



Map 16. Transition Potential from Water body to Built-up

Similarly, the model was generated for transition potential from barren to built-up. The accuracy of the model was 70.68% and the skill measure was 0.41 (Table 22).

Table 22. Parameters and Performance (Transition Barren to Built-up)

Input layer neurons	5
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	276
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.4230
Testing RMS	0.4293
Accuracy rate	70.68%
Skill measure	0.4135

The first variable, is the most influential variable 5 is the least influential for determining the model accuracy (Table 23). The backward stepwise constant is presented in Table 21.

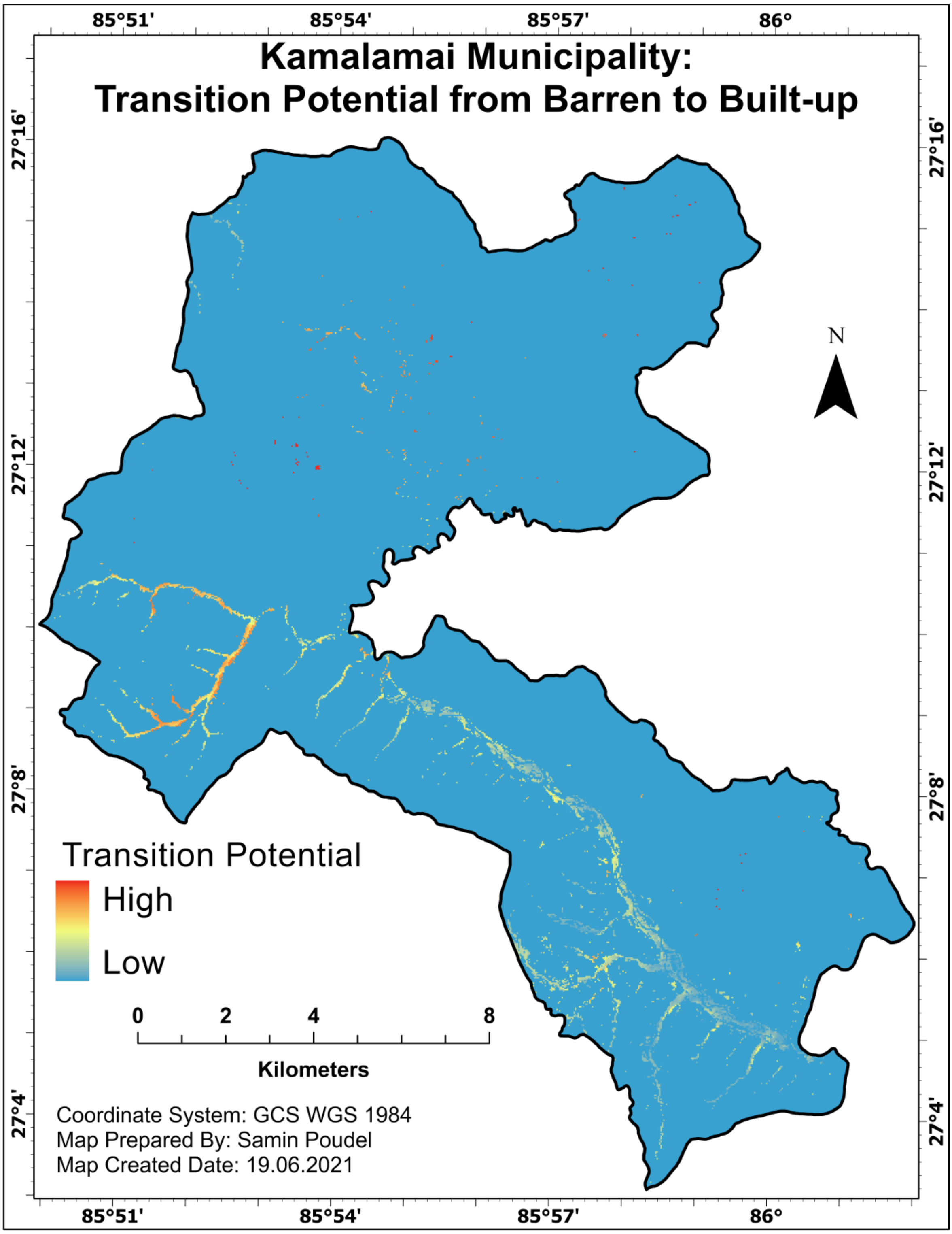
Table 23. Forcing Single Independent Variable to be Constant (Barren to Built-up)

Model	Accuracy (%)	Skill measure	Influence order
With all variables	70.68	0.4135	N/A
Var. 1 constant	64.66	0.2932	1 (most influential)
Var. 2 constant	70.30	0.4060	4
Var. 3 constant	69.55	0.3910	3
Var. 4 constant	69.17	0.3835	2
Var. 5 constant	71.43	0.4286	5 (least influential)

Table 24. Backward Stepwise Constant Forcing (Transition Barren to Built-up)

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	70.68	0.4135
Step 1: var.[5] constant	[1,2,3,4]	71.43	0.4286
Step 2: var.[5,4] constant	[1,2,3]	74.81	0.4962
Step 3: var.[5,4,3] constant	[1,2]	72.18	0.4436
Step 4: var.[5,4,3,2] constant	[1]	71.05	0.4211

The map generated for transition from water to Built-up is presented in Map 17.



Map 17. Transition Potential from Barren to Built-up

Similarly, the transition potential from agricultural to built-up model accuracy was 78.30% with a skill measure of 0.5661. The model result is presented with parameters and performance in Table 25.

Table 25. Parameters and Performance (Transition Agriculture to Built-up)

Input layer neurons	9
Hidden layer neurons	4
Output layer neurons	2
Requested samples per class	1144
Final learning rate	0.0005
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3662
Testing RMS	0.3968
Accuracy rate	78.30%
Skill measure	0.5661

The variable 9 is the most influential while variable 9 is the least influential (Table 26). The backward stepwise constant is presented in Table 27.

Table 26. Forcing Single Independent Variable to be Constant

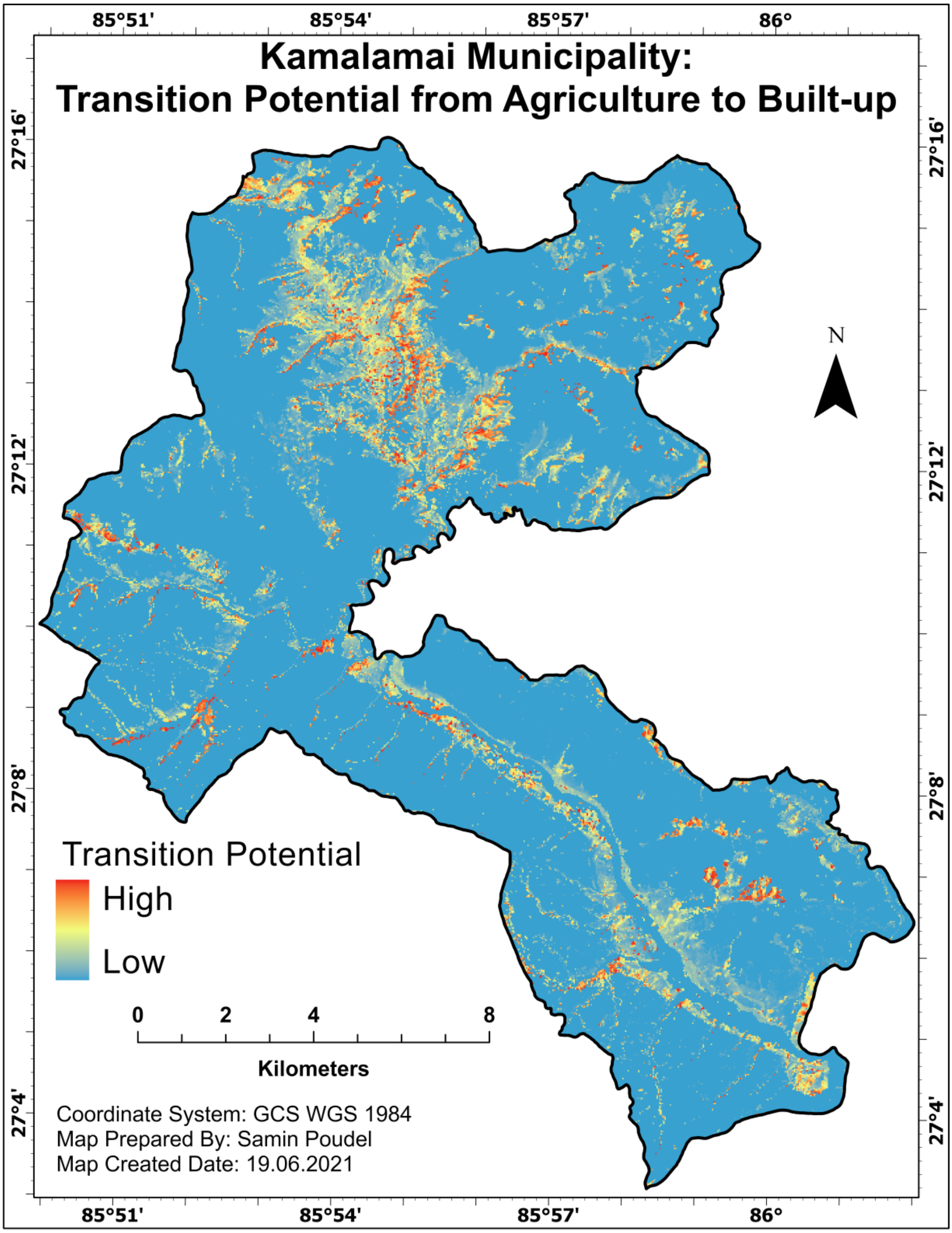
Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.30	0.5661	N/A
Var. 1 constant	75.42	0.5083	4
Var. 2 constant	76.47	0.5293	6
Var. 3 constant	76.20	0.5241	5
Var. 4 constant	62.38	0.2476	2
Var. 5 constant	72.88	0.4576	3
Var. 6 constant	78.13	0.5626	8
Var. 7 constant	77.87	0.5573	7
Var. 8 constant	78.30	0.5661	9 (least influential)
Var. 9 constant	55.38	0.1076	1 (most influential)

