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Spatiotemporal Modeling of Urban Expansion: In a case of Robe town Using Remote sensing and GIS Techniques.

A THESIS SUBMITTED TO GRADUATE STUDIES OF ADDIS ABABA UNIVESITY,INSTITUTE OF TECHNOLOGY IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTERS OF SCIENCE IN GEODESY AND GEOMATICS ENGINEERING (SPECIALIZATION IN GEOMATICS ENGINEERING)

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ABSTRACT

Urbanization is the most powerful and visible force that has fundamental changes Land Use Land Cover around globe. This study was conducted in Robe town to model spatio-temporal of expansion during 2006–2021. SPOT image for 2006 and 2016 as well as Sentinel 2A for image were used for this study. Three different land-cover maps produced at different intervals between 2006 and 2021 were used to evaluate and analyze urban expansion visually and quantitatively. The satellite images were classified and land-use/land-cover maps were produced using Object Based Image Classification using KNN classification method using Envi 5.3 and predict Expansion of Robe Town using CA-Markov model. The classification process was checked by overall accuracy and Kappa statistic accuracy assessments from confusion metrics. Results show acceptable agreement between the classified maps and reference data with overall accuracy value 91% for 2006, 88% for2016 and 93% for 2021. Kappa accuracy value 0.89, 0.85 and 0.91 for classified satellite image of 2006, 2016 and 2021 respectively. Post classification change detection analysis and selected spatial metric indices calculation were made to detect, assess pattern of urban expansion in the study area. Change detection analysis indicated that Robe town is growing rapidly with an average growth rate of 7.8% year during2006–2021. The built-up area was 854 hectare, 1067hectare and 1740 hectare, respectively in 2006, 2016 and 2021, with annual growth rates of 2% and 7.8% in the two study phases respectively during the periods 2006-2016 and 2016-2021. From spatial metrics analysis, largest patch index of built-up area was 7%, 10% and 15% for the years 2006, 2016 and 2021. The increase in the number of largest patch index all through the study periods shows the rapid urban growth process in the study area.CA-Markov model used for modeling and validating kappa statistic is moderate and acceptable to predict for future (2050).Therefore, it is time for policy makers, city managers and urban planners to plan and cope up with the pace of Robe town urban expansion depending on with proper implementation.

Keywords: Urban Expansion, Urban Land use Land cover Change, satellites image, object based image classification

1. Introduction

In today's world, more than half of the global population lives in urban areas and by 2050, this figure is projected to be 65% based on this projection, 2.5 billion people will add to the world's urban population, with nearly 90% of the urban growth concentrated in developing countries. Developing countries started the process of urbanization lately, but they are the ones which are rapidly urbanizing (UN, 2014). As such, in the past few decades, rapid and often unplanned urban expansion has considerably accelerated more in developing countries than in developed nations. This rapid urban growth in developing nations are caused by different factors including social, cultural, rural–urban migration, economic and technological change and rapid population growth (Marshall*et al*., 2009).Such rapid urban growth and consequential change has its own positive as well as negative consequences on the countries' development. Well planned and managed urban growth can serve as a positive development factor,(Alaci, 2010). The benefit of well-planned and managed urban development can be measured in terms of creating job opportunities and infrastructural development such as telecommunication, road and electricity. In contrast, unplanned urbanization as in most developing countries, can affect the natural environment as well as livelihoods in newly establishing urban centers. Nowadays, such unplanned urbanization is affecting local people and their environment.

Today, the issue of urbanization is one of the top agendas in the course of political, socio-cultural, and economic development both in developed and developing countries. Many studies show that developing countries are on rapid phase of urbanization comparing to developed countries (UN-DESA, 2014) reports that Africa is still the least urbanized continent with 40% of urban share Compared to with North America (80%) and Europe (73%). Urbanization is, however, often advancing at a rate of 3% to 4% per year in developing nations, which is significantly faster than in developed nations. Ethiopia, for instance, is among the least urbanized nations in the world with only 19% of its inhabitants living in metropolitan areas Nonetheless, the rate of urbanization in Ethiopia is expanding faster than ever before, thanks to a 2.5 percent annual population growth rate, a high rate of rural-urban movement, and an increase in the number of urban centers. Furthermore, the country's urban population is predicted to rise at 3.98 percent each year, with urban areas accounting for 42.1 percent of the country's overall population by 2050. (UN-Habitat, 2010).

Various studies have been conducted in industrialized and developing nations to quantify the urban expansion model. All of this research, however, has come up with various techniques in terms of urban growth models. However, a frequent strategy is to take into account the behavior of built-up areas and population density as a function of the spatial and temporal changes that are occurring (Berry *et al.,* 1996). Urban sprawl and population increase are related in that the former is a major contributor to the latter. Land use, built-up areas, and population data can be used to model urban expansion using both spatial and temporal characteristics. (Sudhira *et al*., 2004). Recently an integrated approach of Geographic Information System(GIS), Remote Sensing and Cellular automata (CA), a technique developed recently, have been receiving more and more attention in urban and GIS modeling due to its strong capacities for dynamic spatial simulation, simplicity, transparency, and innovative bottom-up approach. Therefore, these approaches were employed to identify and model the patterns of urban growth and provide quantitative and spatial information on developments of urban areas of Robe town.

Robe town is the administrative center of Bale Zone, which is one of the geologically biggest, most financially noteworthy, and most climatically conducive zones in Ethiopia. As of now, the town is serving as a center for numerous administrative and nongovernmental educate. The combined impact of the financial and biological significance of the town is drawing in more people from distinctive regions of the country (Duguma *et al.,* 2018).The towns growing in residential, manufacturing sector and service since it due is the capital city of Bale zone. This has resulted in high-speed economic and social development. Robe, being one of the towns in the developing countries has never been in a position to escape the forgoing undesired realities of rapid urbanization. Urban planning implementation principles and guidelines fundamental to ensure healthy urban growth have never been put in place. In this study, the spatio temporal model functions of GIS and remote sensing techniques to specify the urban expansion characteristics of the town have been used.

2. Materials and Methods

2.1 Study Area

The study was conducted in Robe Town is located in South East part of Ethiopia. It is about 430 km from Addis Ababa, the capital city of Ethiopia. This town is located UTM zone 37 geographically, the study area lies between (609600-610800) m N and (787600-789200) m E. Land areas within the Robe town boundary is 92.22 km2 the town is divided into three administrative kebeles, namely, Oda Robe, Beha Biftu, and Chefe Donsa.This District is bordered by Goro District in the east, Dinsho District in west, Agarfa and Gassera in the north and northeast and Goba District in the south.

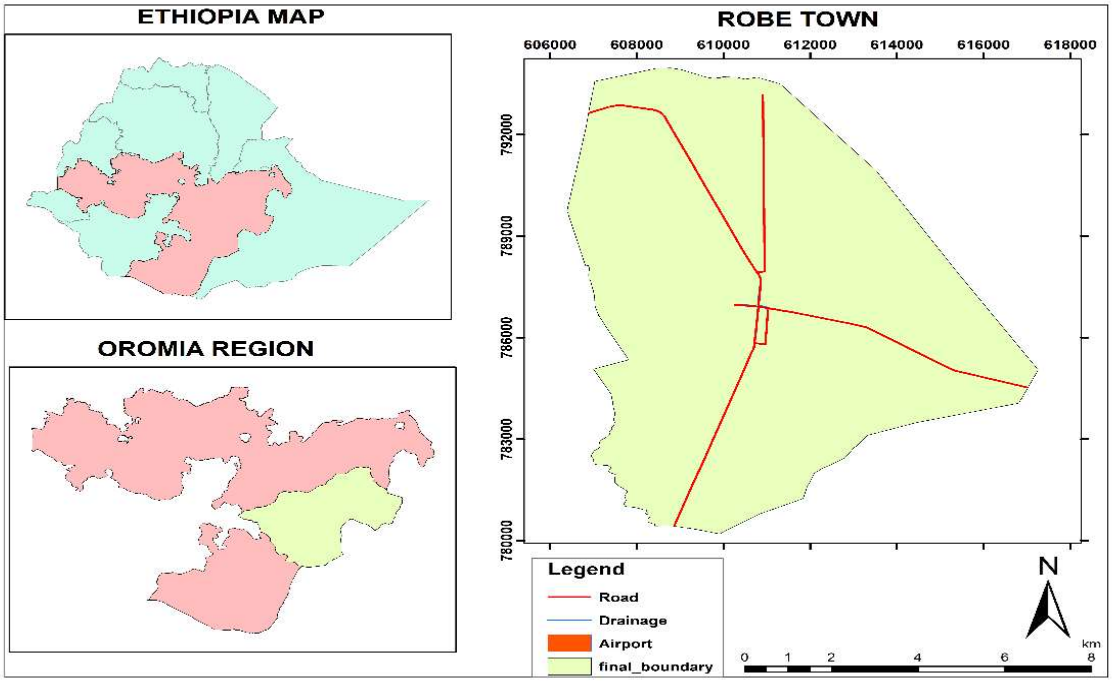

Fig 2. 1Location map of the study area

2.2 Material

For the study different software and survey equipment has been used

Table 2. 1Material used

NO	Software	PURPOSE
1	Arc GIS	Digital image pre processing, storage and Producing map
2	Envi Classic 5.3	Classification image
3	QGIS 3.22.4	Accuracy Assessment
4	Google Earth	Visualization
5	Fragstat 4.2	Spatial Metrics
6	IndrisiSelva 17.0	Modeling and prediction

2.3Data Sources and Types

In this Study Different types of data have been collected from both primary and secondary data sources to success a desired goal. Data from primary sources include GCP data. Secondary data are high resolution satellite image, Cloud-free acquired. Two SPOT images taken in 2006 and 2016has been purchased from the geospatial information institute of Ethiopia having Spatial Resolution 5mx5m and 5mx5m respectively,Sentinel2Aof 2021 Satellite image were obtained from the European space Agency Copernicus Program websites *http;//scihub.copernicous.eu*. Having Spatial Resolution 10mx10m, population, soil, rainfall, shape files, was gathering from different organization and websites.

Table 2. 2 Data Sources and Type

Satellite	Sensor	Spatial Resolution	Path	Row	Resample	Date
SPOT	Spot 5	5mx5m	2164	2746	10mX10m	Semp.2006
SPOT	Spot 5	1.5mx1.5m	7244	9179	10mX10m	Nov,2016
Sentinel	2A	10mx10m	1082	1373	10mX10m	Dec,2021

2.4 Methodology

This section describe the method has been used in this study. Composing of three objectives, the first objective has been the pattern of Urban Expansion with general methods and work flow chart.

