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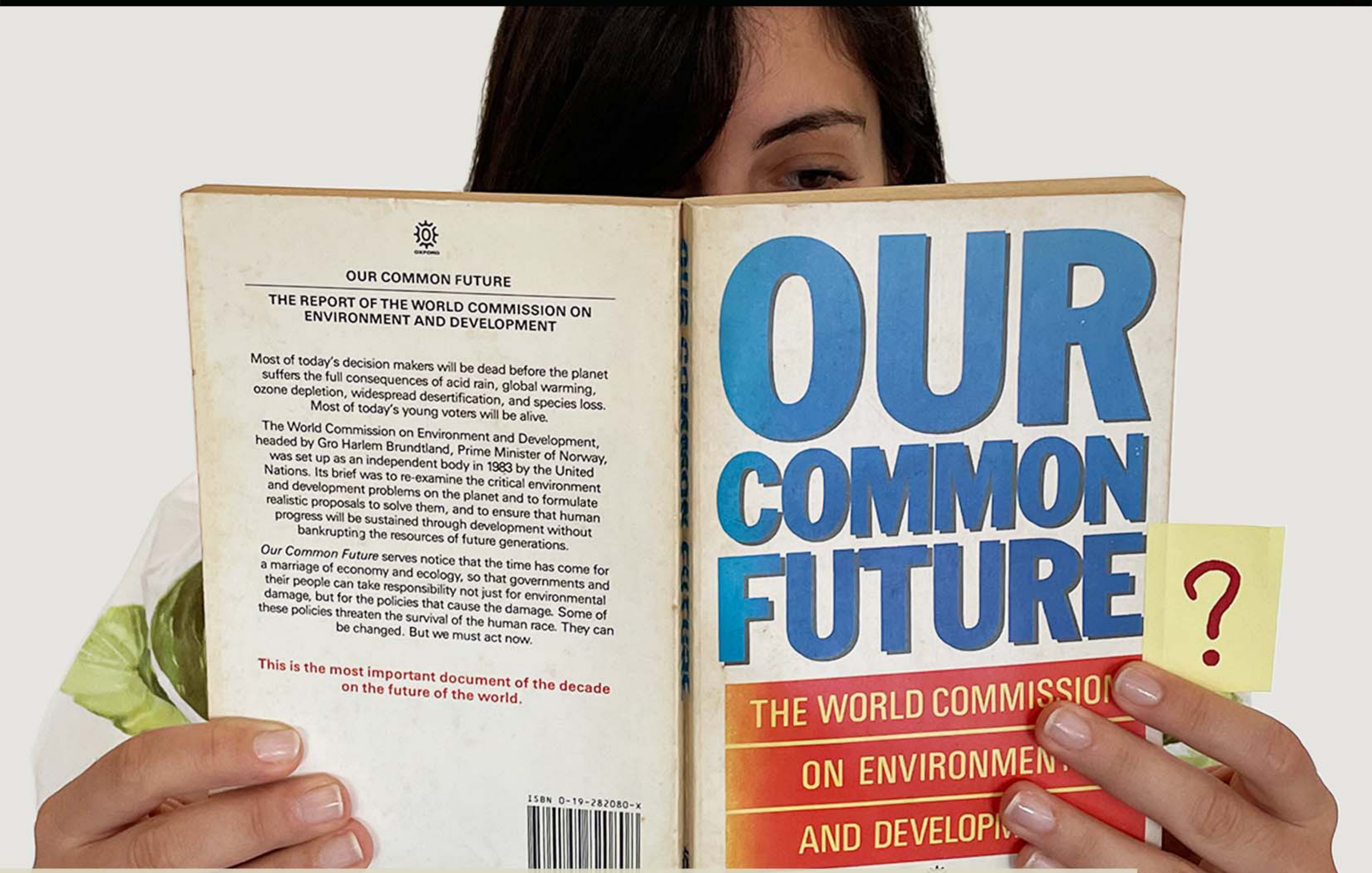

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The cover image shows a copy of the 1987 UN report “Our Common Future – The report of the world Commission on Environment and Developments”. The picture has been taken in TeMA Lab in July 2023. On the bottom, there is a collage made up of four pictures of recent climate disasters (Source: Google images)

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Suitable sites for built-up area expansion in Kamalamai municipality, Sindhuli district, Nepal

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Abstract

Kamalamai municipality has witnessed significant built-up development in recent years but there has been very limited planning and regulation for controlling this trend. Haphazard built-up expansion may risk environmental sensitive areas and could sprawl in areas lacking basic facilities. Identification of suitable areas for built-up development is critical to regulate future development in an efficient manner. The main objective of the study was to identify suitable sites for built-up expansion in Kamalamai municipality. Landsat images of 2001, 2016, and 2021 were used for Land Use Land Cover (LULC) trend analysis. Suitability analysis was done based on Analytical Hierarchy Process (AHP) pair-wise comparison. Multi-layer Preceptor (MLP) neural network was used for transition sub-modeling of each LULC class to built-up. Markov model was used for future urbanization modeling in combination with constraint/incentive to redirect the change in expansion suitable areas. During 2001 and 2021 the built-up had increased from 0.5% (1.09 Km²) to 1.9% (3.95 Km²). The model predicted the built-up to increase to 2.5% (5.13 Km²) by 2031, 3.3% (6.69 Km²) by 2041, and 4% (8.25 Km²) by 2051. The region has significantly urbanized since 2016 mainly contributed by in-migration and is predicted to follow the trend in the future.

Keywords

Built-up Area; Land Suitability Analysis; GIS; Land Use Land Cover.

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1. Introduction

More than half of the world population are currently living in urban areas, and 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). Similarly, the urban population in Asia is projected to be more than 55% by 2030 (Choe & Roberts, 2011). This unprecedented urban population surge especially in low-income nations have in past put immense pressure on governments inducing urban sprawl. Rapid and haphazard urbanization has been linked to devastating geo-hazards causing loss of life and property, and damaging environment (Cui et al., 2019). Moreover, the impact of unmanaged infrastructure development is widespread across many aspects of natural environment. 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).

Nepal has remained one of the least urbanized country but at the same time is one of the fastest urbanizing country 1990's onwards, and it is projected to urbanize at a rate of 2.0 per cent per year until 2050 (UN DESA, 2019). Urbanization scenario in Nepal has been dominated by high growth areas like Kathmandu valley and a few large and medium cities, the valleys, border towns and market towns on highways passages (Bakrania, 2019). The study area, Kamalamai municipality is a market town located along the highway between Kathmandu valley and terai plains linking India. Kamalamai Municipality is also the headquarter of Sindhuli district and a trade hub for hinterlands and rural areas in proximity of the municipality. The urbanization in Kamalamai Municipality is influenced by a variety of social-economic and political factors that shape the current and potential constraints and incentives for urban growth.

Kamalamai Municipality has experienced significant population growth, primarily driven by rural-urban migration. Factors such as limited employment opportunities, lack of basic services, and aspirations for better livelihoods have led rural residents to seek economic opportunities in and around the municipal areas. This influx of people has contributed to the rapid urbanization of Kamalamai Municipality. Similarly, the construction of the national highway connecting Kamalamai Municipality to the capital city and trade routes to India has played a crucial role in enhancing the municipality's importance as a trade hub. The improved connectivity and increased business opportunities along the highway have fueled urban growth and attracted investment in the area. Furthermore, the devastating earthquake in 2015 resulted in the displacement of many people and widespread damage to houses in Nepal. The reconstruction efforts following the earthquake have led to new construction activities in towns like Kamalamai. The need for housing and infrastructure has further contributed to the rapid built-up development in the municipality in recent years.

Similarly on political front, the decentralization and federal restructuring of Nepal in 2015 brought significant changes to the governance structure and power distribution. The centralized structure had encouraged urbanization in Kathmandu, the capital city, but with decentralized structure other central towns like Kamalamai have gained importance. The decentralization effort established towns like Kamalamai as centers of region. This transformation has influenced rural-urban migration patterns, as well as the growth and development of the town. This has opened new possibilities in the municipality with implications for urban planning, infrastructure development, and service delivery. Although urban planning and development strategy are absent in implementation level the political dynamics has put responsibility on the local planning system. The local government has new responsibilities to make policies and initiatives that promote economic activities and investment in Kamalamai Municipality to attract businesses, create employment opportunities, and drive urban growth. Furthermore, the provision of infrastructure and public amenities can further stimulate urban development.

The National Urban Development Strategy (NUDS, 2017) emphasizes the need to promote economic activities and investment in municipalities like Kamalamai by attracting businesses, creating employment opportunities, and improving infrastructure, such as transportation networks, utilities, and public amenities, urbanization. This rapid built-up surge in recent years in not planned nor regulated. The issues like air pollution, water pollution and rapid decline in green 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 & 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. The municipality consists of hills prone to landslides as well as plains which are prone to flooding. The current built-up development may expand inconsiderately towards flood and landslide prone areas, or areas unsuitable for development or is less desirable. Recent incidences in the country have shown that poorly planned settlements have suffered even from low level natural calamities (Bhattarai & Conway, 2021). There is an urgent need for an urban development strategy to preserve good-quality agricultural land and help conserve natural resources (Bhattarai & Conway, 2021).

As urbanization continues in a rapid manner, 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 land use and environmental planning plays a significant role in urban management to obtain sustainable development. One of the pressing issue in land use planning is determining the suitability of locations for development considering physical, environmental, natural and other factors (Karim et al., 2020). Furthermore, urban future is of particular interest to urban and regional planners since the actions and policies of today can be directed towards sustainable future (Rocha & Tenedório, 2018). Urban growth processes are usually difficult to simulate (Barredo et al., 2003), and identifying suitable areas are equally challenging. In recent years, the progress in mathematical calculations and statistical model have opened a new dimension for studying cities while with the invention of computational machines and computers have revolutionized urban development and planning studies (Wahyudi & Liu, 2015). The computerized analysis of urban areas has made it possible analyzing different variables responsible for built-up expansion in a short amount of time and less user effort. The computerized spatial models that depict and re-shape the reality as per input variables have simplified complex spatial patterns (Barredo et al., 2003). (Zullo et al., 2015) emphasizes the significance of identifying areas for urban development due to the negative consequences associated with urban sprawl and its negative impacts on natural ecosystems and landscapes.