Table 27. Backward Stepwise Constant Forcing (Transition Water to Built-up)

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	78.30	0.5661
Step 1: var.[8] constant	[1,2,3,4,5,6,7,9]	78.30	0.5661
Step 2: var.[8,6] constant	[1,2,3,4,5,7,9]	78.13	0.5626
Step 3: var.[8,6,7] constant	[1,2,3,4,5,9]	78.74	0.5748
Step 4: var.[8,6,7,1] constant	[2,3,4,5,9]	75.68	0.5136
Step 5: var.[8,6,7,1,2] constant	[3,4,5,9]	77.87	0.5573

Step 6: var.[8,6,7,1,2,3] constant	[4,5,9]	74.54	0.4908
Step 7: var.[8,6,7,1,2,3,4] constant	[5,9]	64.65	0.2931
Step 8: var.[8,6,7,1,2,3,4,5] constant	[9]	70.69	0.4138

The transition potential from agriculture to Built-up is presented in Map 18.



Map 18. Transition Potential from Agriculture to Built-up

The model results are included in Annex 1 in detail for all five transition potentials included in the study. The derived models were saved and then were used in the processing further while generating change prediction model.

3.8. Built-up Expansion Suitability Modelling 2031, 2041 and 2051

The LCM Transition Potential, Change Prediction and Planning tabs were used for the LULC change analysis. The transition potential was used as input for the change using the transition potential models for forest, barren, shrub, water and agricultural classes to built-up. The Change Prediction section was used for determining the LULC in 2031, 2041 and 2051 as three stage prediction. The Markov Chain model was used for the modelling of LULC. The prediction date was set as 2051 and in the change allocation section the optional component Zoning was checked. The zoning option includes constraints and incentives for allocating areas in development suitable areas.

The Planning section of LCM was utilized for specifying the suitable areas for built-up expansion. The suitability map was used as constraints/incentives map in planning section for transition potential of other classes to built-up to incentivise areas suitable for development and constraints for areas unsuitable for development. The values were assigned for six categories the lower suitable areas were weighted 0, 0.2, 0.3 and higher suitable values were weighted 1, 0.9 and 0.8.

The recalculation stages were set as 3 so that the intermediate stages of 2031 and 2041 would also be calculated in the output model. The recalculation stages; 2031, 2041 and the main image for 2051 were added in ArcGIS pro for further processing and creating maps. According to the modelled maps for 2031, 2041 and 2051 is modelled accordingly and the result shows that the built-up could increase from 1.90% in 2021 to 2.50% in 2031 and would rise to 3.30% in 2041 and increase to 4.00% in 2051. The graph showing the increase in built-up from 2001 to 2051 (Figure 20). This is modelled as a steady increase in built-up area from 2031 to 2051.

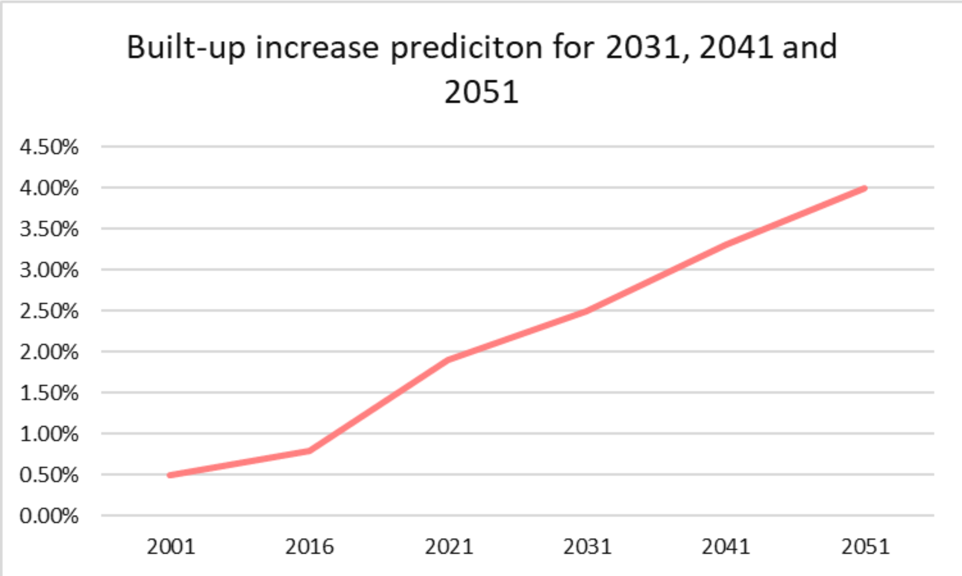


Figure 20. Built-up transition 2001 to 2051

The LULC for 2031 was calculate from the Map 19. The model shows that the Built-up will increase to 2.5% by 2031 with an area of 5.13 Km², while other LULC classes; water will be at 1.0% with an area of 2.15 Km², barren will be at 5.3% with an area of 10.91 Km² (Figure 21).

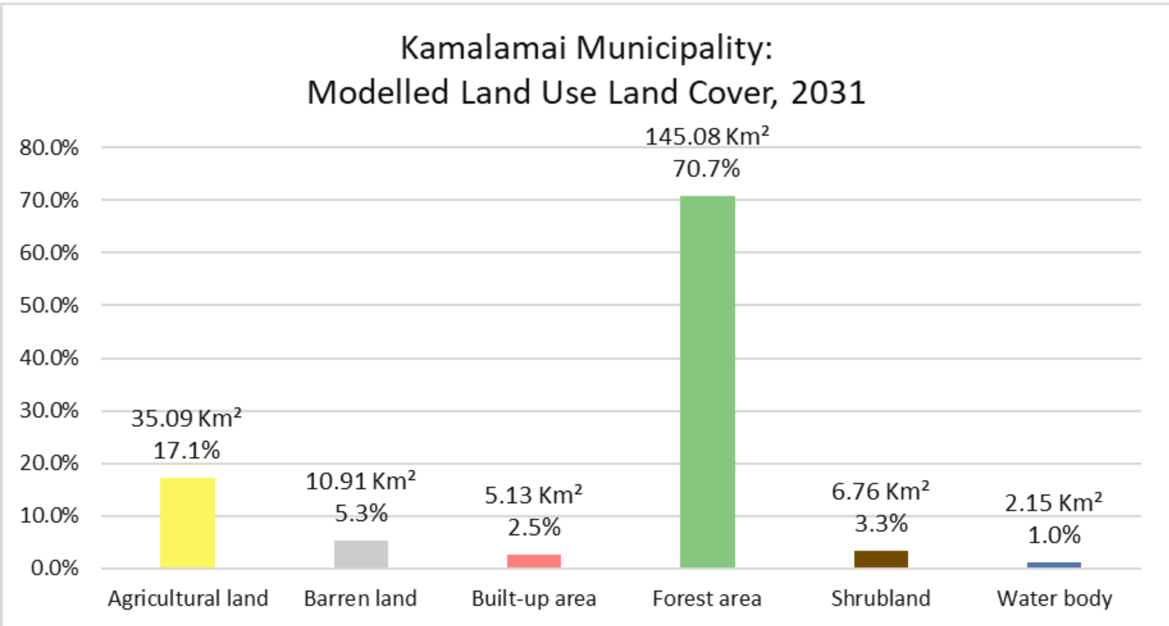
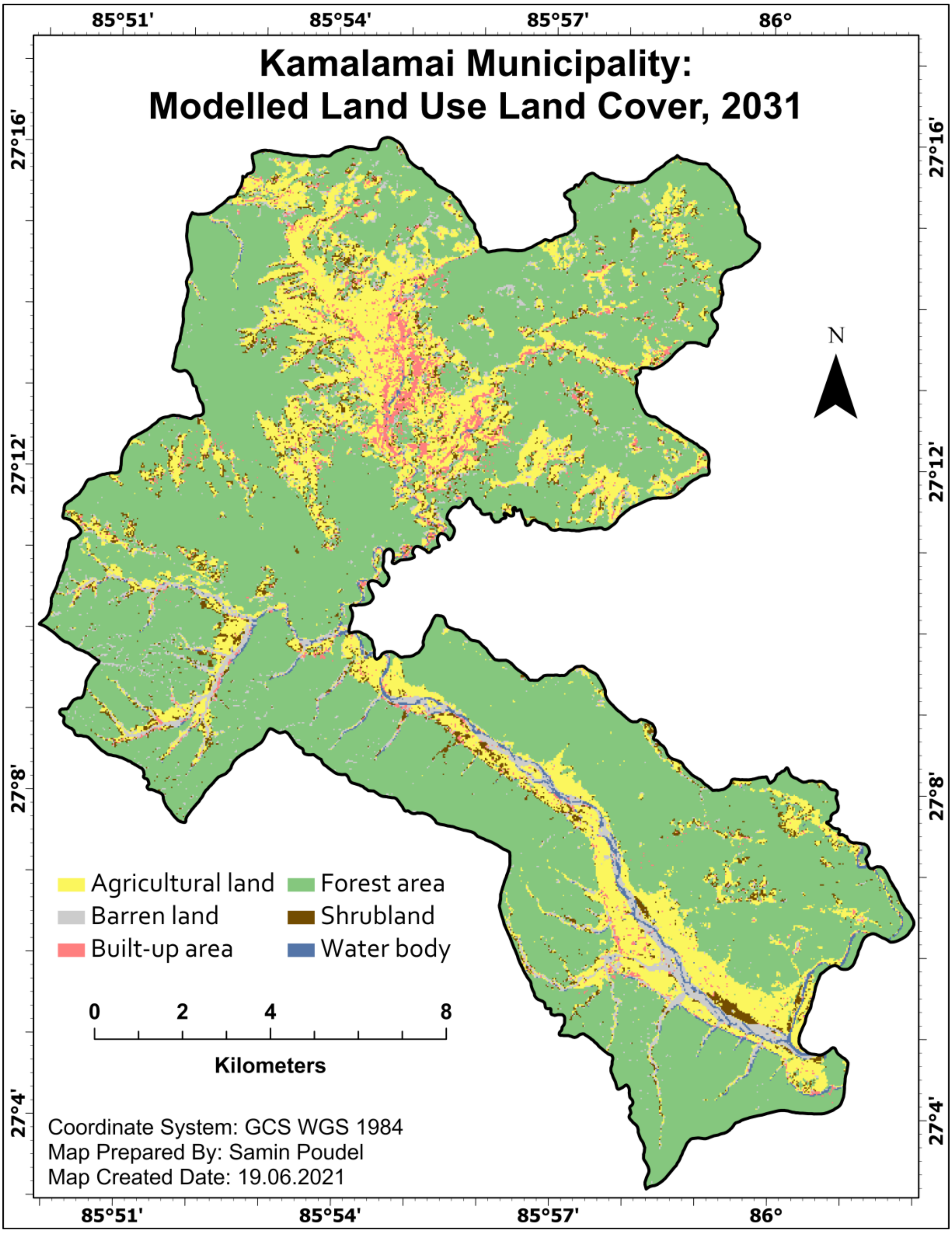