2.4.1 Image processing

Pre-processing involves two major processes: geometric correction and radiometric correction or haze correction. Remote sensing imageries are inherently subjected to geometric distortions. The viewpoint of the sensor optics, the scanning system's motion, the platform's motion (including its height, attitude, and velocity), the relief of the terrain, or the curvature and rotation of the earth may all contribute to these distortions (Lillesand & Kiefer, 2000). Pre-processing aims to correct distorted data in order to create more faithful representation of the original scene, this typically involves the initial processing of raw image data to correct for geometric distortions, to calibrate the data radio metrically, and to eliminate noise present in the data. For 2006 and 2016 Spot satellite image its fully covered of the study area while for Sentinel2A satellite image a single image did not cover the spatial extent of the entire study area, four scenes of images were mosaic on a band-by-band basis and masked by the study area boundary. The data has been projected to the UTM (Universal Transverse Mercator) adindan Zone 37 coordinate system. The process was also comprised of layer stacking, radiometric correction, image enhancement, haze reduction, band combination, resampling and false color combination.

2.4.2 False Color Composite (FCC) Image Preparation

Different color composite images were prepared, in order to select the best band combination, that enhance the raw satellite images for the identification of the different land cover classes in the study area. In this research project the false color composite image made using Spot 5 bands 3-2-1 (R-G-B) and Sentinel 2A 4-3-2 (R-G-B) were found to be best for the identification of major land cover classes in the study area.

2.5 Image classification

The object-based image analysis (OBIA) technique is quite significant with the environment of image classifications. The OBIA technique takes the forms, textures and spectral information into consideration. The initial phase of classification starts with grouping the neighboring pixels into meaningful areas (Oruc *et al.,* 2014).With the increased demand for OBC methods, many GIS software systems are available to use this kind of methods for classification. ENVI is one of the most commonly used software systems and it provides a K-Nearest Neighbor (KNN) object-based classification method. Due to its simplicity in implementation, clarity in theory and good performance in classification, KNN has become one of the most commonly used OBC methods. Therefore, the KNN method was employed for object-based classification in this study. The KNN object-based classification process has two steps: segmentation and classification. OBIA technique gives a better classification result than pixel-based technique for high and very high resolutions (Yu *et al* .,2006).Therefore, this research had been conducted to assess the high-resolution data for classification using object-based technique using ENVI 5.3.

2.5.1 Image segmentation

Segmentation is the way to partition a remote sensing image into different objects by merging pixels with similar attributes (Wolf, 1996).The KNN method was employed to segment an original remotely sensed image into land use segments and then chose a set of segments as training data based on different land use/cover classes to classify the segments. The parameters of segmentation were chosen based on visual inspection and researcher's experience. Too many segments could increase processing time and were not necessary. In segment settings, the value of parameter Edge was set to 50 for detecting edges of features where objects of interest have sharp edges. Adjacent segments with similar spectral attributes can be merged. In this study, the value of Merge Level was set to 90 to merge over-segmented areas by using the Full Lambda Schedule algorithm.

2.5.2 Selection of training

In object-based classification, however, no previous studies have investigated the relationship between sample size and number of features. (Bo & Ling, 2010), proved that the training sample size required for object-based classification (2–3 times the number of features) is far below that required for pixel-based classification. Considering that the classification problem in this study is uncomplicated and that the distribution of classes water body is scarce and selected 10 training sample and other features are Agricultural land, Built-up, Bare land and Vegetation are selected 20 training sample for each. This impedes further sample selection. Finally, we selected 90 training samples, which approximate 2–3 times the number of features for each satellite image totally 270 training sample was selected for this study.Table3.3there were five major Level 1LULC types, as identified in the study and defined based on(DEJENE, 2018).

Table 2. 3Landuse land cover classification Features

No	LULC type	Description
1	Agricultural	Irrigated and rain-fed arable lands, crop land with permanent crops, farming and fallow fields,
2	Bare land	For this study, it mainly refers to open spaces without any function, bare soils, rocky areas, quarries, gravel pits, grazing land, open areas inside vegetation and residential areas; might be covered by grasses.
3	Built-up	Includes all developed areas, roads and transport infrastructures, buildings, housing units, commercial and residential areas and under construction areas
4	Vegetation	Trees, shrubs-lands and semi natural vegetation, deciduous, mixed forest, palms, woods, herbs, climbers, gardens, inner-city recreational areas, parks and playgrounds, grassland and vegetable lands.
5	Water body	Consists of areas with surface water seized in the form river, lake or pound, may be permanent or seasonal.

2.6 Sample size and Accuracy assessment

2.6.1 Sample size

Sample size is dictated by the need to express accuracy in an error matrix. The sample size must be large enough to provide that the error matrix estimates have adequate precision. An error matrix does not fall into the right/wrong binomial scenario but rather a multinomial situation in which there is one correct for each class and n–1 wrongs (where n is the number of map classes). In this research it selected a total of 210 for Agriculture, Bare land and Built-up selected 50 for each and vegetation and water body selected 30 sample points. Total 630 sample used for all three temporal image classifications, stratified random sample points were selected for the validation of classified images for each year.

2.6.2 Accuracy assessment

Accuracy is considered to be the degree of closeness of results to the values accepted as true. Accuracy assessment is an important and essential step in the classification process. One of the most common means of expressing classification accuracy compare on a category by category basis, the relationship between known reference data (ground truth) and the corresponding results of an automated classification. In this study, overall accuracy (OA), user's accuracy (UA), and producer's accuracies (PA) were observed based on field reference data and high spatial resolution images of Google Earth (http://earth.google.com) from multiple dates (2006,2016 and 2021).

2.6.1.1 Overall accuracy

One basic accuracy measure is the overall accuracy, which is calculated by dividing the correctly classified pixels (sum of the values in the main diagonal) by the total number of pixels checked

$Overall\ accuracy\ (\%) = (Correctly\ classified\ pixels / Total\ number\ of\ pixels)$------*Eq1*

Apart from the overall accuracy, the accuracy of class identification needs will be assess. In order to do that, we have to look at non-diagonal cells in the matrix. These cells contain classification errors, i.e. cases when the reference image and the classified image don't match. There are two types of errors: underestimation (omission errors, omission) and overestimation (commission errors, commission).

2.6.1.2 Producer's accuracy

The ratio between the number of correctly classified pixels and the reference total pixels for particular LULC class is called the producer's accuracy.

$Producer's\ accuracy\ (\%) = (Correctly\ classified\ pixels / Reference\ total\ pixels)$---*Eq2*

2.6.1.3 *User's accuracy*

The ratio between the number of correctly classified pixels and the classified totals pixels of particular LULC class is the user's accuracy - because users are concerned about what percentage of the classes has been correctly classified.

$User's\ accuracy\ (\%) = (Correctly\ classified\ pixels\ /Classified\ total\ pixels)$---------*Eq3*

2.7 Measuring Urban Expansion pattern using landscape metrics

Spatio-temporal patterns of Robe Town were analyzed using landscape metrics for the time period 2006-2021. Landscape metrics are effective methods for comparing and describing multi-date themed maps statistically. Metrics are only computed in the research for the built-up class. The outputs for the selected metrics presented in tables are generated for the whole study area using Fragstsats 4.2. These metrics were picked based on their intuitiveness, ease interpretation and their ability to describe the composition and configuration of urban landscape pattern. Landscape metrics describe four dimensions: relative size, absolute size, spatial distribution of patches and complexity of urban form.

2.7.1 Selection of Metrics

Metrics are used to quantify a variety of spatial patterns. Various studies had been conducted to identify the key landscape patterns in order to identify significant and independent metrics, but it was ultimately determined that the choice of metrics depends on the goal of the study as well as the landscape's characteristics. For our purposes, we utilized the following well recognized metrics.

I. **Class area (CA)**: CA measures absolute area of each land cover class. Sometimes also known as total area implying total area covered by land cover class in Hectares, here we deal with the total area of built-up or non-built-up area and it simply describes the growth of urban areas in terms of area and size.

$TA=\sum_{j=1}^{n} aij \left(\frac{1}{10000}\right)$ ---*Eq4*

Class level

Where a_{ij}= area m^2 of patch of ij

Unit Hectare

Range; CA>0 without limit

II. **Total Edge**; Total Edge: TE sums up the lengths (in meters) of all edge segments that contain the similar patch type.

$TE = E$---*Eq5*

E = total length (m) of edge in landscape
Unit Meter

III. **Edge density(ED)**: Another indicator of urban expansion level which measure the total length of the edge of urban patches. It is computed by dividing the length of the urban boundary to total landscape area but in contrast to patch density, it considers the shape and complexity of the patches.

$ED = \frac{E}{A}(10000)$--*Eq6*

Class metrics
Where E = total length (m) of edge in landscape.
Unit; meter / Hectares
Range; ED > 0

IV. **Largest Patch Index (LPI)**: it is the measure of Dominance which is the area covered by the largest patch in the landscape divide by total area of landscape. It is represented in percentage and is relative measure of all patches which can be useful to compare different areas with varying spatial extent.

$LPI = \frac{\underset{j=1}{\overset{n}{Max(aij)}}}{A} * 100$--*Eq7*

Class metrics
Unit; percent (%)
Range; percent 0 < LPI ≤ 100

V. **Number of patches (NP)**: It measures the overall number of patches, or you might say the variety and fragmentation of the terrain. At other words, it is the quantity of discrete urban regions or distinct urban units, but it excludes any backdrop patches inside the landscape or patches in the boundary of the landscape. It serves as a gauge for the size of urban area subdivisions.

NP=Number of patches

$N = P$--*Eq8*

Unit None
NP equals the number of urban patches in the landscape
Range NP > 1

VI. **Patch Density (PD)**: It is also the measure of landscape fragmentation and calculated as the number of patches per unit area. It depends on the grain size i.e. smallest mapping unit of input data and number of different individual class/ it reflects the extent to which landscape is fragmented. It is measured as number of patches per 100 hectares.

$PD = \frac{N}{A(10000)} * 100$--*Eq9*

Class metrics

Unit number per 100 hectares
Range; PD>0 without limit

VII. **Area Weighted Mean Patch Fractal dimension (AWMPFD)**: It is the measure of complexity of urban form or patch shape which describes the convolution and fragmentation of patch as perimeter-to-area ratio.

$$AWMPFD = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\frac{(2\ ln(.25pij)}{lnaij} \quad (\frac{aij}{A}) \right] \text{---} Eq10$$

Unit; none
Range; 1 ≤ AWMPFD ≤ 2

VIII. **Shannon's diversity index (SHDI)**: It's the measure of the variety and relative abundance of patch types represented on the landscape. Patch richness such as the number of land use class or land cover class in the landscape are the major aspects quantified using SHDI in urban planning.

$$SHDI = -\sum_{i-1}^{m} (pi^{\circ} lnpi) \text{--} Eq11$$

Unit; None

Range; SHDI ≥0 without limit

IX. **Shannon's evenness Index (SHEI)**: It is the quantitative measure of abundance or the area distribution of classes of different patch types.

$$SHEI = -\frac{\sum_{i-1}^{m} (pi^{\circ} lnpi)}{lnm} Eq12$$

Unit; None
Range; 0 ≤ SHEI ≤ 1

X. **Contagion (CONTAG)**: This index measures the probability of neighborhood pixels being of same class and describes to what extent landscape are aggregated. It is also the measure of adjacency of similar patches. Highly fragmented patches in the landscape will result low contagion index.

$$CONTAG = \left[1 + \sum_{i-1}^{m} \sum_{k=1}^{m} \left[(pi) (\frac{gik}{\sum_{k=1}^{m} gik}) \left[ln(pi) \, (\frac{gik}{\sum_{k=1}^{m} gik} \right] \right] \right] \text{--------------------------------} Eq13$$

Landscape metrics level
Unit; percent
Range; 0<CONTAG<100

2.7.2 Method of computation

After deciding the types of spatial metrics used to quantify the urban landscape, classified urban maps are entered into the FRAGSTATS software. This software takes ASCII grid, ESRI grid, Geo TIFF format, BIL format as the input of urban area. After selecting the metrics to be calculated and running the software, it creates the four different output files corresponding to the three levels of metrics (patch, class, and land file) and the adjacency matrix. Patch file contains the patch metrics, class file contains the class metrics, and land file contains the landscape metrics. These all files created are comma-delimited ASCII files and viewable and can be exported to spreadsheets and database management programs.