The future is uncertain but predicting it offers leverage for directing present-day plans and policies for a managed development while minimizing the associated risks. Spatial modelling is used for future scenario simulation based on historic information of geographical changes based on quantification of Land Use Land Cover (LULC) changes (Rocha & Tenedório, 2018). Land use simulation assists as a decision support system to explore the anthropogenic interference on natural environment (Liu et al., 2020) and provides the baseline scenario for predicting future patterns of development (Saputra & Lee, 2019). LULC models can be used to examine the transition among LULC categories and analyse multiple causes and consequences of change (Shen et al., 2020). With the use of model analysis and simulation of LULC, spatial pattern change can be identified along with the rate of land use change and LULC class interactions (Han et al., 2015). This modelling and prediction of future LULC and urban growth can enable to understand a futuristic view for sustainable development (Hasan et al., 2020).

Markov chain model has been incorporated with Geographic Information System (GIS) and Remote Sensing (RS) Technologies for an effective simulation and prediction of LULC change (Shen et al., 2020). The spatial modelling method like Markov model can depict the direction of LULC shifts and provide a framework for analysing land use demand on future (Han et al., 2015). The transition probability maps 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). The model generates events and probability of generating subsequent observations dependent on previous state values (Hosom, 2003).

Similarly, 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 and least suitable for development. Identification of suitable areas for land development is especially relevant in hilly areas and even crucial aspect of planning (M. Kumar & Shaikh, 2013). The identification of suitable development areas can ensure economic benefits and environmental protection. Infill built-up development can minimize the pressure on green spaces and agricultural lands (Jehling et al., 2018; McConnell & Wiley, 2011; Mustafa et al., 2018). Urbanization in areas less prone to natural hazards ensures protection of lives and economic security. Suitability analysis helps identify best areas to direct the urban growth and worst areas where urban expansion should be restricted.

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 et al., 2020). Analytical Hierarchy Process (AHP) is one of the decision-making tools involving multi-criteria analysis. AHP was developed by Saaty as a Multi-Criteria Decision Making (MCDM). 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 & Vargas, 2012). 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 & Liu, 2002).

Previous studies have demonstrated the capability of integrating different data sources including LULC, RS, and GIS as a method for land suitability analysis (Youssef et al., 2011). Former studies have measured spatial patterns (Fei & Zhao, 2019; Yu & Zhou, 2018) by analyzing forces driving urban expansion (Dadashpoor et al., 2019a), predicting built-up growth (Cai et al., 2020; Y. Chen et al., 2019; Xu & Gao, 2019; Zhou et al., 2020) and exploring the effects of built-up expansion (S. Chen et al., 2020; Dadashpoor et al., 2019b; Zhou et al., 2020). However there has been no suitability modelling study in the study area. Thus, the aim of this study was to analyze suitable areas for built-up expansion in Kamalamai Municipality and model expansion in suitable areas for 2031, 3041 and 2051. The suitability analysis was based on landslide susceptibility, flood susceptibility, existing LULC, slope, aspect, proximity to existing roadways, proximity to existing settlements and elevation. The LULC trend was analyzed based on Landsat-8 imagery for 2001, 2016 and 2021 by using image classification technique for LULC quantification. The model for future expansion was created using LULC 2001 to 2021 in Land Change Modeler (LCM). The suitability map was integrated to future expansion model as incentives and constraints to achieve suitable built-up areas in 2031, 2041 and 2051.

The study can be useful in urban management of the study area. The areas unsuitable for development can be avoided in future. The areas that are more suitable for development can be encouraged to residents for future development. The identified areas that may have more pressure in future for development can be prioritized for public infrastructure development so to channel the future growth in safe areas that are economic as well for local government investment. The study can be beneficial for policy makers, local government, developers, and planners for safe and sustainable urban development.

2. Study Area

Kamalamai Municipality is situated in hilly region of central-eastern Nepal (Fig.1). Administratively the municipality is 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 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 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. 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.

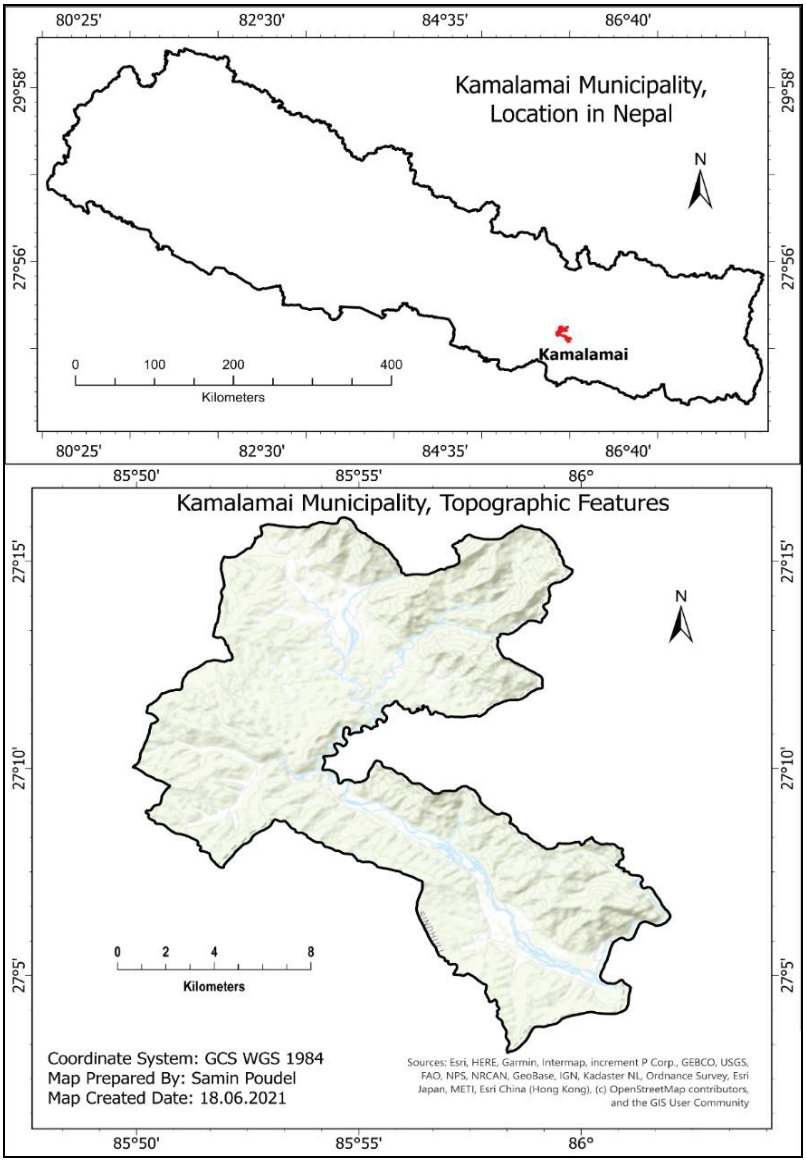

Fig.1 Location of Kamalamai Municipality in Nepal

3. Materials and Methods

3.1 Materials

Landsat images were downloaded from United States Geological Survey (USGS) website in 'Tiff' file format (Tab.1). These images covered entire study area of the municipality.

Date of Acquisition	Satellite	Spatial Resolution
18-01-2001	Landsat 7	30m
04-01-2016	Landsat 8	30m
01-01-2021	Landsat 8	30m

Tab.1 Landsat satellite images specification

Digital Elevation Model (DEM) was downloaded as Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global data. The freely available enhanced void filled elevation model with 30m spatial resolution was downloaded from USGS website. The data of municipal boundary, landslide susceptibility, flood susceptibility, roadway and settlements were acquired from Department of Urban Development and Building Construction (DUDBC), Nepal's municipal database for Kamalamai Municipality.

3.2 Image pre-processing

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 level 2 output products are enhanced products available for download. The downloaded file consisted of 8 spectral bands. The study area was subset to the extent of the study area in ArcGIS Pro for bands 1 to 7. The subset image was composited to single image using "Composite Bands" tool in ArcGIS Pro. The same process was used for images of 2001, 2016 and 2021.

3.3 Land Use Land Cover (LULC) classification

Image was classified using "Image Classification Wizard" in ArcGIS Pro. The supervised image classification technique was used to classify the image. Training samples were assigned for each image of 2001, 2016 and 2021. 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%. 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 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%.

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 images as well (Tzotsos & 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. 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".

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). Accuracy assessment was done using "Stratified random points" in ArcGIS Pro and verified using satellite imagery and google earth base map. The data was verified using confusion matrix including user's accuracy, producer's accuracy, overall accuracy, and Kappa Coefficient. "Compute Confusion Matrix" tool in ArcGIS Pro was used to get an excel table of confusion matrix. An acceptable accuracy limit of more than 85% (ThiLoi, Tuan and Gupta, 2015) was checked for classified images.

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 belonging to that category (Schuckman & 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 ((1)-(4)) (Lahoti et al., 2019):

$$User's Accuracy\ in\ class\ (i) = \frac{n_{ij}}{n_{i.}} \tag{1}$$

$$Producer's Accuracy\ in\ class\ (i) = \frac{n_{ij}}{n_{.j}} \tag{2}$$

$$Overall\ Accuracy = \frac{(\Sigma \mathrm{k}^{\mathrm{i}} = 1 n_{ij})}{n} \tag{3}$$

$$Kappa\ Coefficient = \frac{(n\Sigma \mathrm{k}^{\mathrm{i}} = 1 n_{ij} - \Sigma \mathrm{k}^{\mathrm{i}} = 1 n_{i}.n_{j}\ )}{(n2 - \ \Sigma \mathrm{k}^{\mathrm{i}} = 1\ n_{i}.n_{j})} \tag{4}$$

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.

3.5 Analytical Hierarchy Process (AHP)

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 criterions are considered, and the prioritization of these variables are different from one another (Vargas, 2010). The fundamental comparison scale (Tab.2) is used to make judgement of paired comparison.

1	Equal Importance	Two activities contribute equally to the objective
2	Weak	-
3	Moderate Importance	Experience and judgment slightly favor one activity over another
4	Moderate Plus	-
5	Strong Importance	Experience and judgment strongly favor one activity over another
6	Strong Plus	-
7	Very Strong or Demonstrated Importance	An activity is favored very Strongly over another, its dominance demonstrated in practice
8	Very, Very Strong	-
9	Extreme Importance	The evidence favoring one activity over another is of the highest possible order of affirmation

Tab.2 Fundamental Comparison Scale (Satty and Vargas, 2012)

The scale has been validated for its effectiveness in many applications (Saaty & Vargas, 2012). The steps of measuring inconsistencies; consistency index (CI) and Consistency Ratio (CR) are used to improve the consistency of judgements (Saaty & Vargas, 2012). CI is given by (5) and CR (6) where, Random Index (RI) is the average value of CI and CR must be < 0.1 (Saaty & Vargas, 2012) for correct decision.

$$CI = \frac{(\lambda \max - n)}{(n-1)} \tag{5}$$

$$CR = \frac{CI}{RI} \tag{6}$$

3.6 Suitability Analysis

The suitability analysis was based on flood and landslide susceptibility, existing LULC, aspect, slope, road proximity, settlement proximity and elevation. The DEM was used to derive slope and aspect of the study area using "Slope" and "Aspect" tools in ArcGIS Pro. AHP was used to derive weights to each suitability layers. "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. The weighted overlay method was used for analyzing the values of each variable to find suitable areas for built-up expansion.