Figure 21. Kamalamai Municipality Modelled LULC, 2031

Similarly, the forest will remain the largest LULC covering 70.7% of the municipality with an area of 145.08 Km^2 the agricultural area will be the second highest covering 17.1% with an area of 35.06 Km^2 and Shrubland would cover 3.3% with an area of 6.76 Km^2.



Map 19. Kamalamai Municipality: Modelled LULC, 2031

The stage second of the transition model is presented in Map 20. The transition model shows the LULC in 2041. The data shows that built up would increase from 2.5% with an area of 10.91 Km² to 3.3% in 2041 with an area of 6.69 Km². The water class would not be affected much from the change with just a small decrement which would still account for 1.0% with an area of 2.11 Km² and the barren area was modelled to decrease by 0.1% accounting 5.2% with an area of 10.71 Km² (Figure 22).

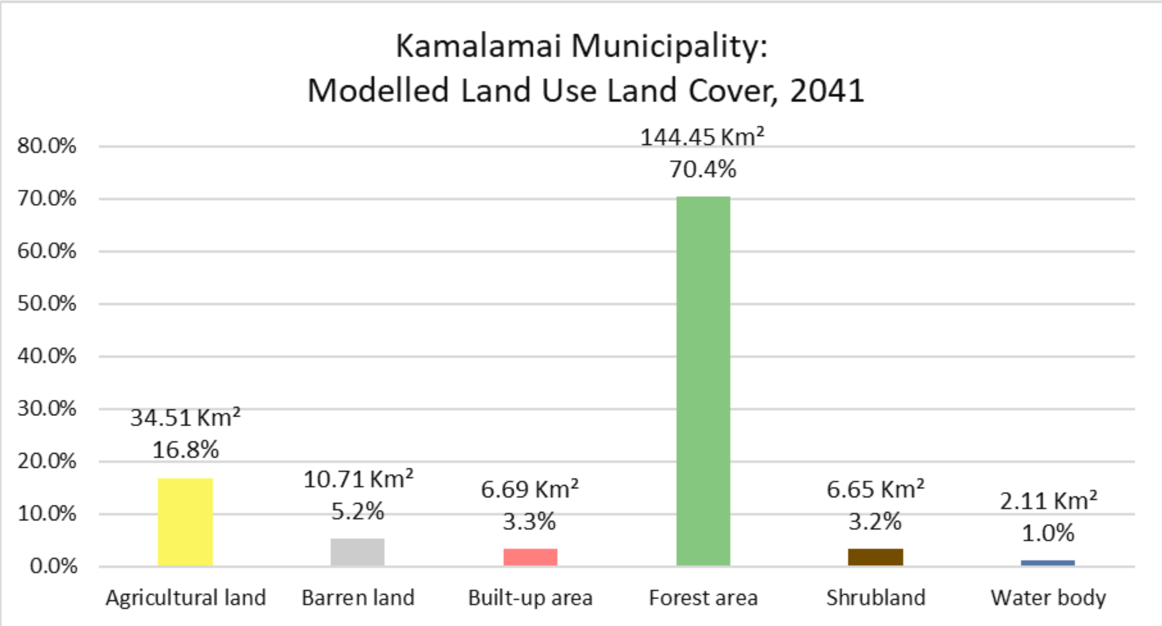
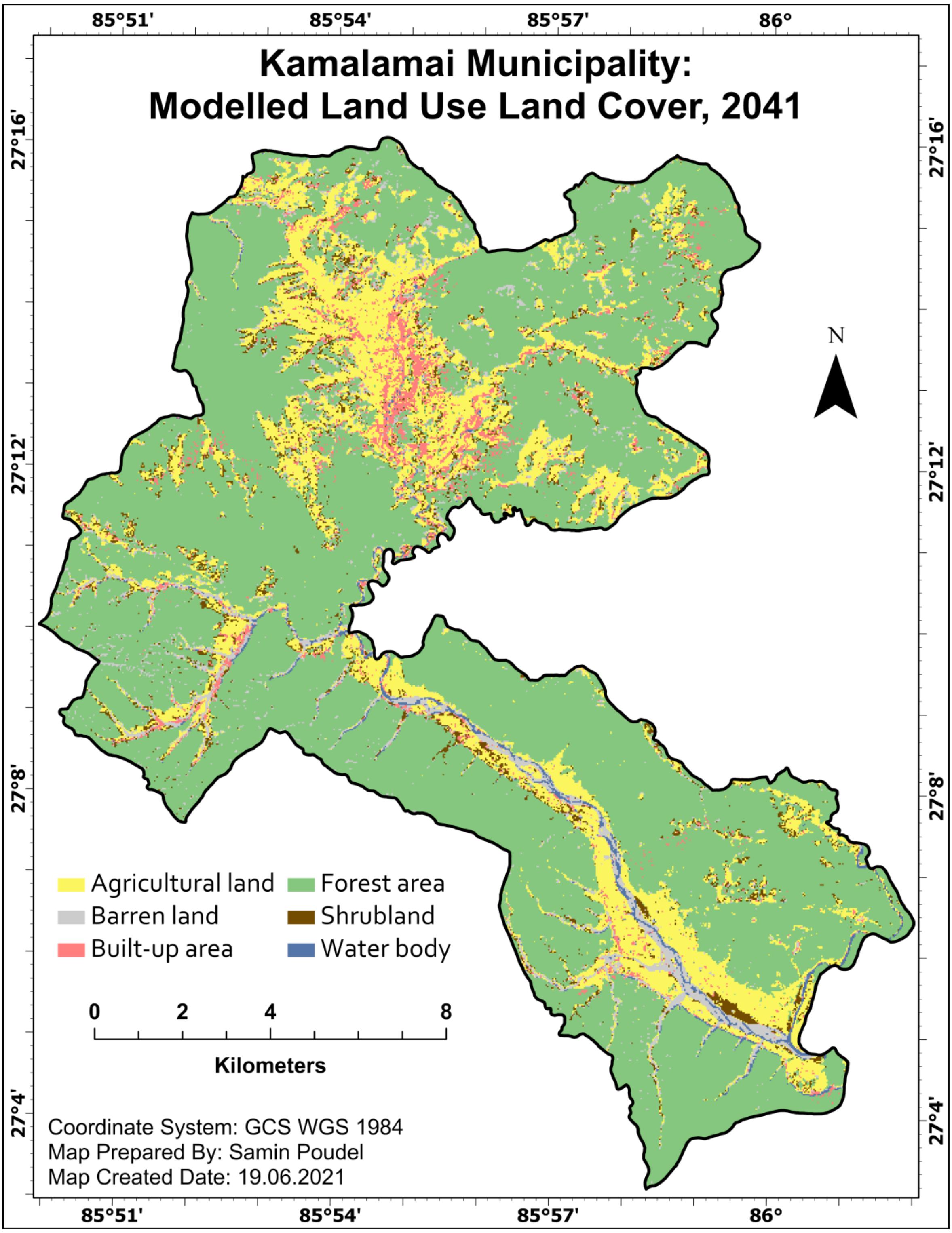


Figure 22. Kamalamai Municipality Modelled LULC 2041

Similarly, the forest area had a decrement of 0.3% making it to cover 70.4% of the area of municipality with highest LULC class and having an area of 144.45 Km², the agricultural area would decrease also by 0.3% from 2031 and would cover 16.8% with an area of 34.51 Km² and finally there would be 0.1% decrease in shrubland which would cover 3.2% with an area 6.65 Km².