2.8 Trigger factors for expansion

2.8.1 The Analytic Hierarchy Process

The Analytic Hierarchy Process is a general theory of measurement it is used to derive ratio scales from both discrete and continuous paired comparisons. These comparisons may be made using actual measurements or a fundamental scale that indicates how strongly different preferences and emotions are expressed. In this study the fundamental scales measurement that is used as table below.

Table 2. 4 Fundamental scale

Intensity of scale	Definitions
1	Equal Importance
3	Moderate importance of one over another
5	Essential or strong importance
7	Very strong important
9	Extreme important

Weight is used to a set of relative weights for a group of factors in a multi-criteria evaluation. Pair wise comparison matrix obtained by decision maker must satisfy Consistency Ratio condition (CR<1), if not decision maker has to revise his decisions and improve the Consistency Ratio to acceptable range (i.e., < 10%)

$CR = \frac{CI}{RI}$--*Eq14*

$CI = \frac{\lambda max-}{n-1}$--*Eq15*

RI is the average random index that depends on matrix order, λmax is the highest Eigen value of matrix A, and n is the size of matrix A(Saaty, 1980).

2.9 Change detection

A GIS environment has been used to examine the change in LULC for the years 2006, 2016, and 2021 utilizing the post-classification change detection approach. As it reduces the potential effects of spatial resolution and sensor discrepancies between the multi-temporal pictures, post-classification change detection will be used. (Lu & Weng, 2004). This method will enables to assess the temporal changes of the LULC types and to compute the extent of LULC conversion induced by the urban expansion.

It was also possible to calculate the amount of increase and/or decrease of each category of land-use and see the changes in percentage in each year using the following formula (Lambin et al., 2001).

$$Changeinpercent(\%) = \frac{(AreainT2 - AreainT1)}{Totalarea} * 100 \text{ --- } Eq16$$

$$Anual\ Change\ (\%) = [\frac{Area\ in\ T2 - Area\ in\ T1}{Total\ area} * \frac{1}{T2 - T1}] * 100 \text{ ---------------------------------- } Eq17$$

Where T1 is earlier image and T2 is later image.

2.10 Modeling Validation and Prediction

The CA-Markov module combines the Multi Criteria/Multi Objective Land Allocation (MOLA) in prediction with the CA and Markov Chain. By comparing the LULC maps of 2006, 2016, and 2021 pair-wise, the Markov analysis was initially utilized to create a transition probability matrix, a transition areas matrix, and a collection of conditional probability pictures. Comparing like with like the transition probability matrix, a transition regions matrix, and a collection of conditional probability pictures from the years 2006 to 2016 were constructed and utilized for simulating and forecasting the LULC in the year 2021. These were all created using the Markov tool in IDRIS Selva. The transition probability matrix, the transition areas matrix, and a set of conditional probability pictures from 2016 to 2021, on the other hand, were created using the LULC of the years 2016 and 2021 and were used to forecast the LULC in the year 2050 the validity of the CA-Markov were assessed using these following statistics which are the Kappa Index of Agreement (KIA) denoted as K standard; Kappa for no information (denoted Kno); Kappa for grid-cell level location (denoted Klocation) and Kappa for stratum-level location (denoted KlocationStrata). These statistics were generated using VALIDATE module in IDRISI Selva. In VALIDATE module, the predicted LULC map of year 2021 was used as comparison data while and the classified map of year 2021 used as reference data in validating the CA-Markov model results.

The Markov model by itself does not provide the location of the future LULC; hence the hybrid CA-Markov was used to achieve the goals. For the initial 10-year run, the transition matrix file was created and applied to the model. Then, throughout the modeling process, the typical 5 x 5 contiguity filter for CA filters was constructed. Based on the analysis used as a filter, The LULC maps of 2016 and 2021 were used as the foundation map to generate LULC maps for the year 2050.

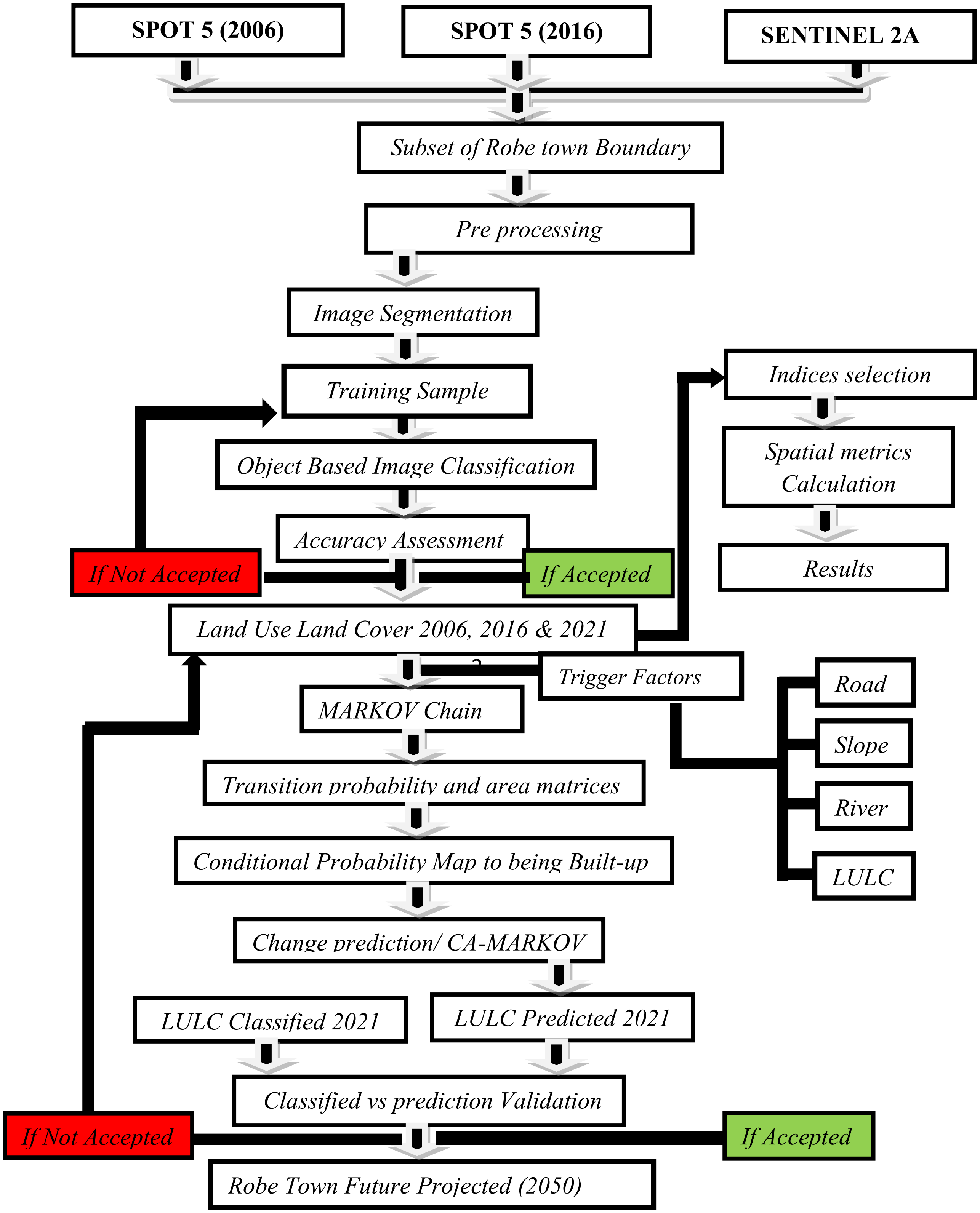

Fig 2. 2Methodology flow char

3. Results

3.1Land use land cover image classification

Training sites are the areas defined for each land cover type within the image and creating the spectral signature for each type of land use land cover. This is done by Envi classic 5.3 this shown in appendix B. The classification of Spot 5 and Sentinel 2A are Object based classification category, Based on the training samples and segments' proximity to neighboring training regions, the KNN with Full Lambda Schedule algorithm for all Robe Town Land use land cover classes of 2006,2016 and 2021.