3.7 Land Change Modeler (LCM)

The modelling of LULC was done in Terr-set Land Change Modeler. LCM Change Analysis was first used to analyze changes in LULC from 2001 and 2016. Transition variables i.e., proximity to roadway, proximity to settlements, elevation, slope, flood susceptible areas, landslide susceptibility, aspect were used to calculate transition potential maps using 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 analyzer, Markov Chain prediction process with prediction date 2021 using transition sub-models for all five possible transition classes, then model was run to obtain hard and soft prediction map for 2021. The model was then used for transition of 2016 to 2021, 2031, 2041 and 2051.

To predict the LULC model for 2031, 2041 and 2051 the constraints and incentives regions were assigned in accordance with suitability map. The maps and models created in Terr-set were added as layers in ArcGIS pro. The map data was calculated in ArcGIS Pro and exported for further data analysis in Excel and maps were prepared in ArcGIS Pro.

3.8 Markov Model

Markov model is convenient tool for simulating landscapes and processes for modelling LULC changes, where future state is simulated based on immediate state (S. Kumar et al., 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).

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 et al., 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 in Markov Model is calculated as (7).

$$S(t+1) = P_{ij} \times S(t) \tag{7}$$

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 (8).

$$\begin{bmatrix} P_{11} & P_{12} & \dots & P_{13} \\ P_{12} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{11} & P_{12} & \dots & P_{1n} \end{bmatrix}$$

$$(0 \leq P_{ij} < 1 \, and \, \Sigma_{j}^{N} = 1 \, P_{ij}, (i, j = 1, 2, \dots .. n)) \tag{8}$$

4. Results

4.1 Classification Results

The Landsat images of 2001, 2016 and 2021 were classified for the study area of Kamalamai Municipality (Fig.2).

The built-up areas accounted 0.5% (1.09 Km²) in the municipality in 2001. The municipality consisted largest area of forest with 73.1% (149.89 Km²) followed by agricultural land 20.4% (41.93 Km²). In 2016 the forest decreased to 70.1% (143.81 Km²) and agricultural area increased to 23.7% (48.51 Km²) while built-up had an increment to 0.8% (1.64 Km²). In 2021 the municipality consisted of 70.9% (145.46 Km²) forest while agricultural area decreased from 2016 to 17.3% (35.40 Km²). The built-up increased considerably from 2016 to 1.9% (3.95 Km²). The analysis of land use change revealed significant transformations in Kamalamai Municipality from 2001 to 2021. The built-up areas exhibited noticeable growth, particularly in the central part of the municipality. Forest cover decreased over time, while orchards, croplands, and settlements increased.

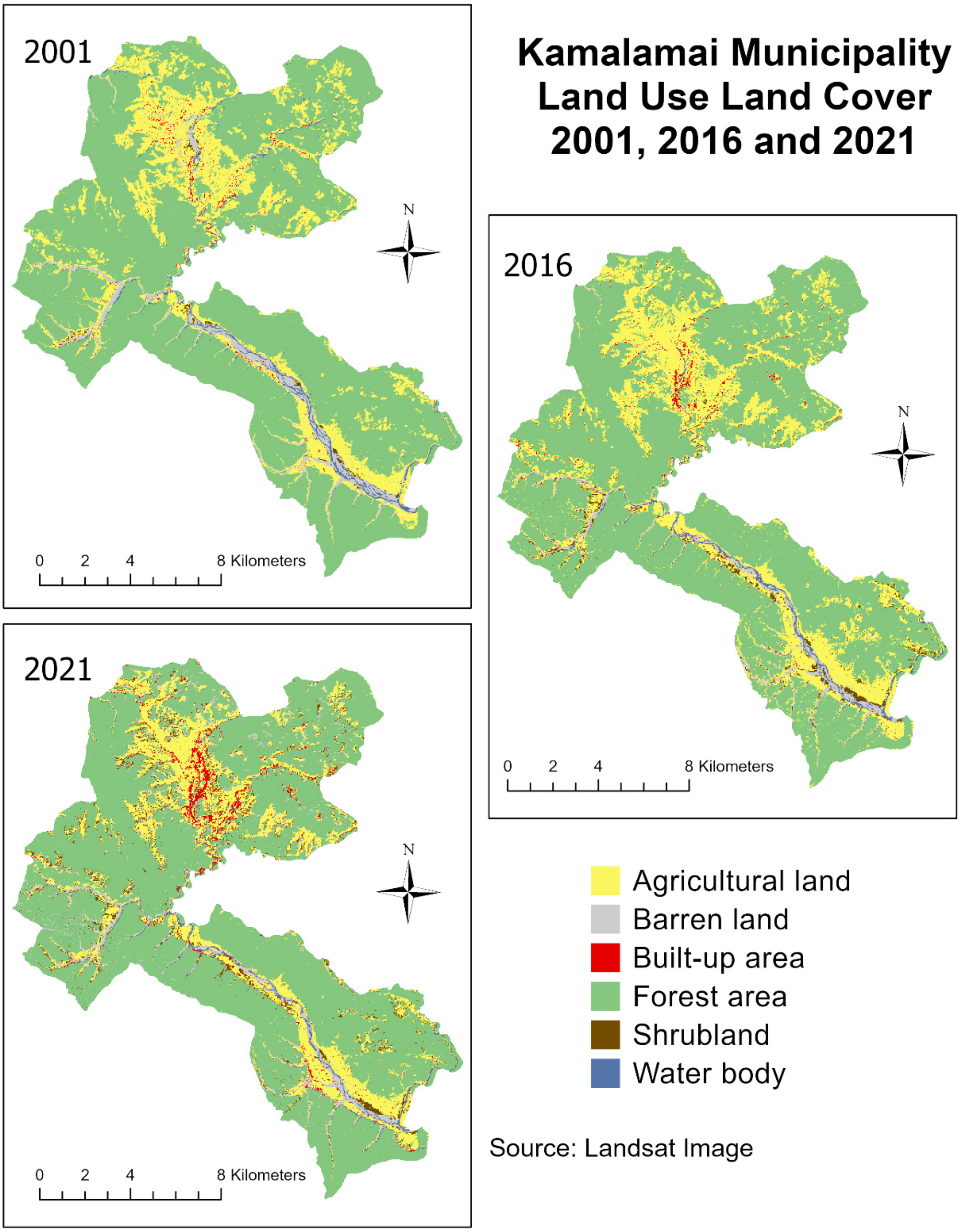

Fig.2 Kamalamai Municipality: Land Use Land Cover 2001, 2016 and 2021

4.2 Accuracy Assessment

The accuracy for each classification was found to be within the acceptable limit of 85% ovearall accuracy (ThiLoi et al., 2015) (Tabb. 3-5).

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

Tab.3 Confusion Matrix: Land Use Land Cover 2001

Class Value	Water Body	Built-up Area	Barren Land	Forest Area	Agricultural land	Shrubland	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

Tab.4 Confusion Matrix: Land Use Land Cover 2016

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

Tab.5 Confusion Matrix: Land Use Land Cover 2021

4.3 Pairwise Comparison

The pairwise weightage was assigned based on fundamental pairwise comparison (Table 2), for suitability parameters, landslide susceptibility, flood susceptibility, existing LULC, aspect, slope, proximity to slope and proximity to settlement (Tab.6).

	Landslide	Flood	Existing LULC	Aspect	Slope	Road	Settlement	Elevation
Landslide	1	1	4	5	6	7	8	9
Flood	1	1	4	5	6	7	8	9
Existing 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	1	3
Elevation	0.11	0.11	0.13	0.14	0.14	0.33	0.33	1

Tab.6 Deriving Priorities for Suitability

The CI was obtained to be 0.114 and CR 0.081. The relative values obtained for each class was, landslide susceptibility = 0.3, flood susceptibility = 0.3, existing LULC = 0.15, aspect = 0.10, slope = 0.07, distance from existing roads = 0.03, distance from existing settlements = 0.03, and elevation = 0.02. The obtained values are further split for each suitability parameters.

4.4 Suitability Analysis

Tab.7 shows the weighted values for each parameter for suitability assessment of the study area.