The map shows the change in built-up along suitable locations in 2041. The southwestern area of the municipality has been predicted to have more expansion similarly north western region of municipality has been predicted to have a major built-up expansion along the river corridor.



Map 20. Kamalamai Municipality: Modelled LULC, 2041

The final stage which was the main simulated LULC model is for the year 2051 (Map 21). The built-up has been predicted to increase by 0.7% from 2041 to 2051 contributing an area of 4.0% which is an area of 8.25 Km² the water class would cover an area similarly at 1.0% as before with an area of 2.07 Km² the barren areas would decrease by 1% from 2041 resulting in 5.1% area coverage contributing an area of 10.51 Km² (Figure 23).

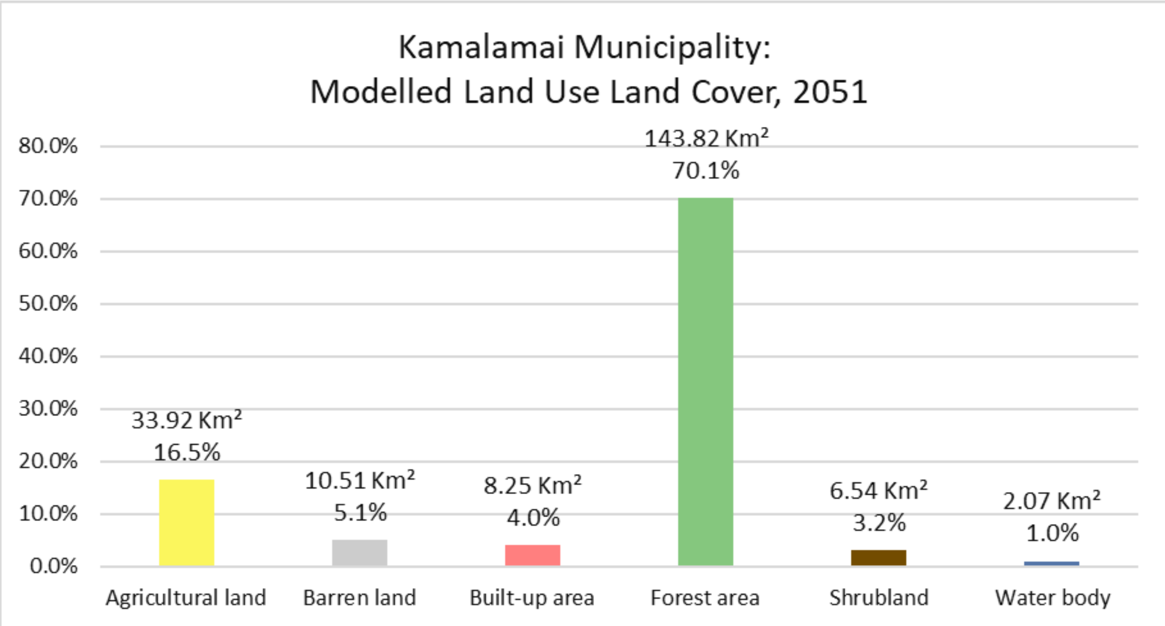
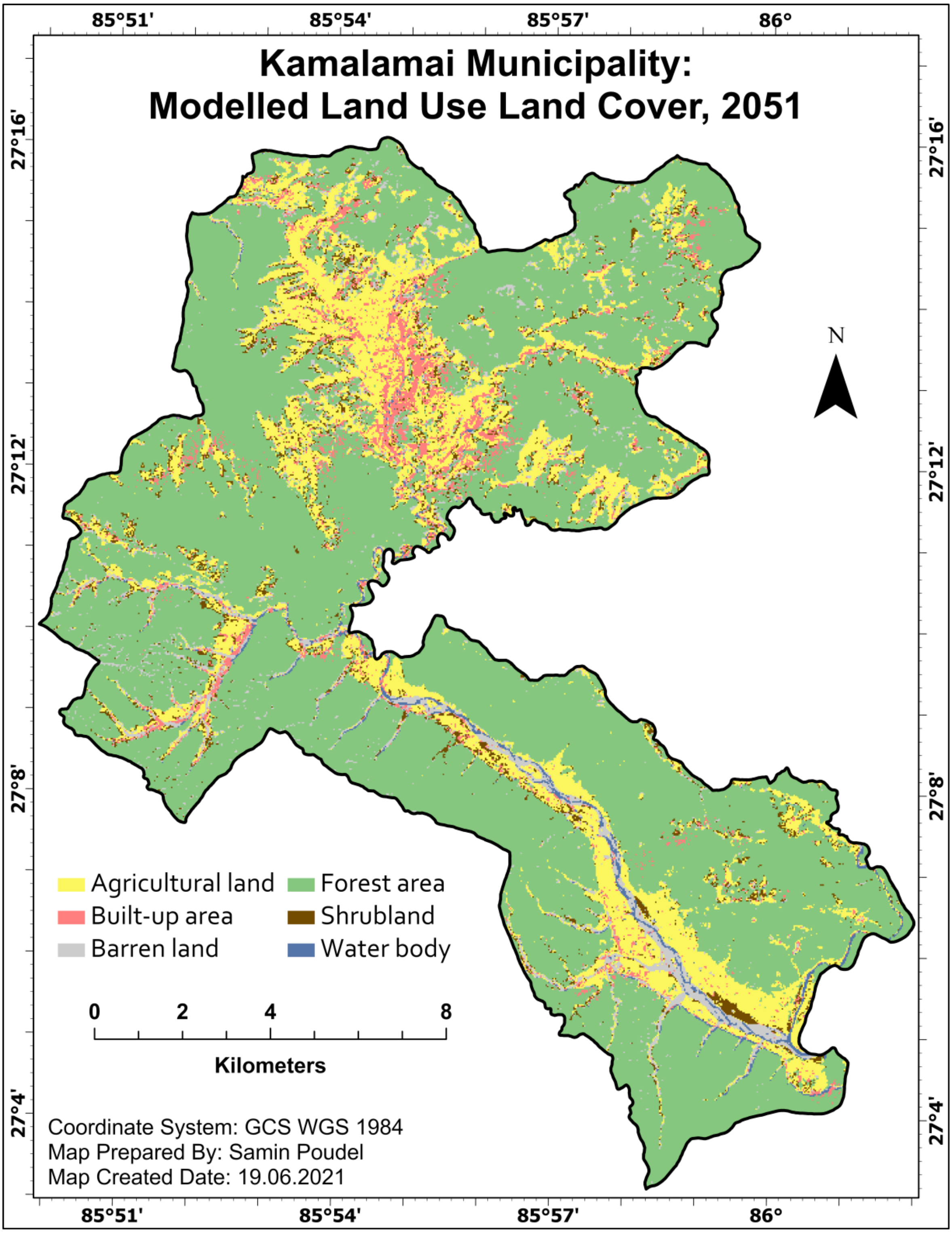


Figure 23. Kamalamai Municipality Modelled LULC 2051

The forest class would have decreased by 0.3% to 70.1% covering an area of 143.82 Km² which would still be the largest LULC class, similarly agricultural class would decrease by 0.3% resulting in an area of 33.92 Km² and covering 16.5% of the municipality making it the second largest LULC class. Finally, the shrubland would remain at 3.2% while having a small decrement in overall area to 6.54 Km².

The modelled LULC map of 2051 shows that the built-up expansion could expand mostly in the south western, north western and the central town region of the municipality. Similarly small sprawling settlements are predicted along the north eastern hilly areas and south-eastern areas along the river bank and also on the edge of the municipality on the south western front. Similar, built-up is predicted on the edge of north western region of the municipality.



Map 21. Kamalamai Municipality: Modelled LULC, 2051

Chapter-4: Discussion and Conclusions

LULC analysis plays an important role in built-up planning which can be integrated with various geographical data to create more meaningful analysis for land use planning. Suitability analysis is one of such important variables for built-up development planning. The suitable area identification is very useful for local government, planning organizations, decision makers and policy makers to understand current status of an area and use the knowledge of future prediction and trend analysis to develop a sustainable future development plan. The risk associated with built-up development can also be reduced and/or minimized using such knowledge.

Since the development of computational software geographic information science has also developed alongside to solve geographic problems including land use planning and urban development. The advancement of RS techniques, geographic information tools have been providing assessment capability of large amount of data in short time. To assist with the processing of large data the mathematical modelling of data has also advanced with scientific calculation models including various modelling tools that can handle both spatial and temporal trends and even analyse future models based on self-learning techniques like neural networks, artificial intelligence using the input data to create model output.

The analysis for built-up expansion suitable areas revealed that Kamalamai Municipality consists 27.4% of area which is not suitable for development which accounts for 56.28 Km^2. Similarly, the 27.1% of the municipality has very low development potential which accounts for and area of 55.50 Km^2 while 16.3% of the municipality with an area of 33.54 Km^2 had high suitability for development and finally the area having very high suitability was 12.8% with an area of 26.20 Km^2. The overall moderate and high areas suitable for development accounted for 35.1% covering an area of 71.91 Km^2. The suitability analysis showed that more areas in the municipality had a low suitability for built-up expansion.

The built-up model for 2031, 2041 and 2051 showed that the built-up could increase from 1.90% in 2021 covering an area of 2.16 Km^2 to 2.50% in 2031 covering an area of 5.13 Km^2 and would rise to 3.30% in 2041 covering an area of 6.69 Km^2 and increase to 4.00% in 2051 covering an area of 8.25 Km^2. The trend of development was predicted mostly along the north western and south western area of the municipality while there was some settlement growth modelled along the Kamala River bank and on the north eastern part of the municipality.