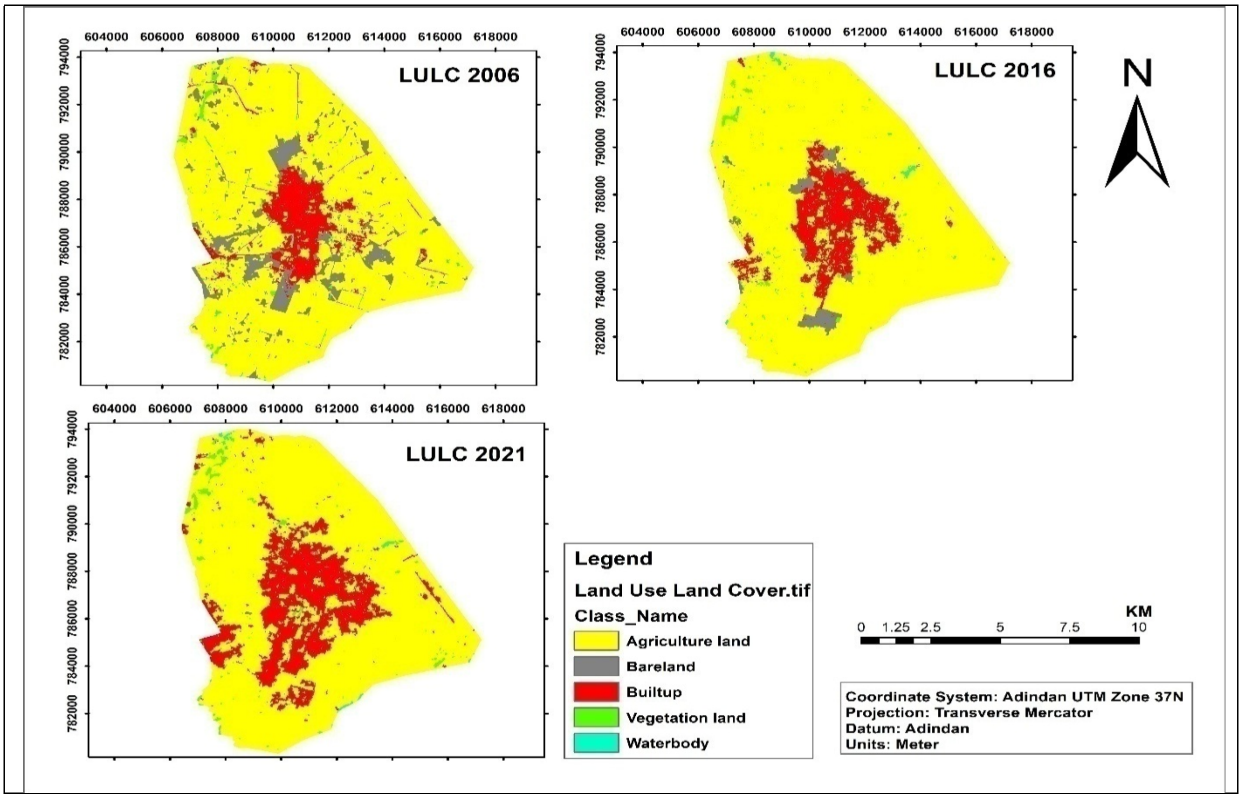

Fig 3. 1Robe Town classified Land use land cover of 2006, 2016 and 2021

3.2Accuracy Assessment of classified Land use land cover image

The Total number of reference points 210 is shown for each LULC Classified map of 2006, 2016 and 2021 shown in the Table below. Based on this equation classified land use land cover map of Robe Town in 2006 has 91 % overall accuracy and 0.89 kappa coefficient, similarly 2016 LULC map has 88% overall accuracy and 0.85 kappa coefficient and finally for 2021 LULC map has 93 % overall accuracy and 0.91 kappa coefficient. Based on Strength of Agreement for Kappa Statistic (Landis, J., 1977) all classified over all kappa and kappa statistics fall in almost perfectly classification.

Table 3. 1Error matrix of Robe Town LULC Classes in 2006

	REFERENCE DATA (2006)							
CLASSIFFIEDDATA 2006)		Agricul ture	Bare land	Built up	Vegeta tion	Water body	Total	U.A
	Agriculture	47	2	0	1	0	**50**	94%
	Bare land	2	47	1	0	0	**50**	94%
	Built-up	3	2	43	1	1	**50**	86%
	Vegetation	1	0	0	28	1	**30**	93%
	Waterbody	2	1	1	0	26	**30**	87%
	Total point	54	50	48	30	28	**210**	
	P.A	**87%**	**94%**	**90%**	**93%**	**93%**		
	Over all accuracy=91%							
	kappa coefficient =0.89							

Table 3. 2Error matrix of Robe Town LULC Classes in 2016

	REFERENCE DATA (2016)							
CLASSIFFIEDDATA		Agricul ture	Bare land	Built up	Vegeta tion	Water body	Total	U.A
	Agriculture	46	2	0	2	0	**50**	92%
	Bare land	2	45	2	1	0	**50**	90%
	Built-up	0	2	45	3	0	**50**	90%
	Vegetation	1	2	2	25	0	**30**	93%
	Waterbody	2	1	3	1	23	**30**	87%
	Total point	54	50	48	30	28	**210**	
	P.A	**85%**	**90%**	**94%**	**83%**	**82%**		
	Over all accuracy=88%							
	kappa coefficient =0.85							

Table 3. 3Error matrix of Robe Town LULC Classes in 2021

	REFERENCE DATA (2021)							
CLASSIFFIEDDATA		Agricul ture	Bare land	Builtu p	Vegeta tion	Water body	Total	U.A
	Agriculture	48	2	0	0	0	**50**	96%
	Bare land	2	47	0	1	0	**50**	94%
	Built-up	0	1	48	0	1	**50**	96%
	Vegetation	2	0	1	27	0	**30**	93%
	Waterbody	1	1	0	2	26	**30**	87%
	Total point	**54**	**50**	**48**	**30**	**28**	**210**	
	P.A	89%	94%	100%	90%	93%		
	Over all accuracy=93%							
	kappa coefficient =0.91							

3.3Spatio-temporal analysis of urban growth pattern using landscape metrics

There are numerous types of spatial metrics that are found in the existing literature, such as area/density/edge metrics, shape metrics, core area metrics, isolation/proximity metrics, contrast metrics, contagion/interspersion metrics, connectivity metrics, and diversity metrics. The large expansion of urban area in the research region is suggested by the categorization of multi-temporal satellite pictures into agriculture, bare land, built-up, vegetated, and water body area for three distinct years, 2006, 2016, and 2021. Calculating the statistical findings of these discoveries is crucial since it will help us comprehend the changes taking place in the town's urban area. Result presented in the Table (3.4) shows.

Table 3. 4Spatial Metrics Calculation of Robe Town of LULC 2006, 2016 and 2021

Year	Spatial metrics	CA	NP	TE	PD	LPI	ED	AREA_MN
LULC 2006	Agriculture	7397.41	259	471120	2.7901	77.7599	50.7513	28.5614
	Bare land	892.16	190	245920	2.0468	1.1655	26.4917	4.6956
	Built-up	854.43	246	226120	2.65	7.0118	24.3587	3.4733
	Vegetation	81.91	131	44540	1.4112	0.257	4.7981	0.6253
	Water body	57	167	56560	1.799	0.0317	6.0929	0.3413
LULC 2016	Agriculture	7819.02	199	289080	2.1437	82.2205	31.1406	39.2916
	Bare land	225.59	12	43100	0.1293	0.9644	4.6429	18.7992
	Built-up	1067.98	192	223550	2.0683	9.6926	24.0815	5.5624
	Vegetation	133.72	610	120560	6.5711	0.1404	12.9871	0.2192
	Water body	36.6	39	18870	0.4201	0.1206	2.0327	0.9426
LULC 2021	Agriculture	7355.07	186	335090	2.0037	76.6891	36.0975	39.5434
	Bare land	12.1	5	5740	0.0539	0.0353	0.6183	2.42
	Built-up	1740.87	148	279440	1.5943	14.7359	30.1026	11.7626
	Vegetation	141.23	199	76020	2.1437	0.1356	8.1892	0.7097
	Water body	33.64	39	17890	0.4201	0.0695	1.9272	0.8626

3.3.1 Class Metrics

According to the results obtained from FRAGSTATS, the built-up area was considerably changed over time in the study area (Table 4.1). The outcomes presented in Table 4.2 show that total built-up area grew from 854.43 Hac (2006) to 1067.98 Hac (2016) and to 1740.87 Hac (2021). It is indicating that, during 2006 to 2016, 213.55 Hac of non- built-up, area was converted to built-up areas. These results point out that a more rapid urban growth (urbanization) was occurring in the study area during the period of 2016 to 2021, about 672.89 Hac compare to the other periods.

Table 3. 5 Result of Landscape Metrics (2006-2021)

Year	LULC	CA	NP	TE	PD	LPI	ED	AREA_MN
2006	Built-up	854.43	246	226120	2.65	7.0118	24.3587	3.4733
2016	Built-up	1067.98	192	223550	2.0683	9.6926	24.0815	5.5624
2021	Built-up	1740.87	148	279440	1.5943	14.7359	30.1026	11.7626

3.3.2 Total Edge

Total Edge (TE) considers true edges values greater than or equal to zero. Larger continuous patches indicate edges with larger values. Figure 3.2 indicates that during 2006 are about 226120 the edges were increase slightly to 223550 in 2016 patches as the landscape was fragmented. In 2021 larger edges indicated that the urban edges are ubiquitous and continuous with about 279440.

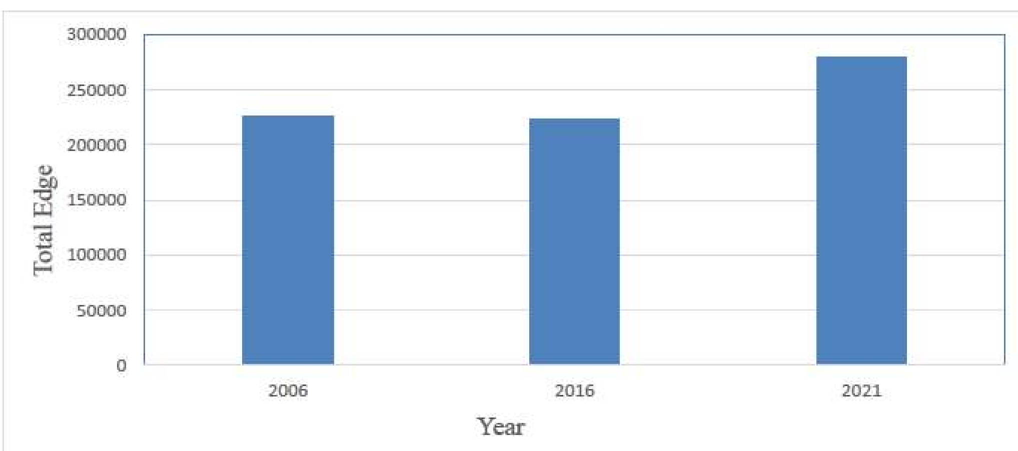

Fig 3. 2 Total Edge

3.3.3 Edge Density

The result of this study revealed that the edge density (ED) slightly decrease from 24.3587 in 2006 to 24.0815 in 2016 and it increase to 30.1026 in 2021 (Figure 9). This shows that there has been significant urban growth with the emergence of various fragmented urban patches observed in the study landscape from 2006 to 2021.

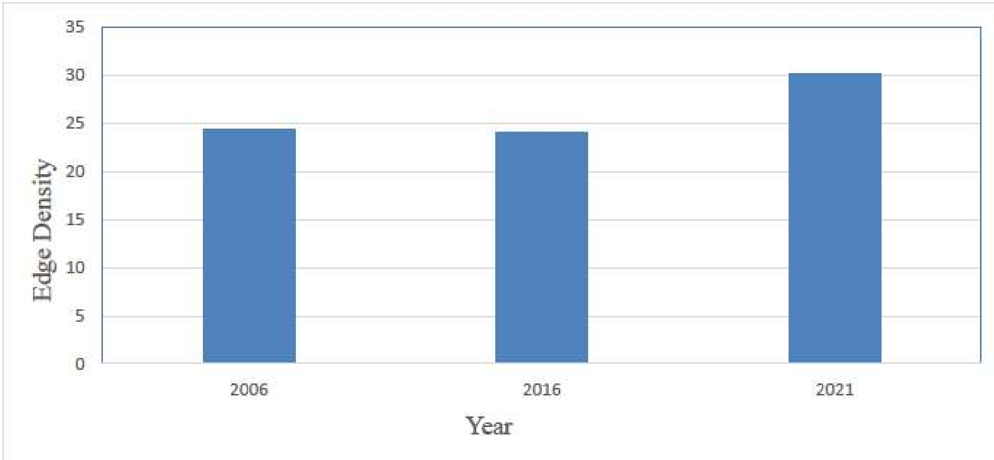

Fig 3. 3Edge Density

3.3.4 Largest patch index

Largest Patch Index Figure 4.8 shows that the value of this metric increased during 2006-2021. Largest patch index increased its dominancy from 7.01 % in 2006 to about 9.69% in 2016 and 14.78% (Fig4.8). This was related to the contagion of small and isolated urban patches into the largest patch and development of other urban areas around the existing largest patch.