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
		Low- Above 1000m	0

Tab.7 Weightage for Suitability Parameters

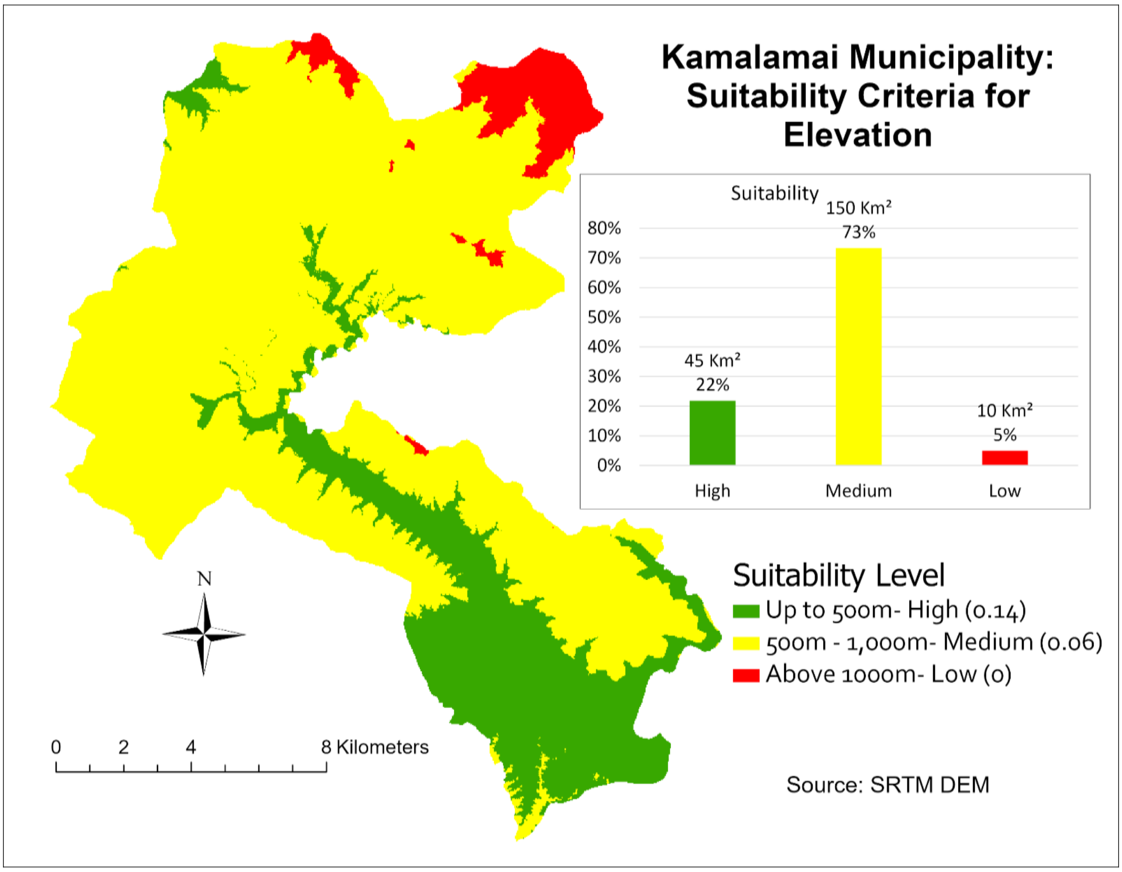

Fig.3 Kamalamai Municipality: Suitability Criteria for Elevation

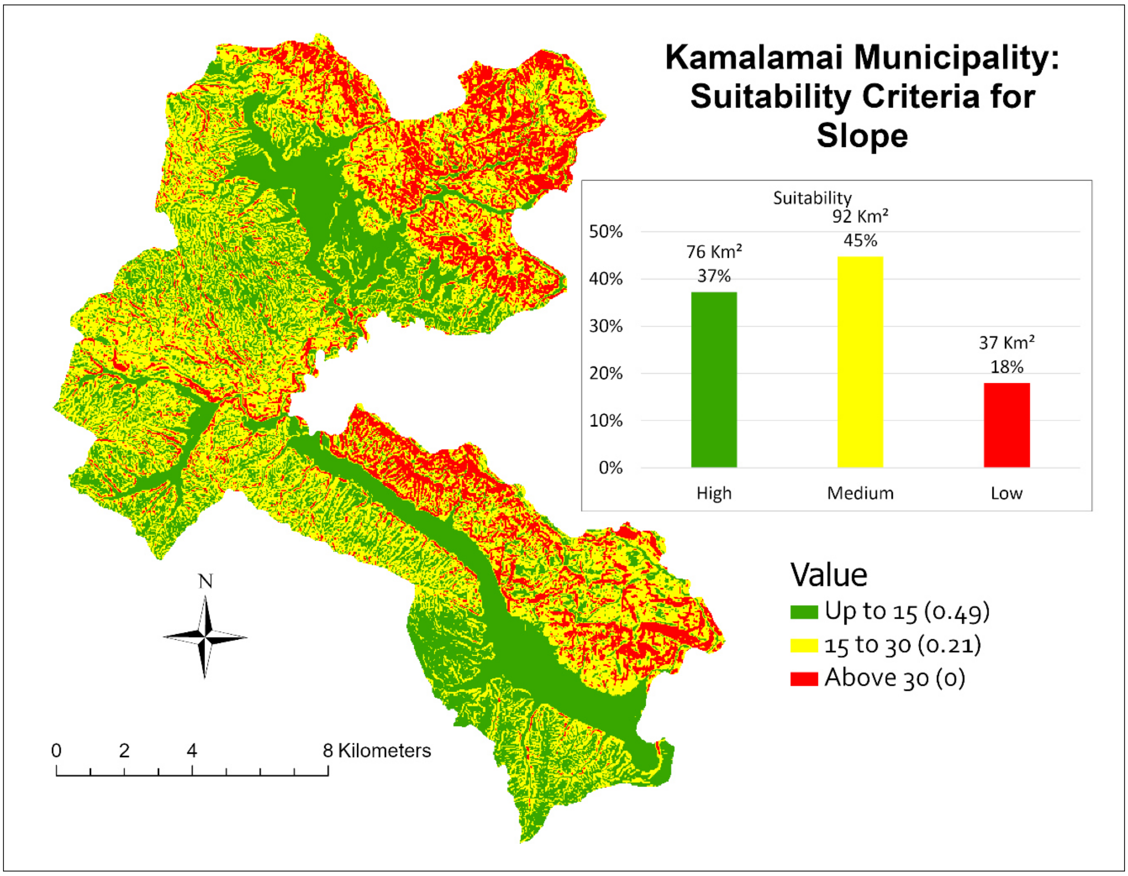

Fig.4 Kamalamai Municipality: Suitability Criteria for Slope

The suitability criteria for elevation included areas of high elevation (Above 1,000 m) as least suitable, the areas between 500 m and 1,000 m as medium suitable and areas up to 500 m as highly suitable. 22% (45 Km²) area was highly suitable, 73% (150 Km²) area had medium suitability and 5% (10 Km²) had low suitability for built-up expansion (Fig.3).

The suitability criteria for elevation included areas of high elevation (Above 1,000 m) as least suitable, the areas between 500 m and 1,000 m as medium suitable and areas up to 500 m as highly suitable. 22% (45 Km²) area was highly suitable, 73% (150 Km²) area had medium suitability and 5% (10 Km²) had low suitability for built-up expansion (Fig.3).

The suitability criteria for Slope included area of high slopes (Above 30°) as least suitable, medium slope (15° to 30°) and low slopes (Up to 15°) as highly suitable. 37% (76 Km²) area was highly suitable for built-up expansion, 45% (92 Km²) area had medium suitability and 18% (37 Km²) had low suitability for built-up expansion (Fig.4).

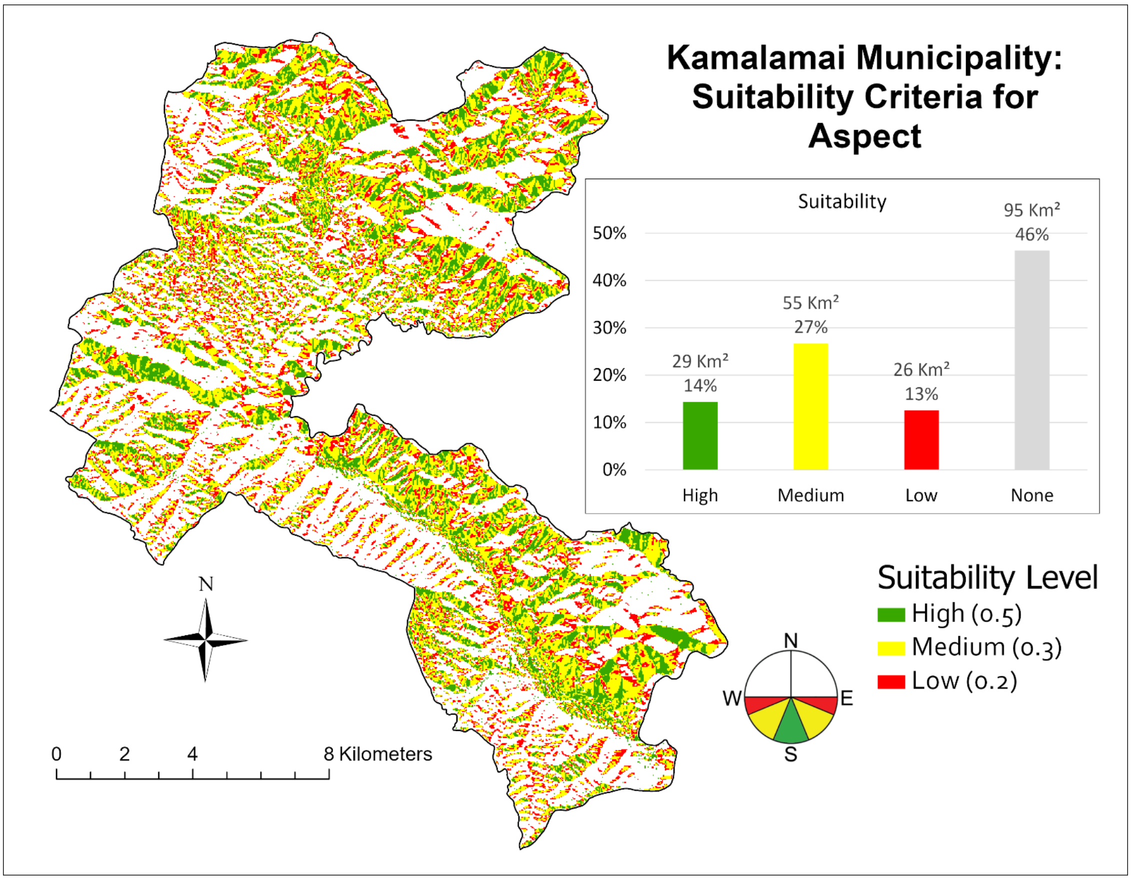

Fig.5 Kamalamai Municipality: Suitability Criteria for Aspect

The suitability criteria for aspect included areas of northern aspect (0-89.5 and 271-360) as not suitable, eastern (90-112.5), and western (247.5-270) aspect as least suitable, south-western (202.5-247.5), and south-eastern (112.5-157.5) aspect as medium suitable and southern aspect (157.5 to 202.5) as most suitable. 14% (29 Km²) area was highly suitable for built-up expansion, 27% (55 Km²) area had medium suitability and 13% (26 Km²) had low suitability for built-up expansion, while 46% (95 Km²) was not suitable (Fig.5).