The suitability analysis was found to be an important tool in urban and environmental planning studies, along with Analytical Hierarchy Method using pair-wise comparison of different variables that may or may not be of similar nature to simply compare. The method was important for assigning different types of layers in comparison among one another to derive meaningful result of areas that were suitable for development or least suitable of development and scales in the middle. Similarly, the RS satellite imagery especially imagery that are available to students, researchers and general public without any cost were found to be an important resource for studying geographic phenomenon.

Chapter-5: Limitation and Recommendation

The study was conducted based on medium resolution Landsat image. The spatial resolution of image of 30m affected the classification process. In some cases, multiple land use land cover was classified in a single pixel. The course resolution meant that water bodies like rivers were mapped as discrete entities rather than continuous river polygons. The small objects in the municipality did not show in the classified image. Similarly, the coarse resolution of classification image can also impact the modelling of land use land cover.

The research concentrated on the landslide susceptibility, flood susceptibility, current land use land cover, slope, aspect, distance from existing roadway, distance from existing settlements and elevation as parameters for suitability assessment. The factors for suitability assessment have other essential components such as environmental factors, climatic effects and fire risk for determining the suitable areas for built-up development. But, lack of data collection possibility and lack of available data meant these could not be analysed as these analyses were not possible during the research. Similarly, the transition analysis for other classes to built-up could not be analysed using any other factors. The transition was also modelled for built-up category only but transition of other land use classes is important as well but were not covered within the scope of this report.

The research was based on geographic analysis of land use land cover and its future prospect. The aspects of land use land cover change in the municipality, suitability for built-up expansion were incorporated in this study. This was though not sufficient to present a socio-economic prospect, health prospects and ecological prospects of land use land cover changes. Built-up expansion areas were analysed based on simulation model for transition of different classes to built-up but the existing zoning were not considered due to the coarse resolution of the imagery.

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Annex -1

1.1. Transition Sub-model: Forest to Built-up

1) Input Files

Independent variable 1	ElevationTransition
Independent variable 2	RoadTransition
Independent variable 3	SlopeTransition
Independent variable 4	SuitabilityTransition
Independent variable 5	AspectTransition
Independent variable 6	SettlementTransition
Training site file	20012021LCM_Train_Forest_Built

2) Parameters and Performance

Input layer neurons	6
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	146
Final learning rate	0.0005
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3740
Testing RMS	0.4041
Accuracy rate	78.17%
Skill measure	0.5634

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Forest to Built-up	0.5616
Persistence : Forest	0.5652

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3
i-Neuron 1	1.4301	0.8959	0.6881

i-Neuron 2	-1.6194	-5.2629	4.7151
i-Neuron 3	-0.8010	-1.1544	0.9515
i-Neuron 4	1.3576	1.4410	-0.3203
i-Neuron 5	-4.8600	-0.1256	-0.9842
i-Neuron 6	-0.5560	-3.1315	2.5805

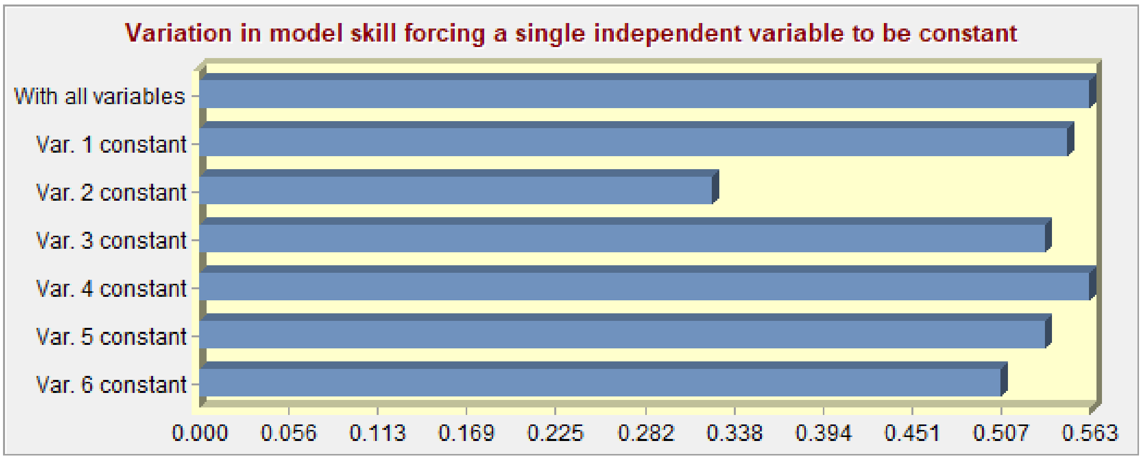
2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2
h-Neuron 1	3.8379	-3.8360
h-Neuron 2	5.7195	-5.7168
h-Neuron 3	-4.3974	4.3952

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

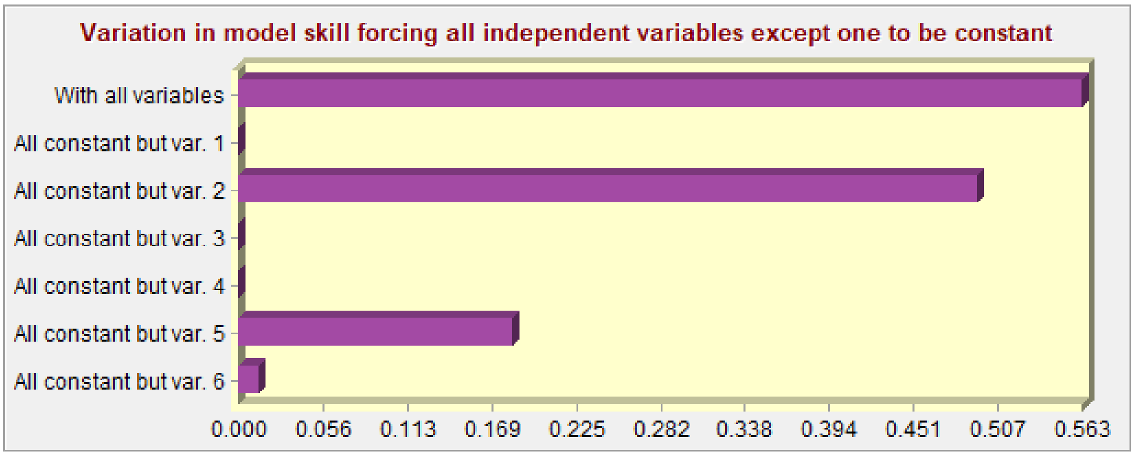
Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.17	0.5634	N/A
Var. 1 constant	77.46	0.5493	5
Var. 2 constant	66.20	0.3239	1 (most influential)
Var. 3 constant	76.76	0.5352	3
Var. 4 constant	78.17	0.5634	6 (least influential)
Var. 5 constant	76.76	0.5352	4
Var. 6 constant	75.35	0.5070	2



2) Forcing All Independent Variables Except One to be Constant

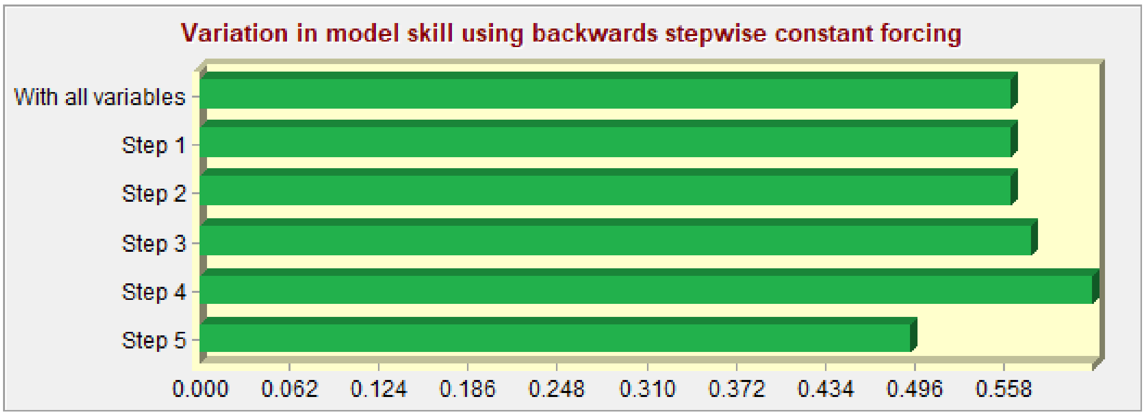
Model	Accuracy (%)	Skill measure

With all variables	78.17	0.5634
All constant but var. 1	48.59	-0.0282
All constant but var. 2	74.65	0.4930
All constant but var. 3	50.00	0.0000
All constant but var. 4	47.18	-0.0563
All constant but var. 5	59.15	0.1831
All constant but var. 6	50.70	0.0141



3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	78.17	0.5634
Step 1: var.[4] constant	[1,2,3,5,6]	78.17	0.5634
Step 2: var.[4,1] constant	[2,3,5,6]	78.17	0.5634
Step 3: var.[4,1,3] constant	[2,5,6]	78.87	0.5775
Step 4: var.[4,1,3,6] constant	[2,5]	80.99	0.6197
Step 5: var.[4,1,3,6,5] constant	[2]	74.65	0.4930



1.2. Transition Sub-model: Shrubland to Built-up

1. General Model Information

1) Input Files

Independent variable 1	ElevationTransition
Independent variable 2	RiverTransition
Independent variable 3	FloodTransition
Independent variable 4	RoadTransition
Independent variable 5	LandslideTransition
Independent variable 6	SettlementTransition
Training site file	20012021LCM_Train_Shrub_Built