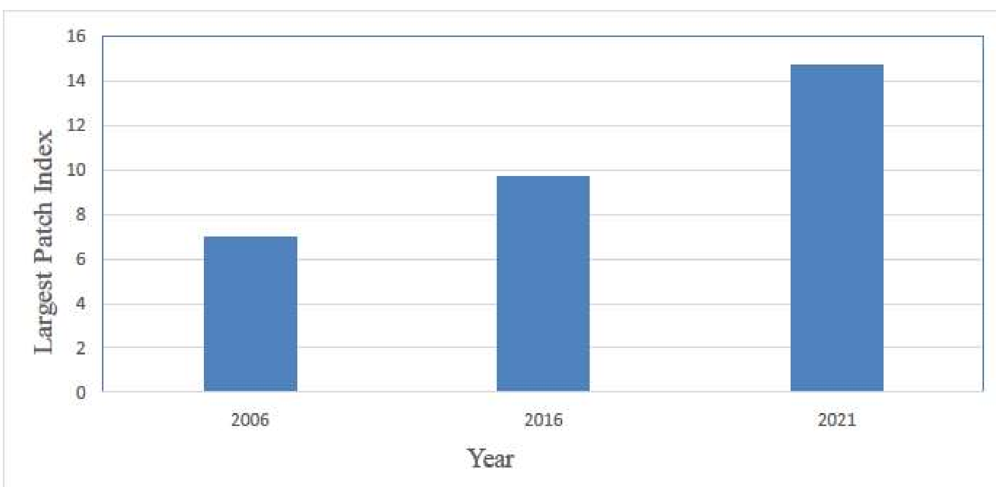

Fig 3. 4 Largest patch index

3.3.5 Number of Patches

The number of patches (NP) metric quantifies the number of individual urban or built area patch and shows how the landscape particularly the built-up area was subdivided into patches or smaller pieces. NP is expected to increase but may experience decrease if urban areas expand and merge into continuous urban fabric (Fragkias, 2005).The study periods shows Continuous decrease of the NP in the landscape all through the study period. In 2006, NP in the study area was 246, and this was decreased to192 in 2016, and the decreased to 148 in 2021 possibly.

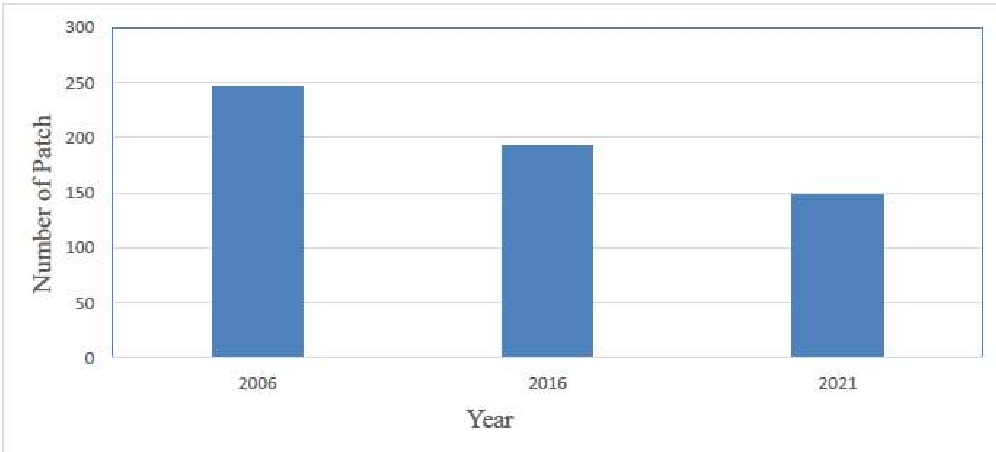

Fig 3. 5 Number of Patches

3.3.6 Area Weighted Mean Patch Fractal Dimension

The area weighted mean patch fractal dimensions (AWMPFD) indicates two conditions (regular form and irregular form). The value of this metrics between 2006 and 2016 is its low than 2021.this indicates in 2021 there is complexity and growing irregularity of urban patches due to fragmentation form of expansion and 2006 and 2016 it indicates condensed regular form of urban expansion of Robe town.

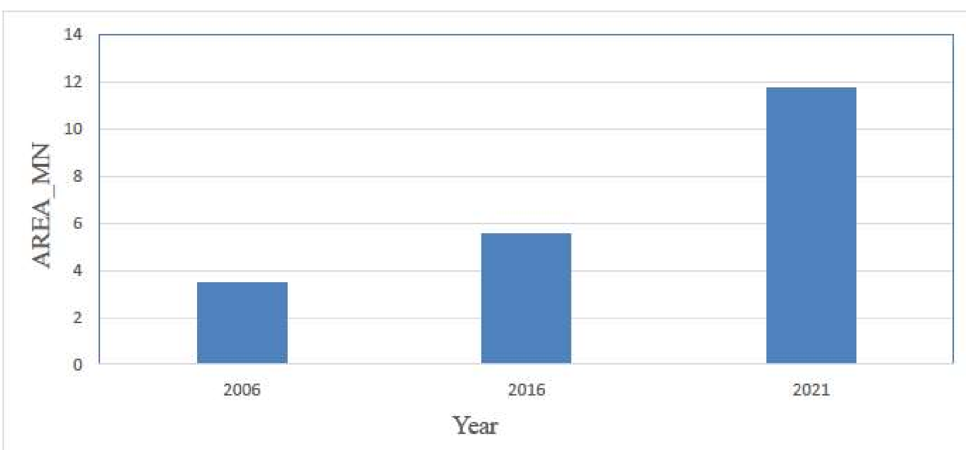

Fig 3. 6 Area Weighted Mean Patch Fractal Dimension

CONTAG, SHDI, and SHEI are landscape metrics to define the overall condition of landscape metrics. CONTAG measures the extent to which different land cover classes are aggregated or clumped. According to table and graphs, CONTAG value is least for 2016. This suggests that the patch of non-built up class were highly aggregated together and the decreasing value of CONTAG suggests that fragmentation on that patch occurred forming new built-ups in 2016 to 2021. The highest value of SHEI and SHDI occur in 2016 this suggests the landscape is being more fragmented, diversified and rich in different patches over time. Hence all metrics of landscape level metrics supports the fragmented growth of town over time.

3.4 Change detection and prediction modeling

3.4.1 Change detection

The Change Analysis used for the rapid assessment of changes such as gains and losses, net change to built up area using Land Cover Modeler on Indrisi selva both in map and graphical form. The change between 2006-2016, 2016-2021 and 2006-2021.are calculated using image difference (later- earlier) of classified LULC Robe Town of three different years.

Table 3. 6 Robe Town Gain and losses of LULC Classes from 2006-2021

LULC Classes	2006	2016	2021	Gain (+) /Losses (-) (2006-2021)
Agriculture	7397.41	7819.02	7355.07	- 42.41
Bareland	892.16	225.59	12.1	- 880.06
Builtup	854.43	1067.98	1740.87	+ 886.44
Vegetation	81.91	133.72	141.23	+59.32
Waterbody	57	36.6	33.64	- 23.36
Total	9282.91	9282.91	9282.91	0=(- 42.41+- 880.06+ 886.44+59.32+23.36

Robe Town LULC classes changes in three temporal study (2006, 2016 and 2021) are: Agriculture land is decreased by 42.34Hac(0.5%) ,Bare land is decreased 880.06 Hac(98.6%) ,Built up area is increased by 886.44 Hac(103.76%), Vegetation is Increase by 59.32 Hac(72.4%) and Water body is decreased 23.36 Hac(40.9%).

Generally using Land Change Modeler in Idrisi Selva Robe Town LULC Classes that contribute to Net change in Built up area for 15 years (2006-2021),Agriculture land more contribute (899.85Hac),Bare land contribute 220.87 (Hac) and Vegetation land is least contribute (10.12Hac) as shown Table below.

Table 3. 7Robe Town LULC classes contributor to net change in Built up area

Changed to Built up area (Hac)			
LULC Classes	2006-2016	2016-2021	2006-2021
Agriculture	359.18	713.78	899.85
Bare land	140.45	125.89	220.87
Vegetation	4.5	42.89	10.12
Water body	8.5	3.75	12.86

3.5 Trigger factors for expansion Robe town

Identifying the Factors and Constraints of study area for this study factors are: slope, distance to Road, types of LULC, distance from Built up area); they indicate the relative suitability of certain areas and Constraints are the locations which are not allowed for urban development.

3.5.1 Proximity to Feature/Raster

The Raster-based proximity tools used to discover proximity distance of each cell from a set of features or that allocate each cell to the closest feature using Euclidean distance function.

3.5.2 Reclassification

Reclassifying the set values of a raster dataset allows the user to simplify the information in their raster by removing no data cell values. There is no specific and standard number for suitable site selection, number and interval vary place to place and researcher to researcher so this table is not standard but using different theory of different factors this is used for study area. According to theory of overlay analysis higher value is very suitable, next higher value is suitable, medium value has moderate suitable ,less value but not least has less suitable and least value has unsuitable. So based on this idea very suitable has 5 values, suitable has 4 value, moderate suitable has 3 value, less suitable has 2 value and unsuitable has 1 value.

Table 3. 8Reclassified Factors and Constraints

Factors	Very suitable	Suitable	Moderately suitable	Less suitable	Unsuitable
LULC	Bareland	Agriculture land		Vegetation land	Waterbody
Road	0-1500m	1500-3000m	3000-4500m	4500-6000m	>6000m
Slope	0-6°	6-12°	12-20°	20-25°	>25°
River	>300m	200-300m	100-200m	50-100m	0-50m

For Road area/site up to 1500m distance is very suitable, area/site 1500m-3000m is suitable, area/site 3000-4500m moderately suitable, area/site 4500-6000m is less suitable and area/site greater than 6000m is unsuitable

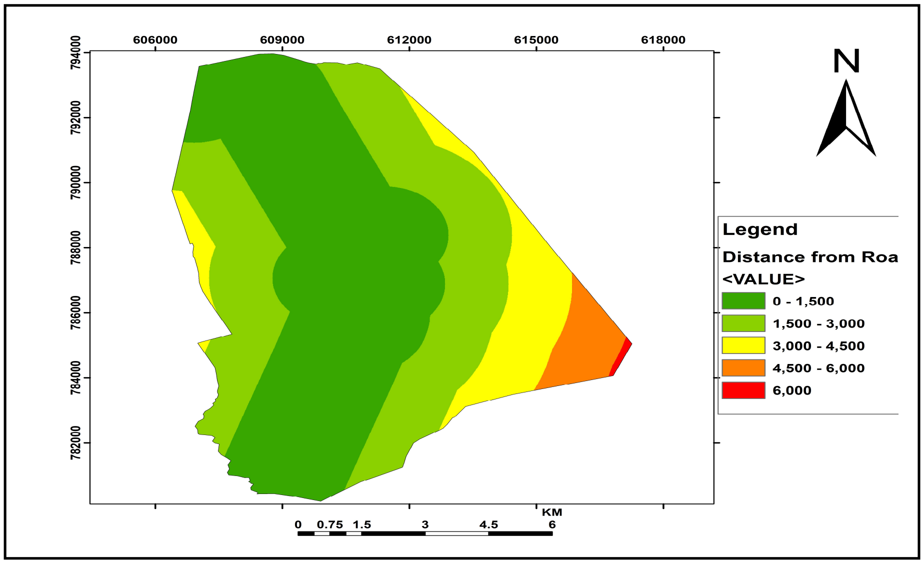

Fig 3. 7The Euclidean distance and Reclassified

For Slope area/ site 0-6 degree is very suitable, area/site 6-12 degree is suitable, area/site 12-20 degree is moderately suitable, area/site 20-25 degree is less suitable and area/site greater than 25 degree is unsuitable