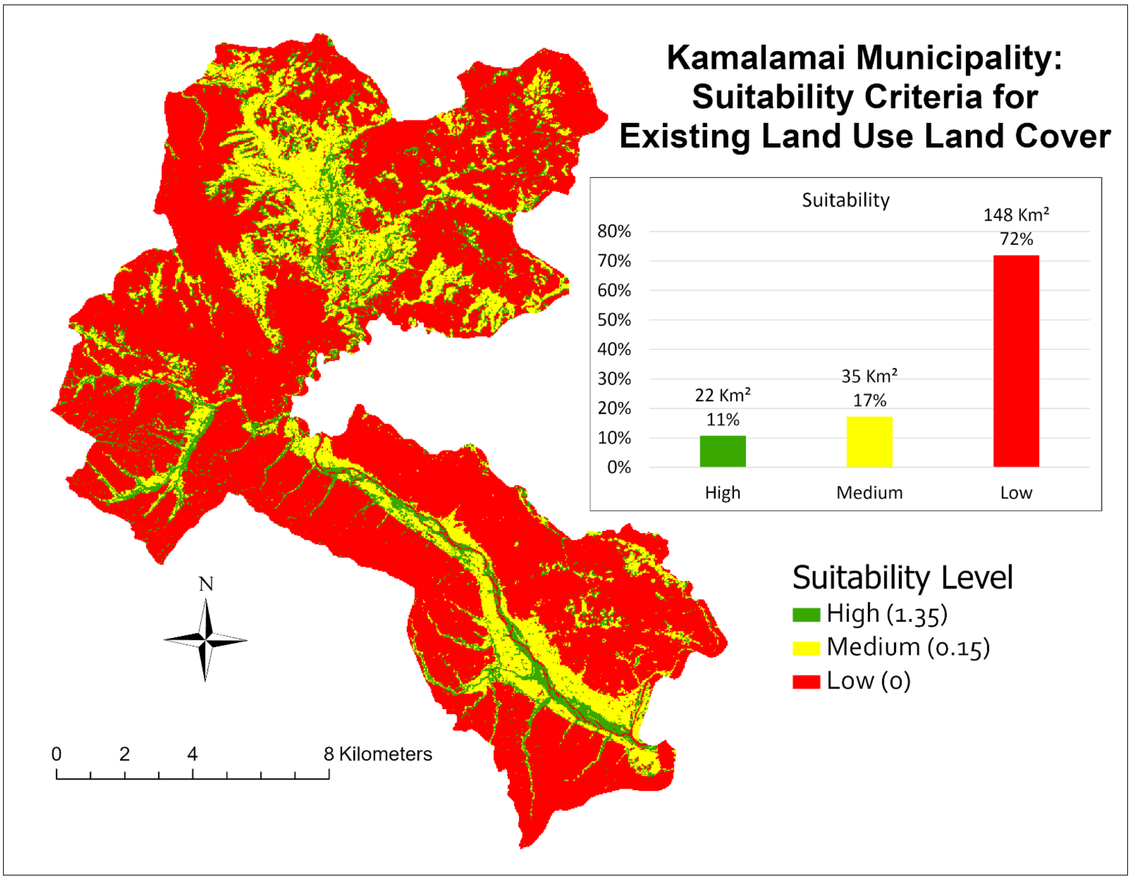

Fig.6 Kamalamai Municipality: Suitability Criteria for Existing Land Use Land Cover

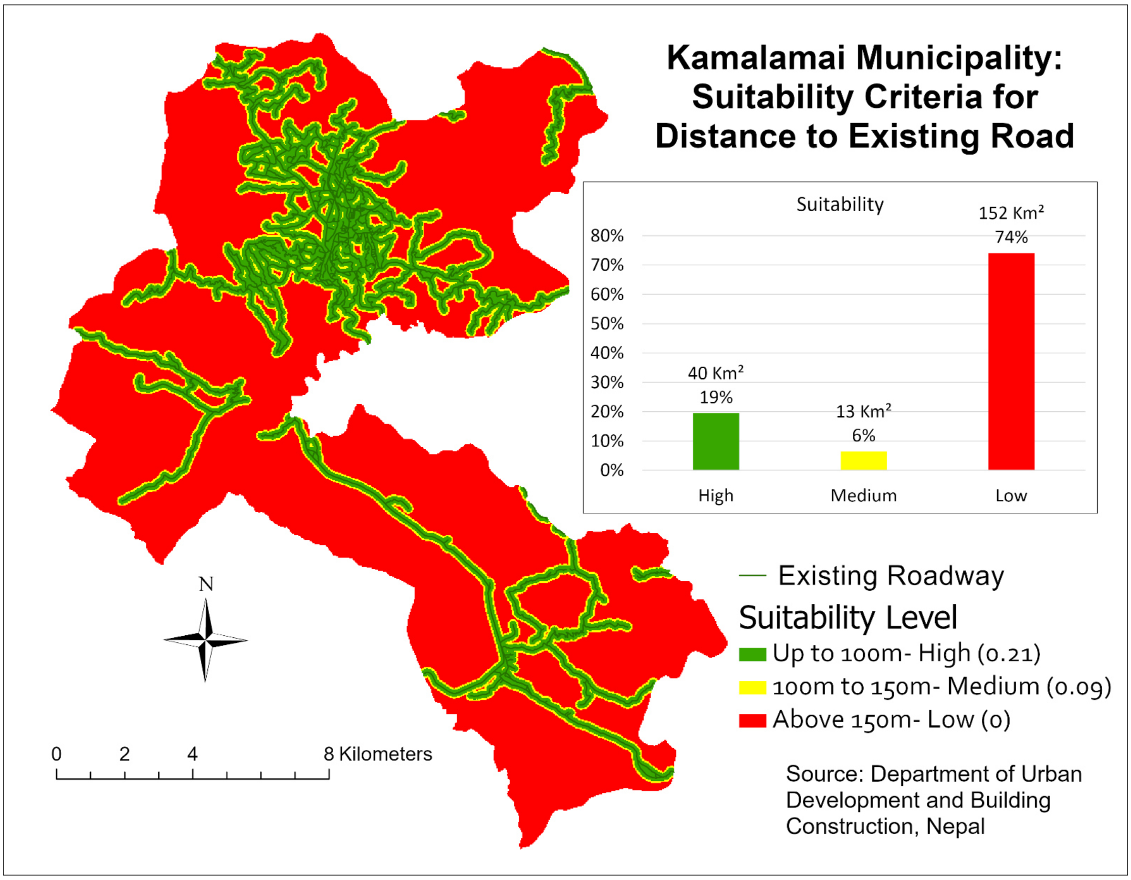

Fig.7 Kamalamai Municipality: Suitability Criteria for Distance to Existing Roadways

The suitability criteria for existing LULC included built-up areas, barren and shrubland as highly suitable, agricultural area as medium suitable and waterbodies and forest as low suitable. 11% (22 Km²) area was highly suitable for built-up expansion including infill in existing built-up, 17% (35 Km²) area had medium suitability and 72% (148 Km²) had low suitability for built-up expansion (Fig.6).

The suitability criteria for roadway proximity included areas farther from the existing roadway (more than 150 m) as not suitable, areas between 100 m and 150 m from the roadways as medium suitable and areas up to 100 m from the roadway as highly suitable. 19% (40 Km²) area was highly suitable, 6% (13 Km²) area had medium suitability and 74% (74 Km²) had low suitability for built-up expansion (Fig.7).

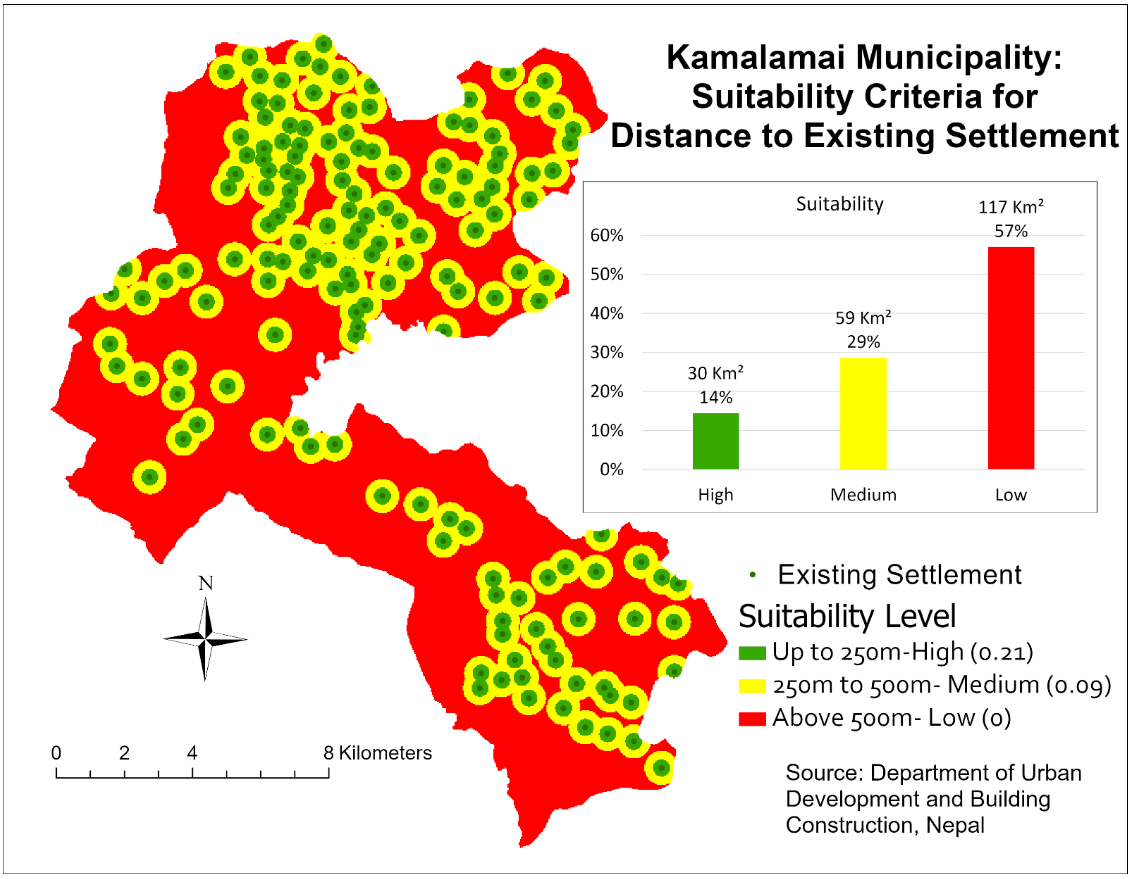

Fig.8 Kamalamai Municipality: Suitability Criteria for Distance to Existing Settlements

The suitability criteria for settlements proximity included areas farther from the existing settlements (more than 500 m) as not suitable, areas between 250 m and 500 m from the settlements as medium suitable and areas up to 250 m from the settlements as highly suitable. 14% (30 Km²) area was highly suitable, 29% (59 Km²) area had medium suitability and 57% (117 Km²) had low suitability for built-up expansion (Fig.8).