2) Parameters and Performance

Input layer neurons	6
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	10
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.4866
Testing RMS	0.4544
Accuracy rate	72.73%
Skill measure	0.4545

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Shrub to Built-up	0.6000
Persistence : Shrub	0.3333

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3
i-Neuron 1	0.4412	-0.2657	-0.0844
i-Neuron 2	0.2471	-0.5454	0.0461

i-Neuron 3	1.0490	-1.4061	-0.7144
i-Neuron 4	-0.1355	0.0643	0.1087
i-Neuron 5	-0.1396	0.1488	-0.1154
i-Neuron 6	-0.3872	0.6408	0.0904

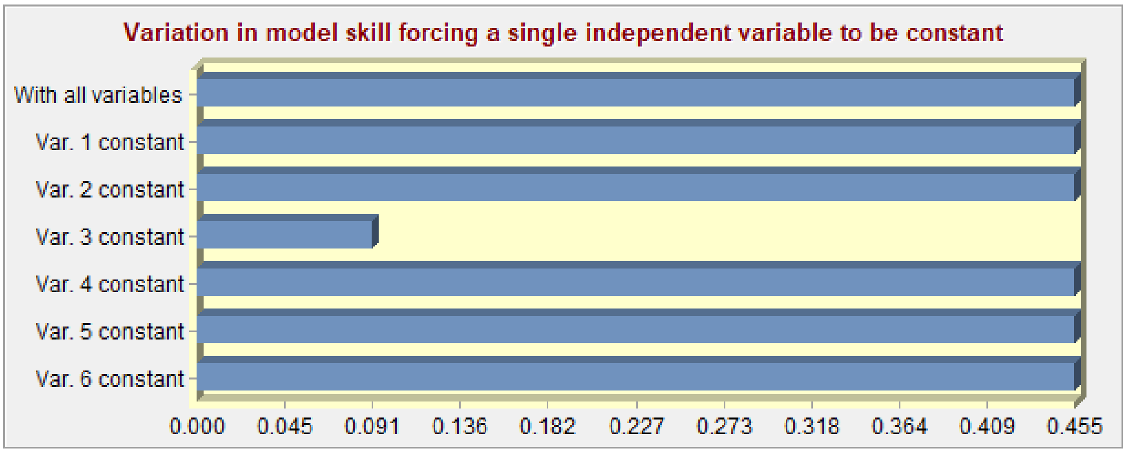
2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2
h-Neuron 1	0.8550	-0.8920
h-Neuron 2	-1.4780	1.2566
h-Neuron 3	-0.4306	0.6619

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

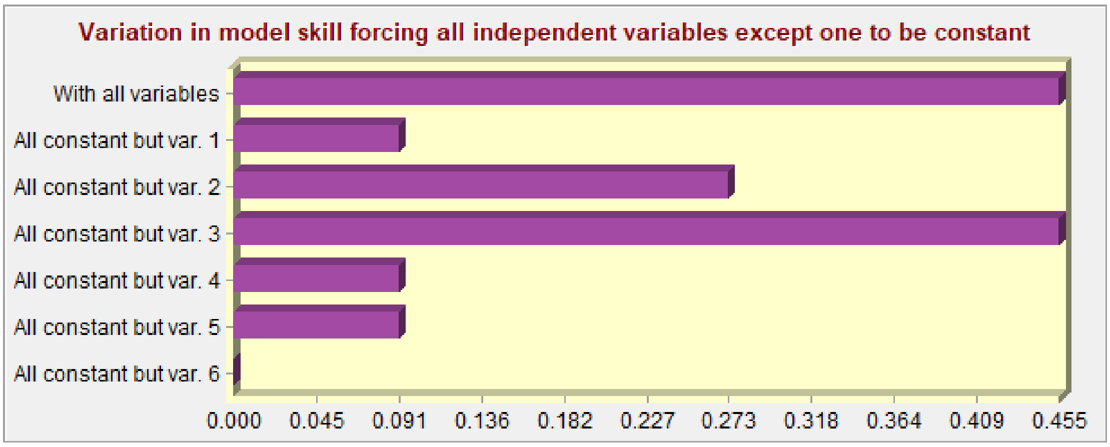
Model	Accuracy (%)	Skill measure	Influence order
With all variables	72.73	0.4545	N/A
Var. 1 constant	72.73	0.4545	2
Var. 2 constant	72.73	0.4545	3
Var. 3 constant	54.55	0.0909	1 (most influential)
Var. 4 constant	72.73	0.4545	4
Var. 5 constant	72.73	0.4545	5
Var. 6 constant	72.73	0.4545	6 (least influential)



2) Forcing All Independent Variables Except One to be Constant

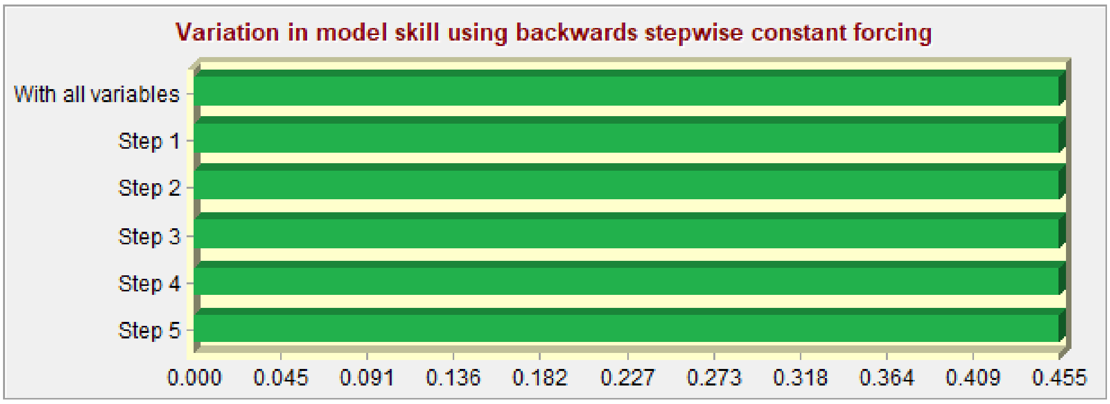
Model	Accuracy (%)	Skill measure
With all variables	72.73	0.4545
All constant but var. 1	54.55	0.0909
All constant but var. 2	63.64	0.2727

All constant but var. 3	72.73	0.4545
All constant but var. 4	54.55	0.0909
All constant but var. 5	54.55	0.0909
All constant but var. 6	36.36	-0.2727



3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	72.73	0.4545
Step 1: var.[1] constant	[2,3,4,5,6]	72.73	0.4545
Step 2: var.[1,2] constant	[3,4,5,6]	72.73	0.4545
Step 3: var.[1,2,4] constant	[3,5,6]	72.73	0.4545
Step 4: var.[1,2,4,5] constant	[3,6]	72.73	0.4545
Step 5: var.[1,2,4,5,6] constant	[3]	72.73	0.4545



1.3. Transition Sub-model: Water to Built-up

1. General Model Information

1) Input Files

Independent variable 1	ElevationTransition
Independent variable 2	SlopeTransition
Independent variable 3	RoadTransition
Independent variable 4	SettlementTransition
Independent variable 5	SuitabilityTransition
Independent variable 6	LandslideTransition
Independent variable 7	Agri2001Transition
Training site file	20012021LCM_Train_Water_Built

2) Parameters and Performance

Input layer neurons	7
Hidden layer neurons	4
Output layer neurons	2
Requested samples per class	114
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3748
Testing RMS	0.4019
Accuracy rate	76.67%
Skill measure	0.5333

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Water to Built-up	0.4035
Persistence : Water	0.6508

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4
i-Neuron 1	-3.9562	-5.3163	5.7790	-3.3145

i-Neuron 2	-0.4531	0.5592	-0.5198	-0.8235
i-Neuron 3	-0.4357	0.8070	-1.1445	-0.6605
i-Neuron 4	-0.7019	0.9804	-1.3329	-0.5314
i-Neuron 5	-0.4677	0.2136	-0.9370	-1.1345
i-Neuron 6	0.3142	0.0356	0.3760	0.4978
i-Neuron 7	3.6442	6.2191	-6.3768	2.5539

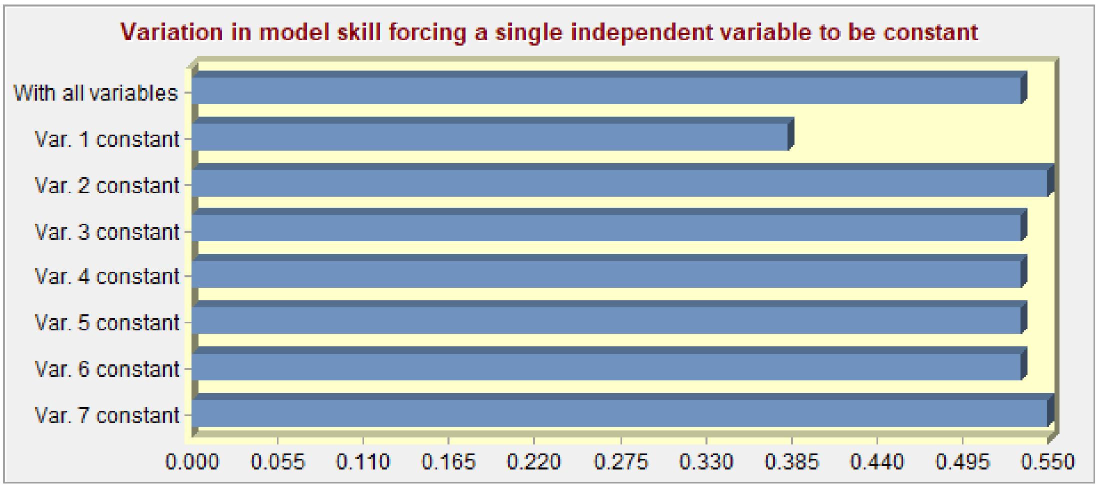
2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2
h-Neuron 1	-6.7458	6.9306
h-Neuron 2	-8.9649	8.9052
h-Neuron 3	7.0026	-7.0027
h-Neuron 4	-5.6789	5.5655