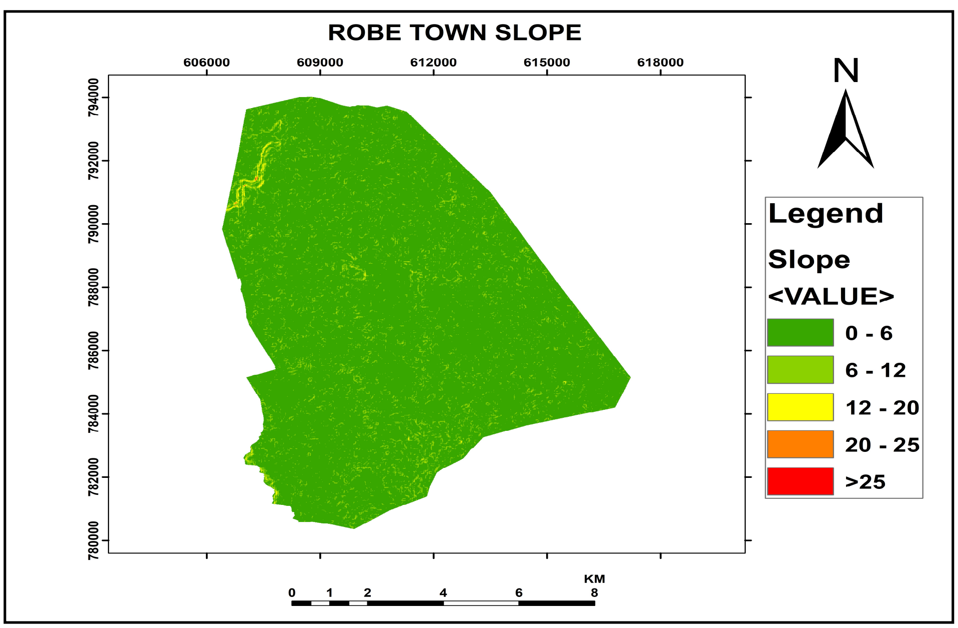

Fig 3. 8Robe Town Reclassified Slope map

LULC type Bareland is very suitable for Built-up area, Agriculture land is suitable, Forest land is less suitable and Water body is unsuitable.

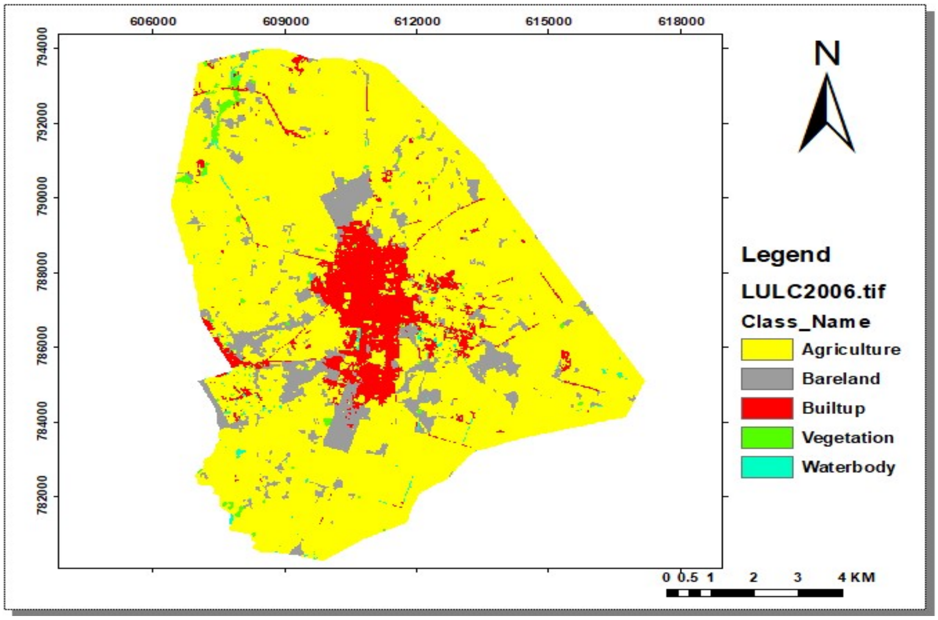

Fig 3. 9 Robe Town Reclassified LULC 2006 Map

For River area/site greater than 300m is very suitable, area/site 300-200m is suitable, area/site 200- 100m is moderate suitable, area/site 100-50 is less suitable and area/site within 50m is unsuitable.

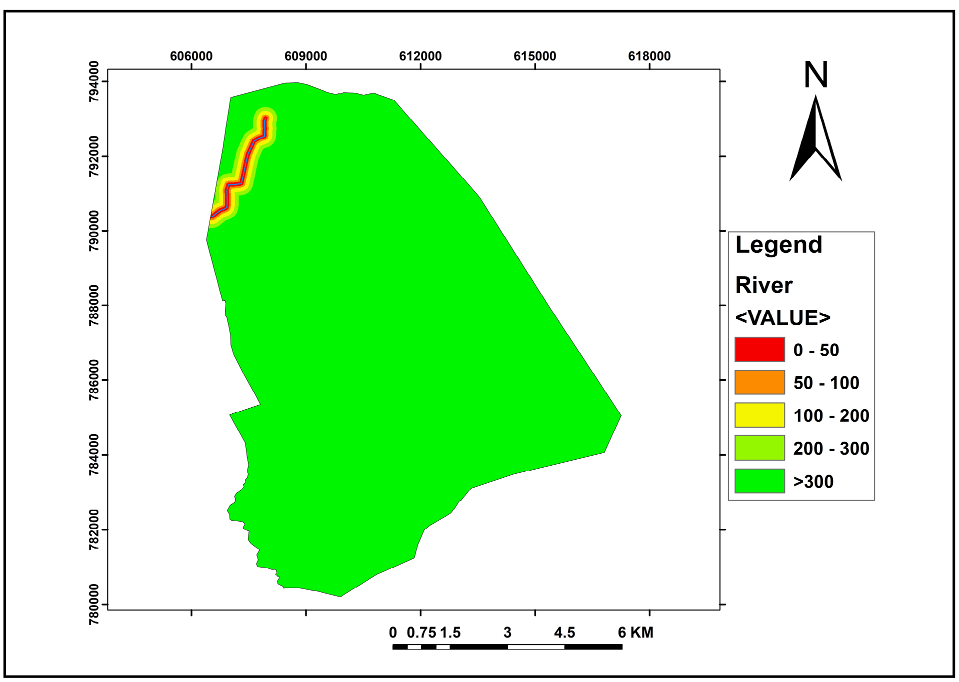

Fig 3. 10Robe Town Reclassified River map

3.1.1 Analytical Hierarchy Process

The relative importance and weight of each individual element and sub-factor contributing to the urban expansion of Robe Town were determined using the AHP approach. AHP is a multi-objective, multi-criterion decision-making method that enables users to select one final solution from a range of potential solutions (Saaty, 1980). AHP is one of the multiple criteria decision-making methods that provide measures of consistency. Pair wise comparison matrix obtained by decision maker must satisfy Consistency Ratio condition (CR< 10%). Consistency Ratio (CR) is acceptable because is less than 0.1 CR=CI/RI<0.1.

Table 3. 9Analytical Hierarchy Process (AHP) weight of Factors Pair wise comparison

	Road	Population	LULC 2016	Slope	River
Road	1				
Population	1/3	1			
LULC 2006	1/5	1/3	1		
Slope	1/7	1/5	1/3	1	
River	1/9	1/7	1/5	1/3	1

Table 3. 10Eigenvector of weights of constraints and factors

The Eigenvector of weights of factors	
Factors	Factors weights
Road of Robe Town	0.5128
Population of Robe Town	0.2615
LULC 2016 of Robe Town	0.1290
Slope of Robe Town	0.0634
River of Robe Town	0.0333

The main mode of transport giving service for the community is Road transportation. Robe town has a total road network length of 331.45km, from which, asphalted Road is 38.9km (11.74%), 182.16km of gravel road (54%), and cobble stone road is 80.39km (24%) and 30km un-surfaced road (9%). The town has access to the nearby towns such as Gobbaa, Hoomaa, Diinshoo, Adaabbaa, Dodolaa, Asaasaa, Shaashamannee, Asallaa, Adaamaa and Abbakara townswith ongoing asphalt road. The road at present serve as a major arterial street is the road segments of Finfinne to Gobbaa highway this serves the urban expansion of the town.

3.6Markov Chain Model

The Transition probability of Robe Town from all Land use land cover classes to Built up area for 2006, 2016 and 2021 are generated. Transition all LULC to Built-up area means change of

Agriculture, Bare land, Vegetation and Water body to Built up area within 2006-2016 and 2016-2021.Using Markov chain Analysis the following transition area and transition probability was obtained using LULC map of year 2006-2016,2016-2021 and 2006 -2021. In year 2006-2016 the chance of Built-up remaining unchanged was 0.6699 (67%) while the probability of changing to Built-up from other land cover are Agriculture land, Bare land, Vegetation and Water body was 0.0758 (8%), 0.1741 (2%), 0.0451 (5%) and 0.1633 (2%), Respectively. The high probability of Agriculture land changing to impervious land cover is indicates agriculture land is changed into Built-up this leads that urban Expansion it occurs in the study area as shown Table below.