The landslide susceptibility data indicated areas prone to landslide as highly susceptible which were assigned low suitability values, areas where landslide would rarely occur as medium prone areas were assigned medium suitability values and areas where it was unlikely to be affected by landslides as highly suitable. 53% (109 Km²) area was highly suitable with low landslide risk, 29% (59 Km²) area had medium suitability and 18% (37 Km²) had low suitability for built-up expansion and high landslide risk (Fig.9).

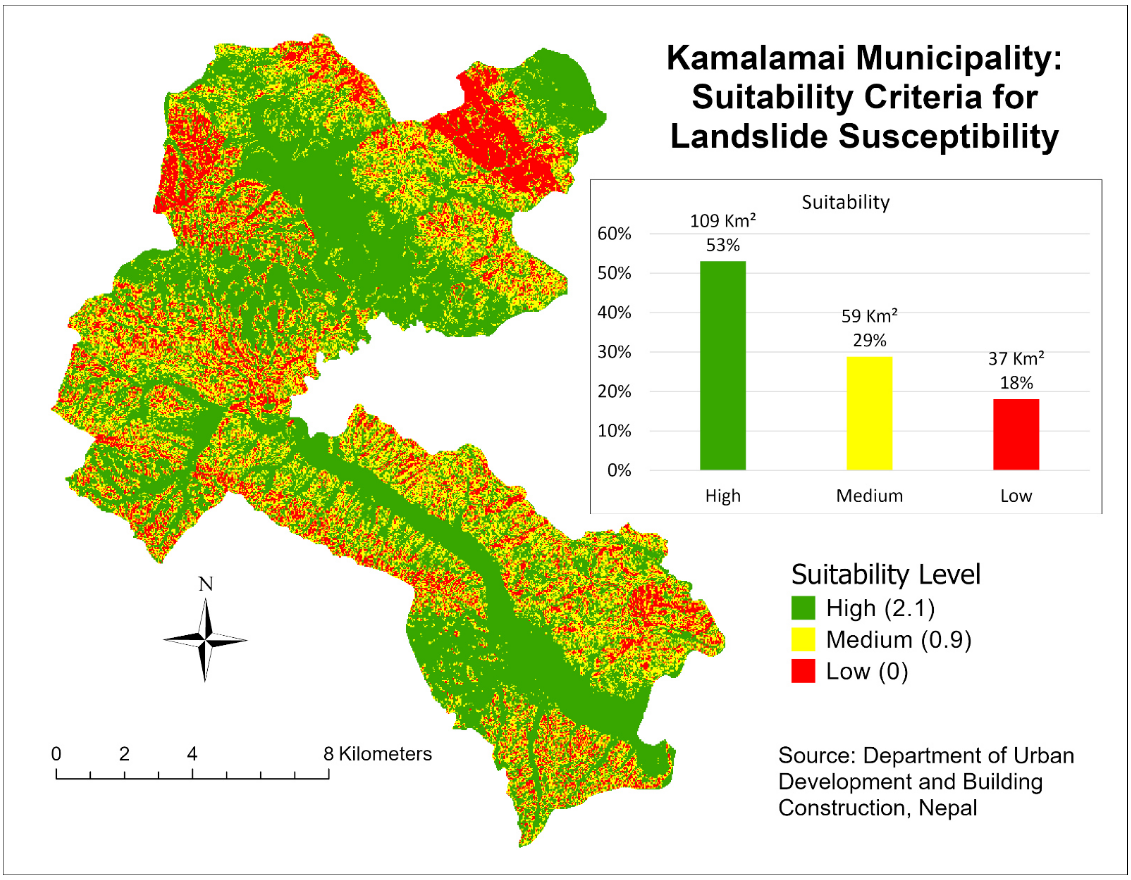

Fig.9 Kamalamai Municipality: Suitability Criteria for Landslide Susceptibility

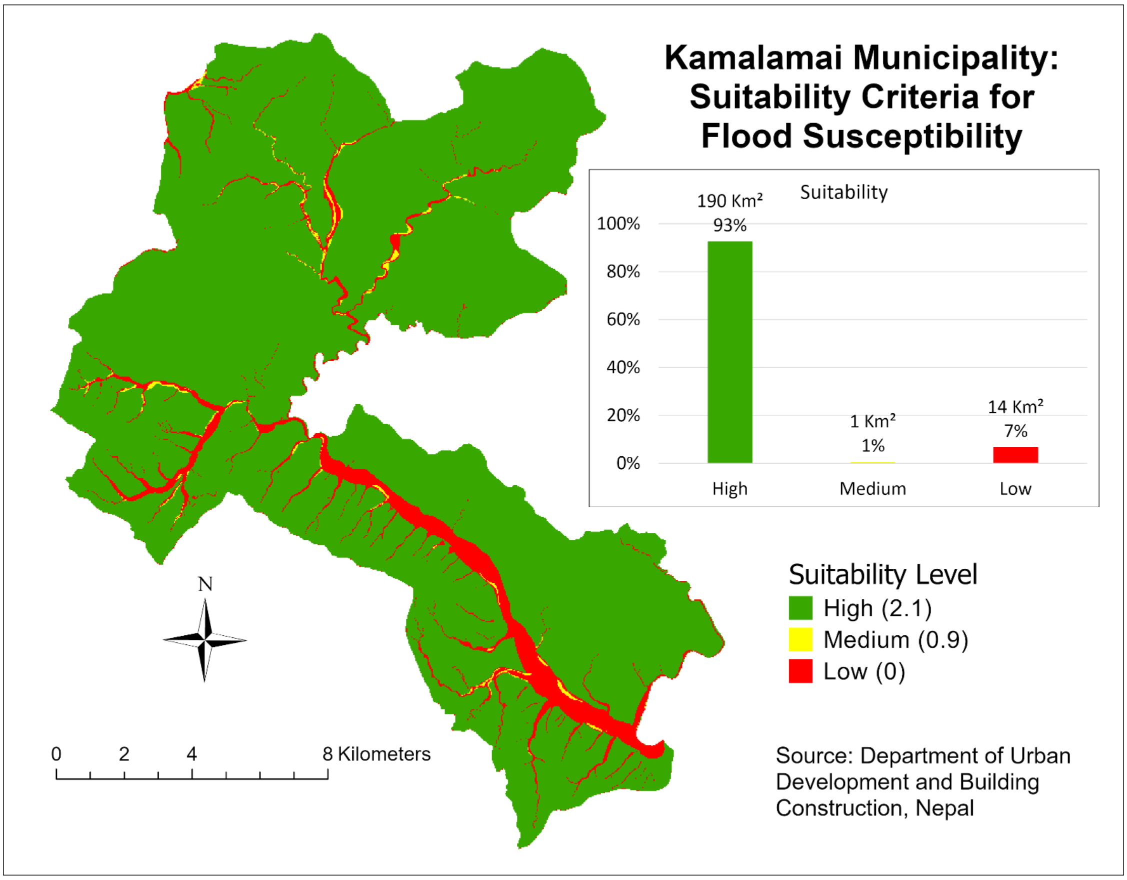

Fig.10 Kamalamai Municipality: Suitability Criteria for Flood Susceptibility

Similarly, the flood susceptibility data indicated places prone to flooding as high flooding areas with low suitable values, places near riverbanks with medium flooding areas as medium suitable and areas where flood was unlikely to occur as highly suitable. 93% (190 Km²) area was highly suitable with low flood risk, 1% (1 Km²) area had medium suitability and 7% (14 Km²) had low suitability for built-up expansion and high flood risk (Fig.10).

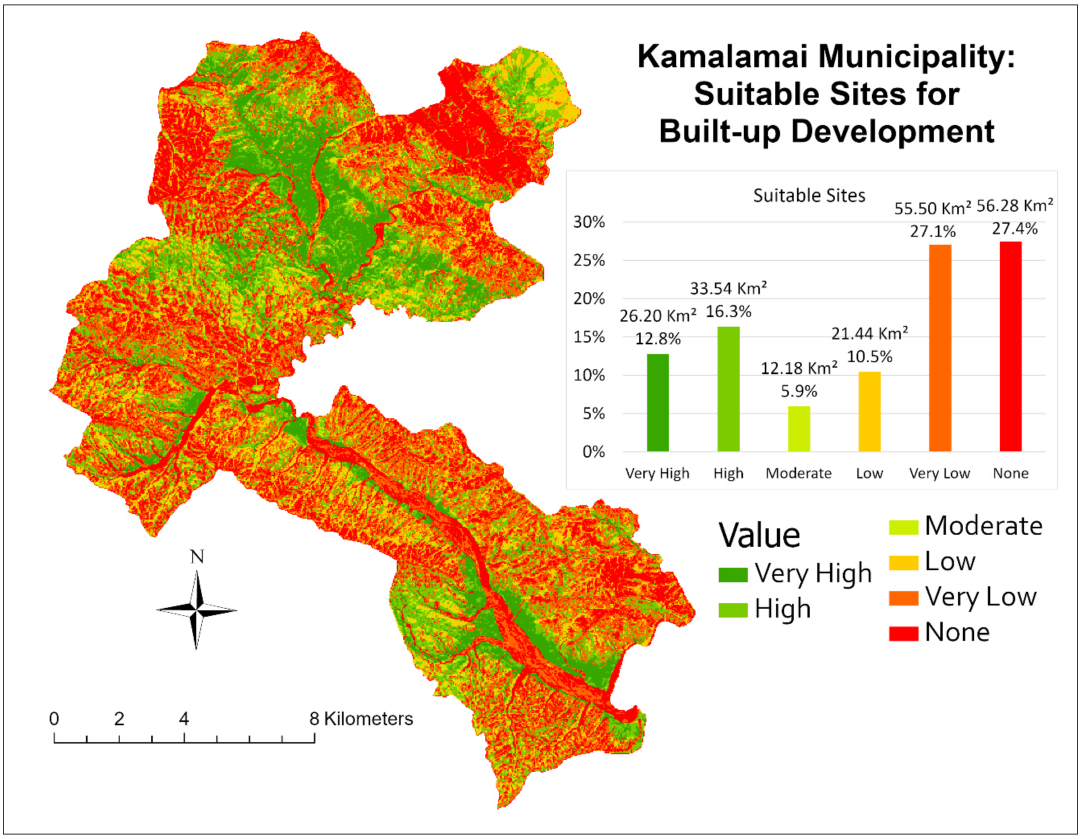

Fig.11 Kamalamai Municipality: Site Suitable for Built-up Expansion

The suitability analysis showed that 27.4% (56.28 Km²) area of the municipality had no suitability for built up expansion 27.1% (55.50 Km²) had a very low suitability, 10.5% (21.44 Km²) had a low suitability while 5.9% (12.18 Km²) had a moderate suitability, 16.3% (33.54 Km²) had a high suitability and 12.8% (26.20 Km²) had a very high suitability (Fig.11).