3. Sensitivity of Model to Forcing Independent Variables to be Constant

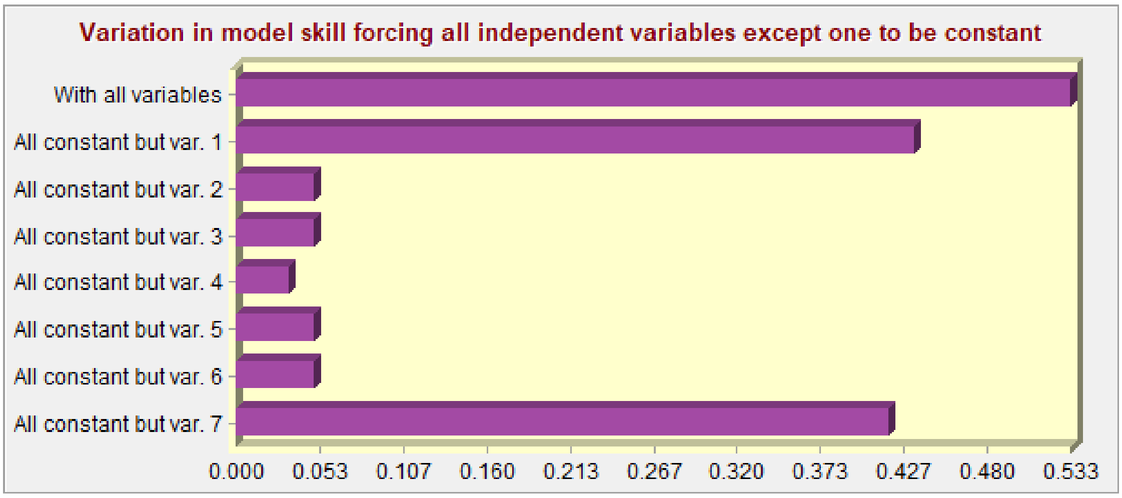
1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	76.67	0.5333	N/A
Var. 1 constant	69.17	0.3833	1 (most influential)
Var. 2 constant	77.50	0.5500	7 (least influential)
Var. 3 constant	76.67	0.5333	5
Var. 4 constant	76.67	0.5333	4
Var. 5 constant	76.67	0.5333	3
Var. 6 constant	76.67	0.5333	2
Var. 7 constant	77.50	0.5500	6



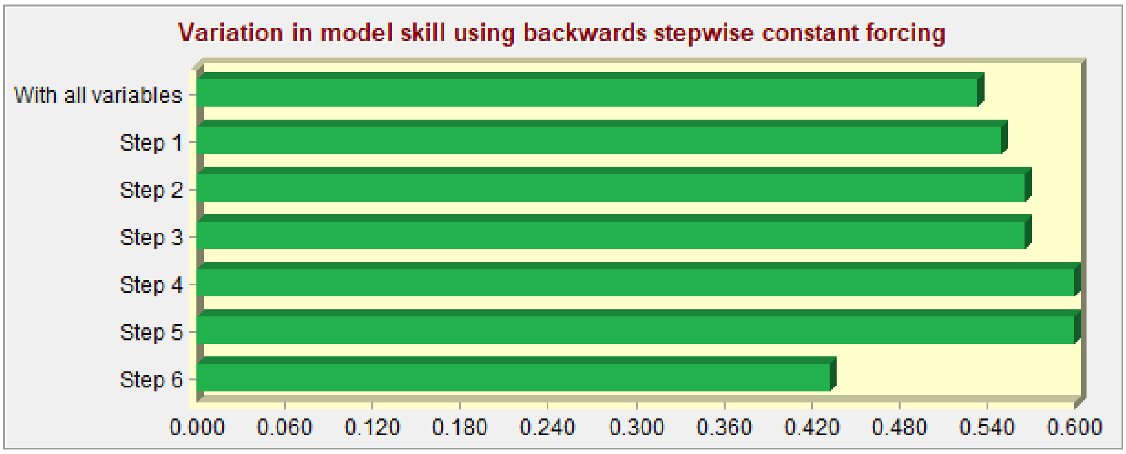
2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	76.67	0.5333
All constant but var. 1	71.67	0.4333
All constant but var. 2	52.50	0.0500
All constant but var. 3	52.50	0.0500
All constant but var. 4	51.67	0.0333
All constant but var. 5	52.50	0.0500
All constant but var. 6	52.50	0.0500
All constant but var. 7	70.83	0.4167



3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	76.67	0.5333
Step 1: var.[2] constant	[1,3,4,5,6,7]	77.50	0.5500
Step 2: var.[2,3] constant	[1,4,5,6,7]	78.33	0.5667
Step 3: var.[2,3,4] constant	[1,5,6,7]	78.33	0.5667
Step 4: var.[2,3,4,6] constant	[1,5,7]	80.00	0.6000
Step 5: var.[2,3,4,6,5] constant	[1,7]	80.00	0.6000
Step 6: var.[2,3,4,6,5,7] constant	[1]	71.67	0.4333



1.4. Transition Sub-model: Barren to Built-up

1. General Model Information

1) Input Files

Independent variable 1	ElevationTransition
Independent variable 2	RoadTransition
Independent variable 3	SettlementTransition
Independent variable 4	AspectTransition
Independent variable 5	RiverTransition
Training site file	20012021LCM_Train_Barren_Built

2) Parameters and Performance

Input layer neurons	5
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	276
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.4230
Testing RMS	0.4293
Accuracy rate	70.68%

Skill measure	0.4135

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Barren to Built-up	0.4058
Persistence : Barren	0.4219

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3
i-Neuron 1	4.2531	-1.4856	-6.2205
i-Neuron 2	-4.3985	-1.1771	0.5794
i-Neuron 3	-6.1584	-0.5289	-3.0322
i-Neuron 4	-0.6722	-0.5770	0.5523
i-Neuron 5	3.5277	-0.0736	-4.1464

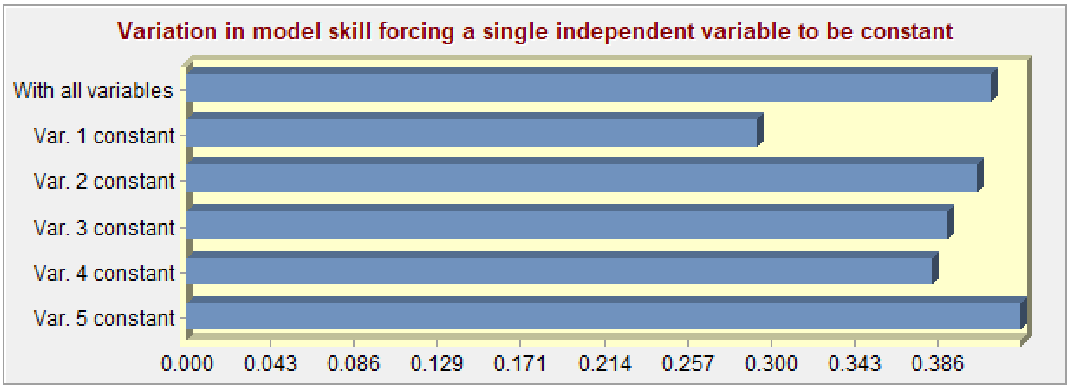
2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2
h-Neuron 1	5.2524	-5.2292
h-Neuron 2	-2.6804	2.6321
h-Neuron 3	-13.2153	13.2329

3. Sensitivity of Model to Forcing Independent Variables to be Constant

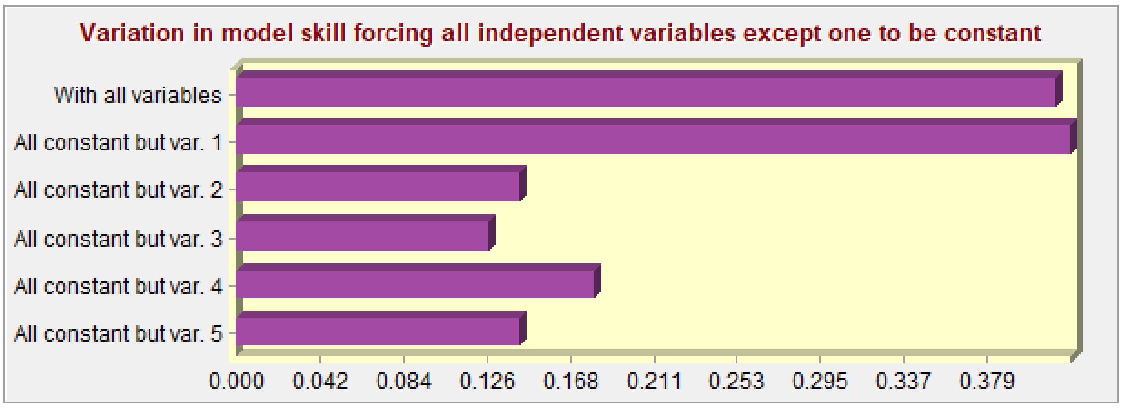
1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	70.68	0.4135	N/A
Var. 1 constant	64.66	0.2932	1 (most influential)
Var. 2 constant	70.30	0.4060	4
Var. 3 constant	69.55	0.3910	3
Var. 4 constant	69.17	0.3835	2
Var. 5 constant	71.43	0.4286	5 (least influential)