Table 3. 11Markov chain transition probability of Robe Town (2006-*2016)*

Markov chain Transition probability of Robe Town LULC 2006-2016 (in cells)						
	Agriculture	Bare land	Built-up	Vegetation	Water body	Total cells
Agriculture	0.8191	0.0655	0.0758	0.0288	0.0108	1
Bare land	0.7428	0.0562	0.1741	0.0218	0.0051	1
Built-up	0.2634	0.0194	0.6699	0.0473	0.0000	1
Vegetation	0.8082	0.0237	0.0451	0.0813	0.0417	1
Water body	0.6940	0.0000	0.1633	0.1189	0.0238	1
Total cells	3.3275	0.1648	1.1282	0.2981	0.0814	5

Table 3. 12 Markov chain transition area of Robe Town (2006-2016)

Markov chain Transition probability of Robe Town LULC 2006-2016 (in cells)						
	Agriculture	Bare land	Built-up	Vegetation	Water body	Total cells
Agriculture	1096880	87693	101558	38597	14452	1339180
Bare land	16758	1268	3927	491	116	22560
Built-up	28135	2068	71548	5047	0	106798
Vegetation	10807	318	603	1087	557	13372
Water body	2551	0	600	437	88	3676
Total cells	1155131	91347	178236	45659	15213	1485586

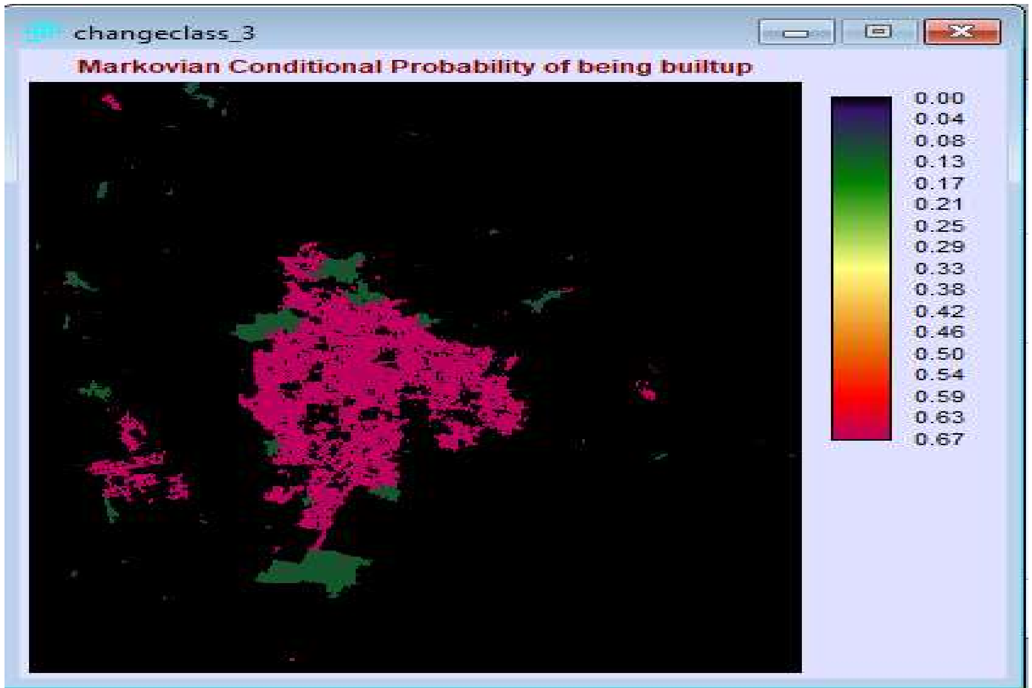

Fig 3. 11Markovian Conditional Probability of being class built up area (for predict2021)

3.7Future Prediction (Projected) and Modeling for 2021

Ca-Markov model has been selected for simulating land cover map of Robe Town for the year 2021 for validation and predict the final land use land cover map for 2050 year. As shown below Fig 4.12 There are two types of Map in, the first on the classified Map and the second is the predicted of Robe Town 2021 year that used for validation.

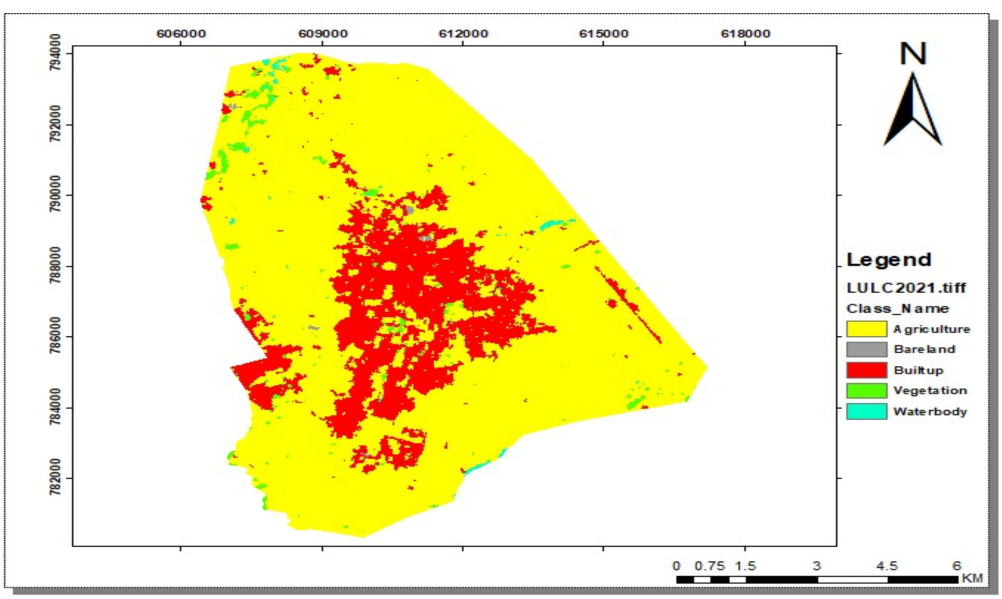

Fig 3. 12Robe Town LULC Classified 2021

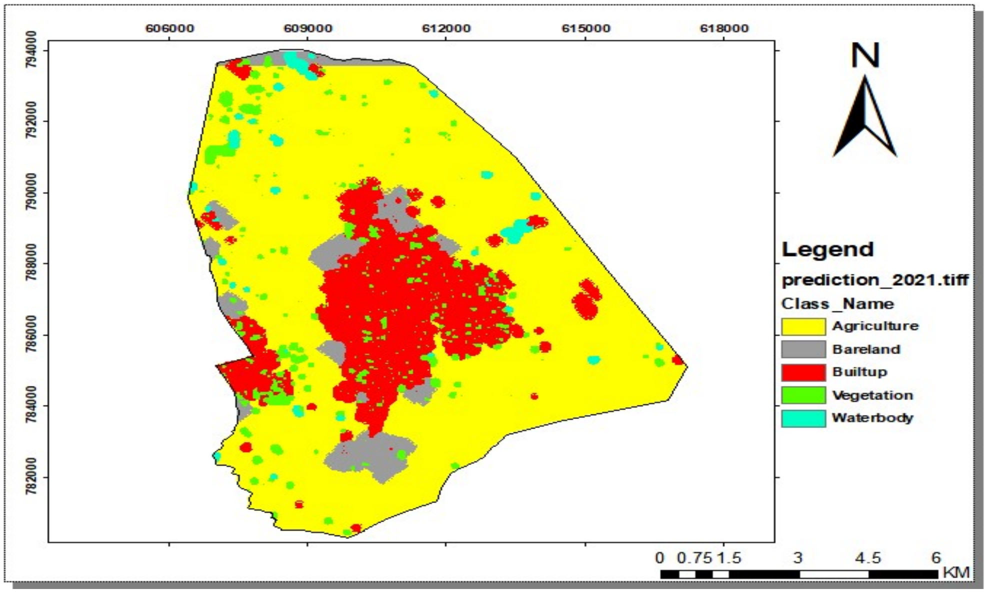

Fig 3. 13Robe Town LULC predict

3.8 Change Prediction (simulation) Modeling for 2050

The Change Prediction (simulation) modeling for 2050 was based on the Cellular Automata. The validation of the model accuracy is needed, in order to achieve acceptable accuracy, this study had employed an approach to simulate LULC of 2021 from the historical LULC process for 2006 and 2016 and then the simulated result was compared the reference LULC map of 2021 (classified LULC map 2021). The simulated LULC in 2021 was successful and value was 81.38 % that is excellent agreement between the reference map and the Predicted (simulated) map. So using the historical LULC process from 2016 to 2021 is accurate and reliable to predict LULC patterns in 2050.Generating the transition probability of all land use land cover classes of 2016 and 2021 with similar procedures and Predict Land use land cover classes of Robe Town of 2050 year. Markov Chain Model Analysis that shown Transition area and transition Probability in Table 4.15 and 4.16. Table 4-15 Markov chain transition area of Robe Town (2016-2021.

The transition probability of unchanged Built-up in the year of 2016-2021 is 0.3115 (31%) while the probability of changing to Built-up from other land cover are Agriculture land, Bare land, Vegetation and Water body was 0.2939 (29%), 0.3086 (30%), 0.2555 (26%) and 0.2013 (20%), Respectively. In 2016 -2021 the high probability of bare land other than LULC are changed into Built-up. The Markovian Conditional Probability of being class Built up area are below figure 4.13 and other conditional probability of being Agriculture, Bare land, Vegetation and Water body.

Table 3. 13Markov chain transition probability of Robe Town (2016-2021)

Markov chain Transition probability of Robe Town LULC 2016-2021 (in cells)						
	Agriculture land	Bare land	Built-up	Vegetation	Water body	Total cells
Agriculture land	0.6857	0.0012	0.2939	0.0156	0.0036	1
Bare land	0.6789	0.0010	0.3086	0.0094	0.0021	1
Built-up	0.6747	0.0015	0.3115	0.0101	0.0022	1
Vegetation	0.7333	0.0010	0.2555	0.0081	0.0021	1
Water body	0.7864	0.0008	0.2013	0.0096	0.0018	0.9999
Total cells	3.559	0.0055	1.3708	0.0528	0.0118	4.9999

Table 3. 14Markov chain transition area of Robe Town (2006-2016)

Markov chain Transition area of Robe Town LULC 2016-2021 (in cells)						
	Agriculture land	Bare land	Built-up	Vegetation	Water body	Total cells
Agriculture	886489	1601	379974	20136	4602	1292802
Bare land	822	1	373	11	3	1210
Built-up	117449	260	54230	1764	384	174087
Vegetation	10356	14	3608	114	30	14122
Water body	2646	3	677	32	6	3364
Total cells	1017762	1879	438862	22057	5025	1485585

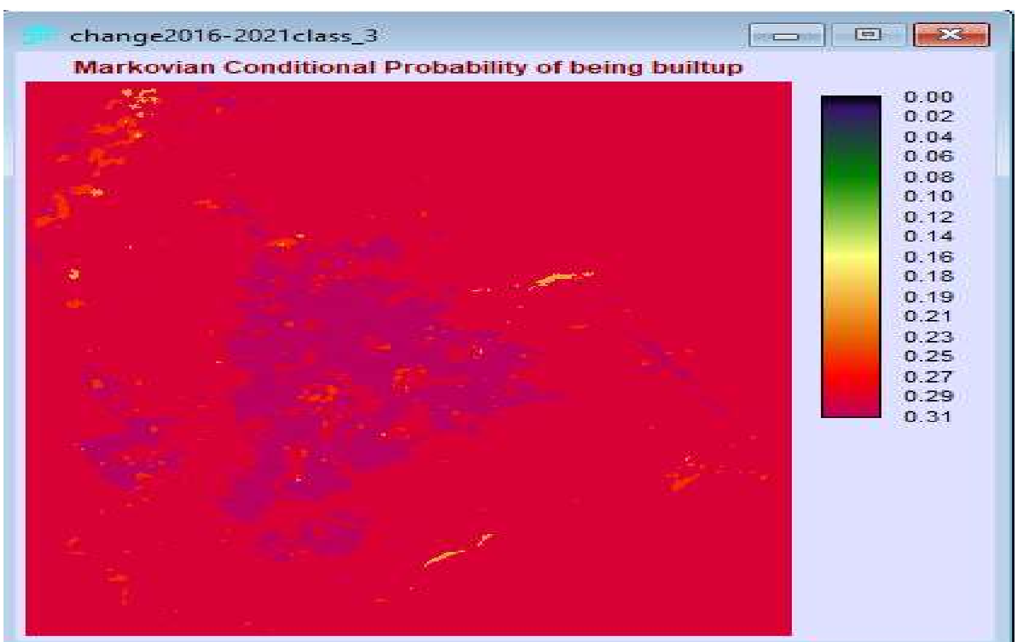

Fig 3. 14Markovian Conditional Probability of being class Built up area (for predict2050)