The suitability analysis revealed that elevated regions in the eastern and southern parts of the municipality were less suitable for built-up expansion due to steep slopes and potential landslide susceptibility. The central part of the municipality, with its flat terrain and proximity to existing infrastructure, showed high suitability for urban expansion.

4.5 Transition Potential Modelling

The study used a land change transition model to predict the potential transition from various land classes to the built-up class. MLP Neural Network was used to develop sub-models for each transition and predict future development. The sub-models were specifically selected for transitions from water, shrub, barren, forest, and agriculture to built-up, excluding other parameters. The models were trained automatically with dynamic learning rate training parameters. The results of the models were evaluated based on accuracy and skill measures. The results show the parameters and performance of each sub-model, including the number of neurons in the input, hidden, and output layers, requested samples per class, learning rate, momentum factor, acceptable RMS, iterations, training and testing RMS, accuracy rate, and skill measure. The model accuracy ranged from 70.68% to 78.30%, with skill measures varying from 0.4135 to 0.5661.

The sensitivity analysis identified the most and least influential variables for each transition, indicating their impact on model accuracy. A backward stepwise analysis was conducted to determine the variables necessary to achieve the same accuracy as the full model. Maps were generated to visualize the transition potential from each land class to built-up (Fig.12).

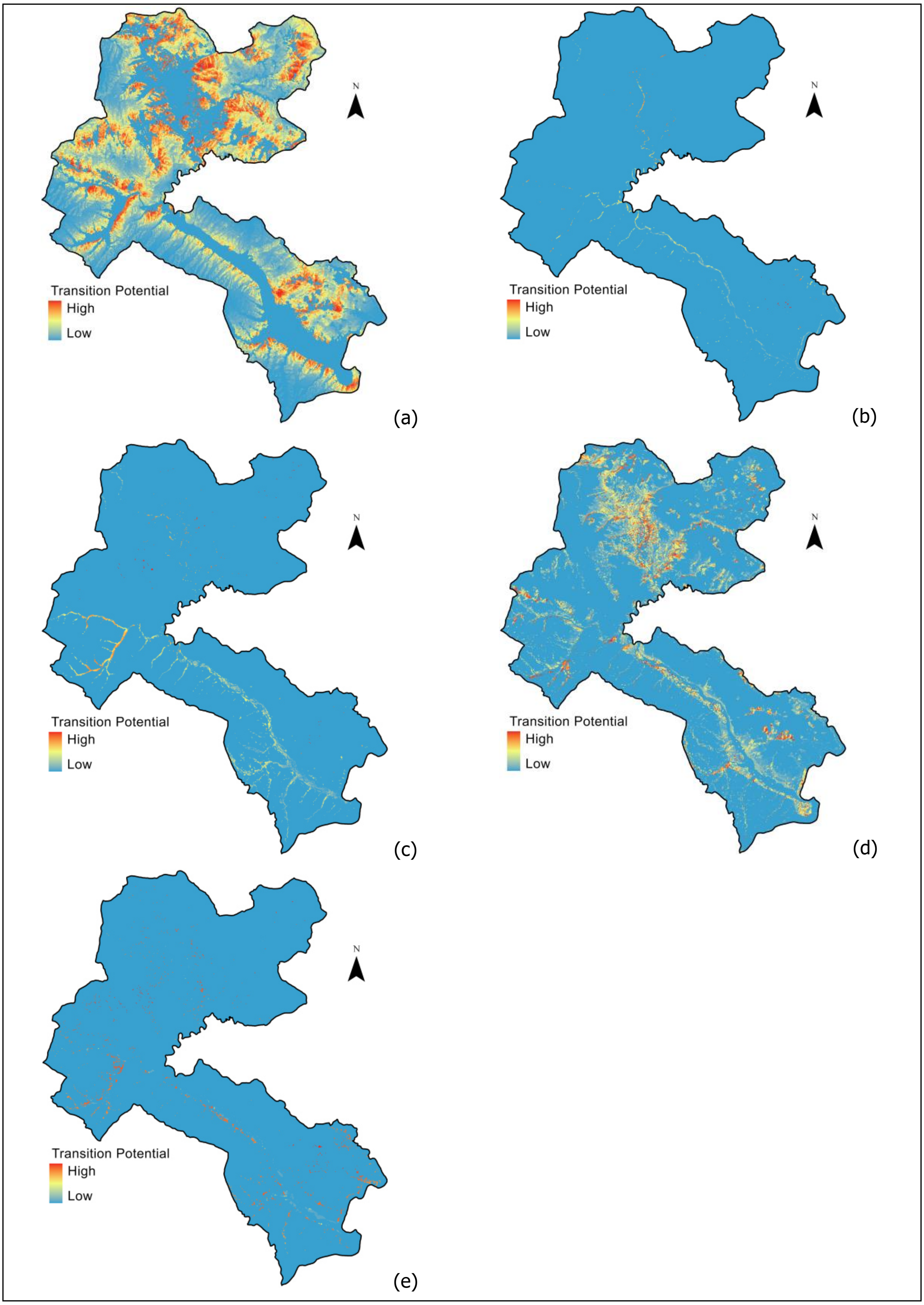

Fig.12 Transition Potential (a) Forest to Built-up (b) Waterbodies to Built-up (c) Barren to Built-up (d) Agriculture to Built-up (e) Shrubland to Built-up

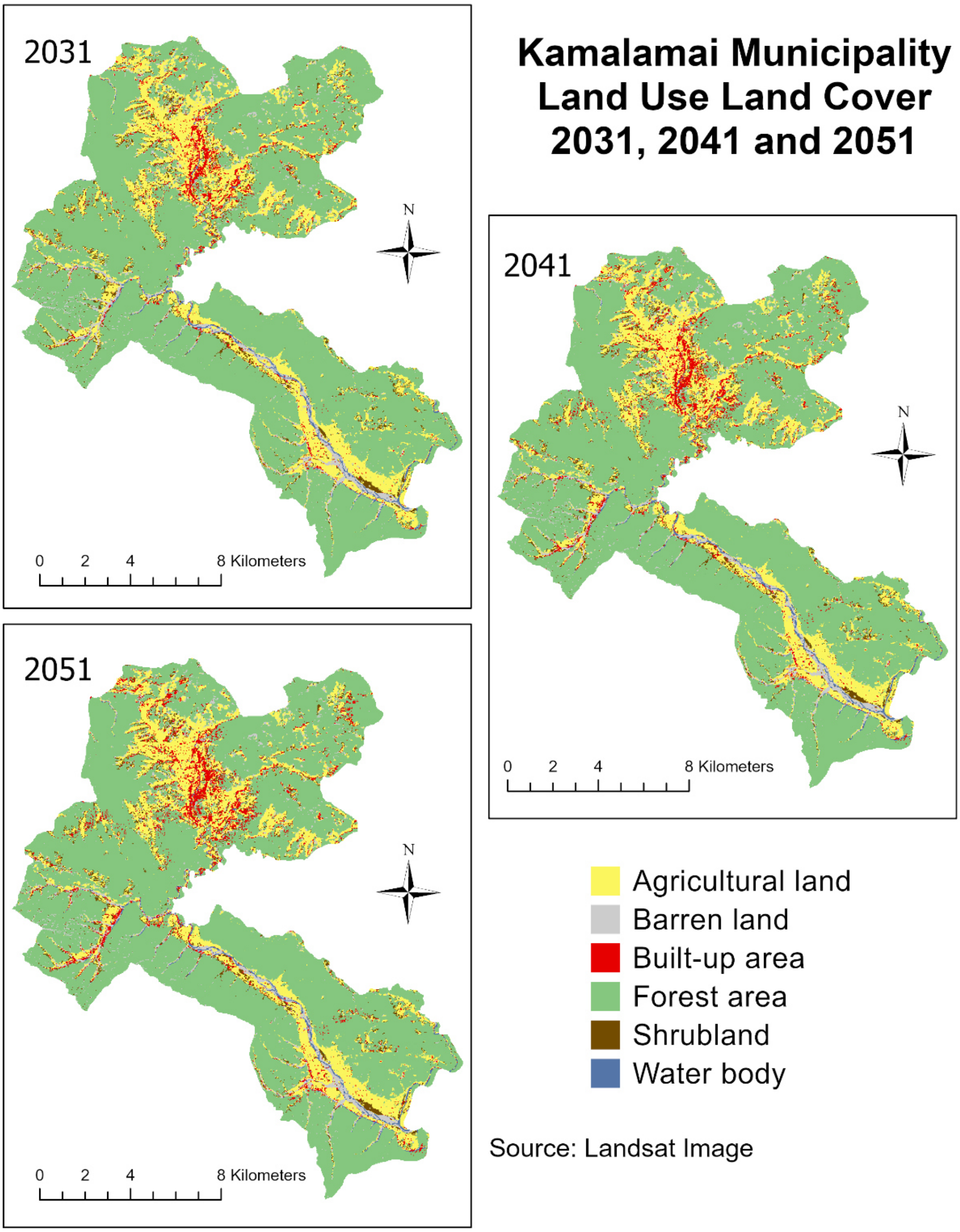

Fig.13 Kamalamai Municipality: Simulated Land Use Land Cover 2031, 2041, 2051

The suitability map was used for incentives and constraints for the simulation of built-up to 2031, 2041 and 2051 (Fig.13). The suitable areas being incentives and unsuitable areas being constraints. The simulated LULC showed that the built-up could increase from 1.90% (3.95 Km²) in 2021 to 2.5 % (5.13 Km²) in 2031 in first stage, then built-up could increase to 3.3% (6.69 Km²) in 2031 and in final stage could reach 4.0% (8.25 Km²) (Fig.14).