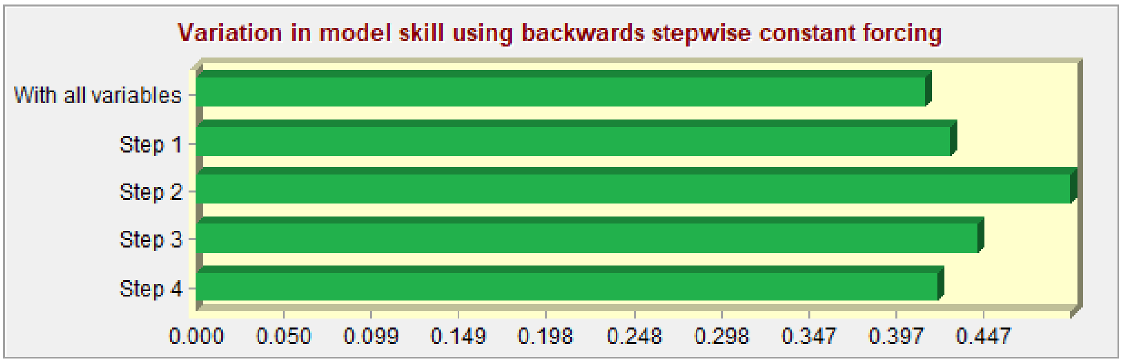
2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	70.68	0.4135
All constant but var. 1	71.05	0.4211
All constant but var. 2	57.14	0.1429
All constant but var. 3	56.39	0.1278
All constant but var. 4	59.02	0.1805
All constant but var. 5	57.14	0.1429



3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	70.68	0.4135
Step 1: var.[5] constant	[1,2,3,4]	71.43	0.4286
Step 2: var.[5,4] constant	[1,2,3]	74.81	0.4962
Step 3: var.[5,4,3] constant	[1,2]	72.18	0.4436
Step 4: var.[5,4,3,2] constant	[1]	71.05	0.4211



1.5. Transition Sub-model: Agriculture to Built-up

1. General Model Information

1) Input Files

Independent variable 1	ElevationTransition
Independent variable 2	RiverTransition
Independent variable 3	FloodTransition
Independent variable 4	SuitabilityTransition
Independent variable 5	LandslideTransition
Independent variable 6	SettlementTransition
Independent variable 7	RoadTransition
Independent variable 8	Agri2001Transition
Independent variable 9	AspectTransition
Training site file	20012021LCM_Train_Agriculture_Built

2) Parameters and Performance

Input layer neurons	9
Hidden layer neurons	4
Output layer neurons	2
Requested samples per class	1144
Final learning rate	0.0005
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3662
Testing RMS	0.3968

Accuracy rate	78.30%
Skill measure	0.5661

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Agriculture to Built-up	0.6049
Persistence : Agriculture	0.5271

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4
i-Neuron 1	2.7502	-1.5503	-3.1830	1.5905
i-Neuron 2	-2.8720	-0.7674	-1.4236	-2.0852
i-Neuron 3	-2.2727	6.4698	1.7881	2.7244
i-Neuron 4	-9.6790	-1.6460	4.7126	2.8067
i-Neuron 5	1.7412	-0.8302	-4.5941	-1.9554
i-Neuron 6	2.0091	-1.9172	-2.5123	-0.5681
i-Neuron 7	-1.9092	-1.1961	-0.4152	-1.6094
i-Neuron 8	0.2806	-0.1513	0.1371	0.0289
i-Neuron 9	3.7351	-4.8684	-1.3631	-9.2714

2) Weights between Hidden Layer Neurons and Output Layer Neurons

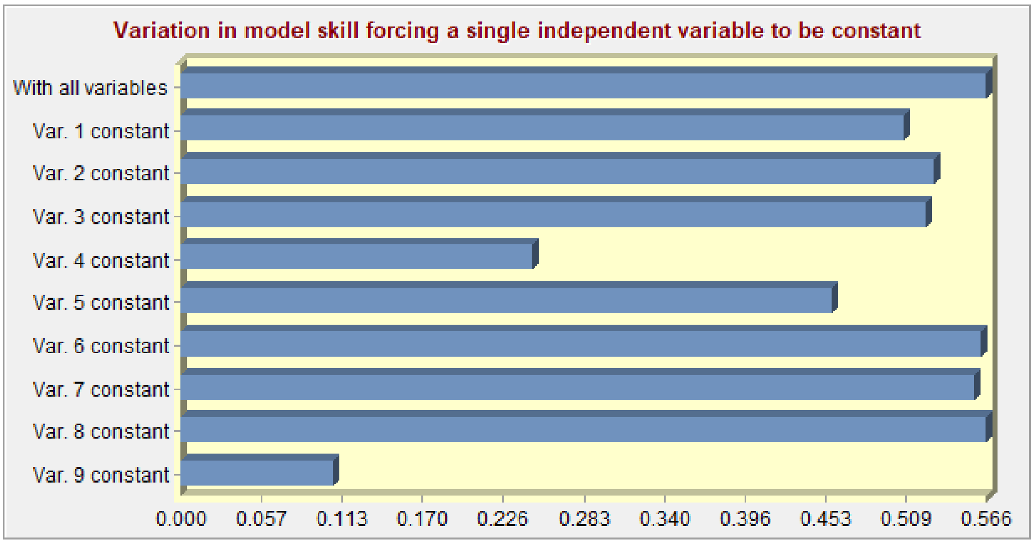
Neuron	o-Neuron 1	o-Neuron 2
h-Neuron 1	11.9132	-11.9107
h-Neuron 2	-5.0115	5.0106
h-Neuron 3	-4.9166	4.9156
h-Neuron 4	9.8976	-9.8958

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

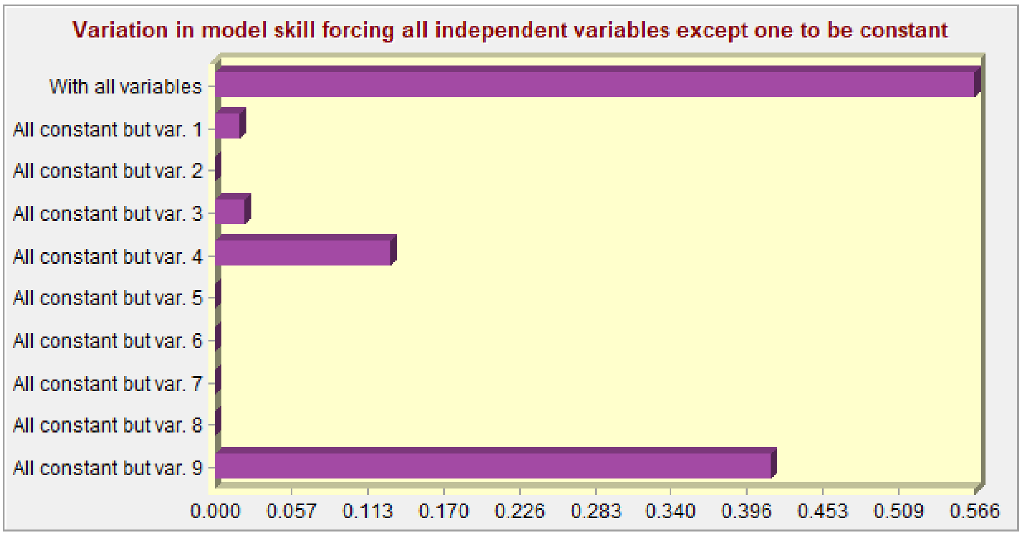
Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.30	0.5661	N/A
Var. 1 constant	75.42	0.5083	4
Var. 2 constant	76.47	0.5293	6

Var. 3 constant	76.20	0.5241	5
Var. 4 constant	62.38	0.2476	2
Var. 5 constant	72.88	0.4576	3
Var. 6 constant	78.13	0.5626	8
Var. 7 constant	77.87	0.5573	7
Var. 8 constant	78.30	0.5661	9 (least influential)
Var. 9 constant	55.38	0.1076	1 (most influential)



2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	78.30	0.5661
All constant but var. 1	50.92	0.0184
All constant but var. 2	49.96	-0.0009
All constant but var. 3	51.09	0.0219
All constant but var. 4	56.52	0.1304
All constant but var. 5	49.87	-0.0026
All constant but var. 6	49.96	-0.0009
All constant but var. 7	49.96	-0.0009
All constant but var. 8	49.96	-0.0009
All constant but var. 9	70.69	0.4138



3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	78.30	0.5661
Step 1: var.[8] constant	[1,2,3,4,5,6,7,9]	78.30	0.5661
Step 2: var.[8,6] constant	[1,2,3,4,5,7,9]	78.13	0.5626
Step 3: var.[8,6,7] constant	[1,2,3,4,5,9]	78.74	0.5748
Step 4: var.[8,6,7,1] constant	[2,3,4,5,9]	75.68	0.5136
Step 5: var.[8,6,7,1,2] constant	[3,4,5,9]	77.87	0.5573
Step 6: var.[8,6,7,1,2,3] constant	[4,5,9]	74.54	0.4908
Step 7: var.[8,6,7,1,2,3,4] constant	[5,9]	64.65	0.2931
Step 8: var.[8,6,7,1,2,3,4,5] constant	[9]	70.69	0.4138