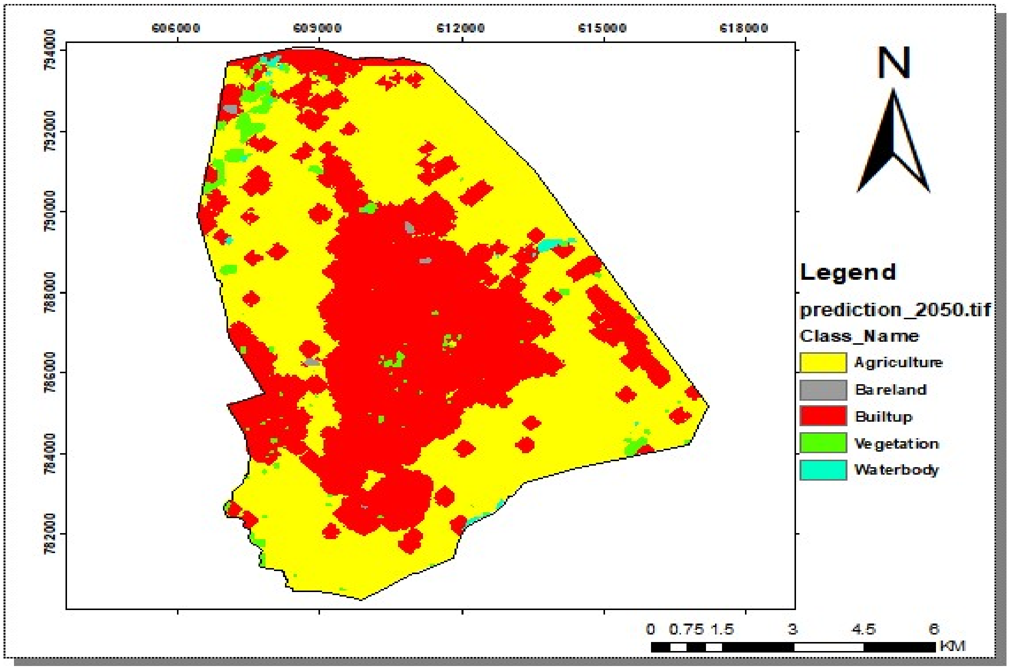

Fig 3. 15 Prediction Land use land cover of Robe Town (2050)

Using transition probability of 2006-2016 future projected Robe Town LULC in 2050 will contains 4604.77 Hac (50%) of Agriculture land, 18.8Hac (0.5%) of Bare land, 4388.67Hac (47%) of Built-up, 220.53Hac (2%) of Vegetation and 50.14Hac (0.5%) of Water body. Based on this predicted result the Built-up area is increased from 1740.87Hac in 2021 to 4388.67Hac in 2050G.C. Built-up area land use land cover type is increasing in an alarming rate over the years While the major contributors are Agriculture land and Water body.

Table 3. 15Robe Town Land use lands cover changes (2006-2021) and predicted (2050)

Robe Town Land use land cover changes (2006-2021) and predicted (2050)				
year	2006	2016	2021	2050
Agriculture	7397.41	7819.02	7355.07	4604.77
Bare land	892.16	225.59	12.1	18.8
Built-up	854.43	1067.98	1740.87	4388.67
Vegetation	81.91	133.72	141.23	220.53
Water body	57	36.6	33.64	50.14
Total area	9282.91	9282.91	9282.91	9282.91

4 Discussion

Urban expansion has both positive and negative impacts on urban development. It is a way of civilization and engine of development; on the other hand, its consequences affect the urban environment particularly in developing towns like Robe Town. The town is rapidly expanding into the Agriculture land. Thes tudies findings reveals that the planed boundary of the town was increasing from 2006-2021.

A Robe Town urban land use change (Urban expansion) is increased by 854.43 Hac (2006) to 1067.98 Hac (2016) and to 1740.87 Hac (2021) and increased 4388.67Hacfor future three decades (2050). The spatiotemporal patterns of urban expansion changed between each research year due to the fast urbanization over the previous 15 years. The extent, direction and location of urban expansion in each study area have mainly been associated with variances in their physical setting, administrative conditions, demography, Hospital, New bus station and University. The topographic and physical constraints that shaped the directions and shaped the growth of the town were clearly seen in the physical development of all three cities. The result is in harmony with the recent study in Ethiopia cities such as Addis Ababa, Adama and Hawasa city by (Berhanu*et al*, 2019), who reported that a city with higher administrative status is more likely to obtain a large area of land for development and subsequently acquire the high potential for urban expansion as well as economic growth. Other similar result by(DEJENE, 2018) thesis spatio-temporal analysis for monitoring urban growth using geospatial tools (1994-2017) and predict the future urban growth of Adama City using the Landsat satellite images of 1994, 2004and 2014. According to his research 49.5% of the total study area will be converted into Built-up area in 2017. (Amanu, 2019).Analyze modeling spatio-temporal urban land use changes in Burayu Town using Landsat 1990, 2000, 2010 and 2019. According to his results expansion of built up increase This study results show Urban land use land cover changes (urban expansion) of Burayu Town area highly increased from 100 Hac (1%) to 4600Hac (46%) in last three decades (1990-2019).Likewise, the study also coincides with the findings of (Lingereh, 2016), which is conducted in Debre Markos town expansion from 1987 to 2016. The study result showed that the built-up area has expanded by 0.32km2 per year by snatching lots of land from farmlands, forests and open areas. Moreover, the study result has also agreed with the findings of(Fenta, et al., 2017) thesis The dynamics of urban expansion and land use/land cover changes using remote sensing and spatial metrics the case of Mekelle City of northern Ethiopia the findings revealed that the built-up area rose by 10%, 9%, and 8% annually during the time periods 1984–1994, 1994–2004, and 2004–2014, respectively, with an average annual increase of 19% (100 Hac year), from 531 ha in 1984 to 3524 Hac in 2014. Approximately 88% of the increase in built-up area between 1984 and 2014 was from the conversion of agricultural lands, which fell by 39%. The primary growth type throughout the periods of 1984–1994–1994, 1994–2004–2014, and 2004–2014 was the extension of existing urban areas, which accounted for 54%, 75%, and 81% of the total new development, respectively..

The negative effects of urban expansion in Robe Town highly increased; the land use and land cover changes and becomes many problems such as loss of prime agricultural land, displacement of farm communities. Robe Town Urban land Change Map i.e. the Transition from all LULC Classes to Built-up area for three decades (2006-2016) from Agriculture land (899.85Hac), Bare land (220.87Hac), Vegetation (10.12 Hac) and Water body is (112.86Hac) changed to Built-up area.

These Predicted Robe Town urban land use land cover change results are obtained by classification of land use land change within the Boundary of study. Built-up area is 4388.67Hac (47%), Agriculture land 4604.77 Hac (50%), Bare land 18.8 Hac(0%), Vegetation 220.53 Hac(3%) and water body is 50.14Hac (0%).Based on this predicted result the Built-up area is increased from 1740.87Hac (19%) in 2021 to 4388.67Hac (47%) in 2050. Built-up area land use land cover type is increasing in an alarming rate over the years. While the major contributors Agriculture land and bare land types. The previous area of Robe Structural plan was 8023.8 hectare in the year of 2008 and currently it was expanded to total area about 9282.91hectares it is increased by 1387.6 Hac (14%) (Robe Structural Plan, 2018).The major trigger factor for cause of expansion is road network of the town especially the constructed of Asphalt road and The population of Robe Town was rapidly increased from 41452 in 2006 to 159863 in 2021.This indicates that, nearly after 11 years the populations of Robe town will double itself. This is a short doubling time when compared with the doubling time of Ethiopia, which is 23 years. The small doubling time is due to large influx of people from rural area to Robe town in line for seeking urban job opportunities and for better urban life. The other factors for short doubling time is different facilities like education which attract people especially students from other places to attend high schools, preparatory education, technical education and university in the town. This is especially true of the presence of different privately and publicly owned colleges that render trainings in a number of fields or professions in the town. The majority of trainees are not only from the town and the surrounding rural hinterlands rather come from other parts of Oromia and the whole country. So, these have partly increased the population of the town that would make the doubling time of Robe town be shorter. This implies that the ongoing plan should facilitate better livable conditions for fast growing number of population (Robe Structural Plan, 2018).

5 Conclusions

Urban development is impacted by urban expansion in both positive and negative manner. It is a mode of civilization and a force for growth, but on the other hand, the urban environment is notably affected by its effects at all spatial and temporal dimensions in growing towns like Robe town. Robe Town was chosen for this study primarily due to concerns about the negative impacts of urban expansion, The current extraordinary and dispersed expansion also affects productive farmland, increases the number of squatter settlements in environmentally sensitive areas, Inadequate development of infrastructure and pollutes the physical environment, including the water, soil, and air. As a result, there are major social, economic and environmental issues Therefore, it has become a top priority for researchers and politicians worldwide to monitor and mitigate the negative effects of expansion while maintaining the production of vital resources. The town is quickly enlarging into the nearby agricultural areas. The study finding reveals that the planed boundary of the town was increasing by from 2006 to 2016 and by from 2016 to 2021. In the year from 2006 to 2021, all land uses of the town showed a decreased except vegetation and Built-up area. During fifteen years 887 hectare of land was included to urban use. Generally, the coverage of the built up area increases from time to time from 854.43 hectare (7%) to 1740.87 hectare (14%) in last three decades (2006-2021) and for future three decades 4388.67 hectare (47%) in 2050.The main cause for urban expansion of Robe town is road network high population growth. The driving force of population growth is migration and natural increase through birth. This study has been conducted by integrating GIS, remote sensing and Land use land cover modeling tools to Model spatio temporal urban expansion not only provides the scientific way to understand the future urban growth but it also provides a methodology for assessing urban land use cost effectively and in less time period. The present study is useful for decision-making process and helpful for planners and authorities to formulate suitable plan for sustainable urban development in the region. Generally, Economic growth is a critical goal for every government to accomplish, to enhance way of life and increase the competence of providing goods and services to satisfy human needs and parallel to this, they have to been paid attention to the environmental conservation.

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