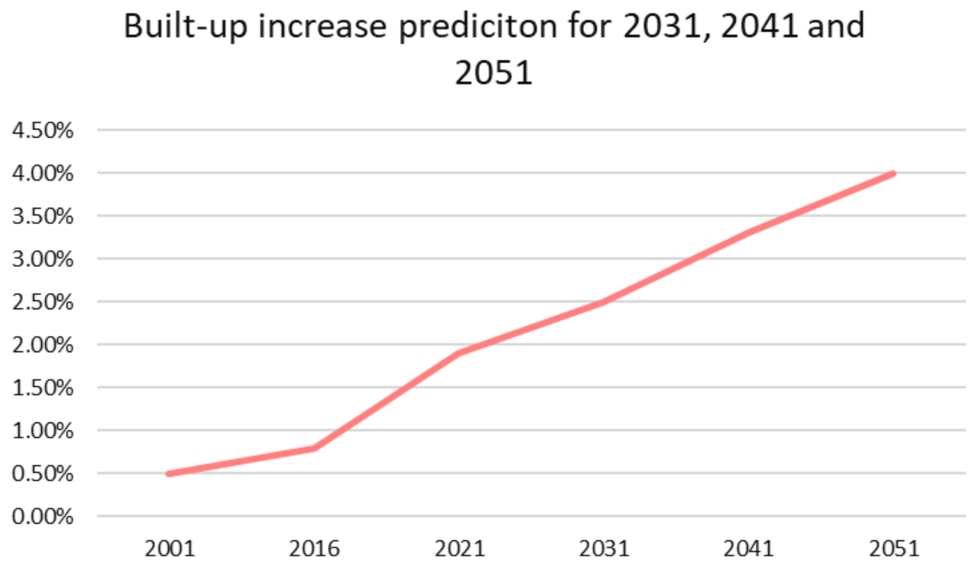

Fig.14 Built-up Transition 2001-2051

5. Discussion

Rapid urbanization in combination with exploitation of natural resources have had significant impact on ecosystem creating a fragile urban region (Deng et al., 2009). Land use suitability analysis can assist in identifying future land use to specific preferences, requirements and predictors of some activity (Collins et al., 2001; Hopkins, 1977; Malczewski, 2004). Similarly, the simulation of future LULC is of significant importance to maintain sustainable future (Wang et al., 2018). The built-up expansion suitability with integration of future simulation provides a decision support overview for an effective management of urban areas. (Santos & Moura, 2019; Ustaoglu & Aydınoglu, 2019)highlight the use of suitability analysis using AHP, multicriteria assessment and weighted sum as methods for land analysis. Urban areas can be vulnerable to various risks, primarily influenced by three key factors: location, proximity to coastal regions, major rivers, and low-lying zones prone to coastal erosion, flooding, sea-level rise, and other related hazards (Zucaro & Morosini, 2018). This study has integrated LULC study with risk factors and infrastructure availability to deliver a holistic simulation result. The analysis of land use change in Kamalamai Municipality revealed significant transformations over the study period. The observed increase in built-up areas, accompanied by a decrease in forest cover, highlights the ongoing process of urbanization and agricultural expansion. These changes are indicative of the growing population and the corresponding need for infrastructure development and land for agricultural purposes. The expansion of settlements and orchards can be attributed to changes in people's occupation and economic activities. The analysis showed that the built-up was mainly concentrated in the central part of the municipality, which is also the market area and few scattered settlements in other parts of the municipality in 2001. The agricultural lands were mainly around the built-up area and along the riverbanks of the municipality.

The built-up areas in the municipality had increased from 2001 to 2016, with the expansion of built-up in the central part of the municipality and new settlements development around the municipality. The study found that the forest area had decreased while orchards, cropland and settlement increased from 2001 to 2016 in-line with the previous study by (Neupane & Dhakal, 2017). There was considerable increase in Shrublands in the same period which may be attributed to the change in people’s occupation and resulting changes in agricultural lands to shrub lands. The barren and water areas changes can be because of the seasonal rivers flow change. The built-up change as not significant till 2016 but tater, the built-up areas increased significantly in 2021. This increase could be attributed to the completion of highway from Kathmandu to

Terai plains through the municipality increasing the in-migration seeking commercial opportunities as well as the earthquake in 2015 which displaced many rural population to nearby towns.

The lack of urban form and structure in built-up expansion highlights the problem of lack of effective implementation of the local planning system. Despite the presence of a planning system required (NUDS, 2017), it appears that it is not being utilized adequately to control land use changes and guide sustainable development. Weak rules and regulations related to urban planning could have contributed to haphazard growth and uncontrolled land use changes. In relation to the broader national planning system of Nepal, the findings of this study shed light on the existing mechanisms for urban and land use planning and control. The effectiveness of the local planning system in Kamalamai Municipality is influenced by the broader national planning framework and its implementation.

The national planning system provides the legal and institutional framework for land use planning and management at the local level. However, it seems that the national planning system in Nepal has faced challenges in terms of coordination, capacity building, and enforcement. Also, the full implementation of decentralized planning and effective coordination between different levels of government is yet to be achieved.The weak enforcement and implementation of rules and regulations related to urban planning at the national level have also had an implication for local planning practices. In the case of Kamalamai Municipality, the limited effectiveness of the local planning system may be attributed, in part, to the broader challenges faced within the national planning system. This may have affected the ability of the municipality to enforce land use regulations, monitor development activities, and guide sustainable growth.

The simulation results of land use and land cover for 2041 and 2051 offer a glimpse into the potential future scenarios based on current trends and patterns. (Iacono et al., 2015) suggested that the integration of transportation networks and land use could provide a more comprehensive understanding of the dynamics of land use change which was implemented in the study. The suitable built-up simulation till 2041 showed that the southwestern area of the municipality could have more expansion along with northwestern region of municipality along the river corridor. The modelled LULC 2051 showed that the built-up expansion could expand mostly in the southwestern, north-western and the central town region of the municipality with expansion of small settlements along the north-eastern hilly areas and south-eastern areas along the riverbank and on the edge of the municipality on the south-western front and north-western edge of the municipality. The projected increase in built-up areas and the continued loss of forest cover emphasize the need for sustainable urban development practices. These findings could have several implications for future urban development and land use planning.

To encourage sustainable land use and construction practices, incentives including providing tax benefits or grants for developers and property owners for developing within the provided suitable development scenarios for 2041 and 2051 as identified in the study. The maps can be used for strengthening local planning system to create regulations for sustainable town development. The scenarios could be a effective material to review and update existing land use regulations to ensure their effectiveness in guiding urbanization and development. This study can guide an urban development strategy to preserve good-quality agricultural land and help conserve natural resources.

Moreover, future planning efforts should focus on promoting compact and efficient urban growth, integrating green spaces, and adopting sustainable land use policies. Considering the potential impacts of climate change, future land use planning should also incorporate measures for adaptation and resilience. The projected expansion of built-up areas may increase the vulnerability of the municipality to natural hazards and extreme weather events. Integrating climate change considerations into land use planning can help identify areas prone to risks and develop strategies for resilient infrastructure and disaster preparedness. Given the challenges within the national planning system, future efforts should focus on improving the integration between national and local planning authorities. Strengthening coordination mechanisms, enhancing capacity at the local level, and aligning the local planning system with national goals and strategies are essential for effective land use planning. The projected scenarios for 2041 and 2051 highlight the need for sustainable practices, effective governance, climate change adaptation, community engagement, and integration between national and local planning efforts. These learnings can guide policymakers, planners, and stakeholders in shaping a more sustainable and resilient future for the municipality.

6. Limitation

The study concentrated on the landslide susceptibility, flood susceptibility, current LULC, 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 analyzed as these analyses were not possible during the research. 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 LULC and its future prospect. The aspects of LULC 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 LULC changes. The transition to public spaces could not be modelled as the scope of the study focused mainly on built-up expansion yet the future study could emphasize on the planning of service infrastructure and public spaces within the identified suitable expansion areas.

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 LULC 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 LULC.

The methods used for the study was effective in identifying built-up expansion area in consideration of suitable areas in the municipality. Future studies can make use if high resolution imagery for analysis of LULC. Similarly, more geographic data could make the study more effective like soil property in the area, ecological indicators, and socio-economic factors. Similarly, more risk datasets like fire hazards, thunderstorms, soil erosion, drought could be used within suitability mapping for more holistic overview. Future research could consider not only built-up change simulation but change from each land use category to another and simulation in consideration of all land use class changes.

7. Conclusion

There has been considerable built-up increase in Kamalamai Municipality, but the increase has not been regulated or planned which could spill to the environmentally sensitive areas, disaster prone areas and/or economically unfeasible areas. The study has presented a future model for Kamalamai Municipality, focusing on addressing the challenges of urbanization and land use planning. Through a detailed analysis of the urbanization trend, suitability analysis and simulation results, future development scenarios have been identified for the sustainable development framework for the municipality. The identified suitable built-up areas for 2041 and 2051 urban scenario model can enable effective building control by providing guidelines and regulations for construction activities. It can be integrated into zoning regulations, ensuring appropriate building permits, and promoting safe and sustainable construction practices. This aspect could contribute to the orderly growth of the municipality and prevents haphazard urban expansion.

The model incorporates the protection of environmentally important areas. By enforcing building control measures, the model aims to prevent haphazard and unplanned urban expansion. The model incorporates environmental considerations such as protection of forests, shrublands and vegetated areas while focusing development on existing settlements. This ensures that development activities are carried out in a manner that minimizes negative ecological impacts and promotes sustainability. The proposed model recognizes the interdependence between construction activities, the provision of essential services, and the creation of public spaces. It emphasizes the integration of infrastructure development, such as transportation networks to create well-connected, functional, and aesthetically pleasing urban environments.

Integrating construction and services within the modeled built-up area could promote the development of well-planned and efficient urban infrastructure. This leads to improved connectivity, accessibility, and functionality within the municipality. The study provides a comprehensive framework for managing and planning urban development in Kamalamai Municipality. By focusing on building control, considering environmental constraints, and integrating construction, and services, the proposed model offers a holistic approach to sustainable urbanization. The expected results include orderly urban growth, environmental sustainability, and enhanced quality of life for residents. The adoption of this model could contribute to the municipality's long-term prosperity and serve as a valuable reference for urban planners and policymakers in Nepal and beyond.

The use of RS data and GIS techniques can assist in identification and planning of built-up expansion area. The Landsat images of 2001, 2016 and 2020 were used to map LULC change in that period using supervised image classification technique. ArcGIS Pro was used for preprocessing and classification of satellite imagery. The use of DEM made it possible to map elevation, slope, and aspect of the study area. The integration of flood susceptibility, landslide susceptibility, existing LULC, slope, aspect, proximity to roadways, proximity to settlements, and elevation was used for suitability analysis in the municipality for built-up expansion using AHP weighing method. The LULC change maps were used for change simulation for 2031, 2041 and 2051 while suitability map was used as incentive/constraints for built-up expansion. The technique has helped identify suitable areas for future built-up expansion by channeling the change in desired locations. The built-up expansion suitability model can be used by planners and policy makers for land use intervention.

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Image Sources

Fig.1 - Fig.14: All figures are created by the Authors.

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