

Supervised Maximum Likelihood Approach for Land Use Land Cover Dynamics of Semi-Urban Region

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Abstract— Remote sensing offers a unique environmental monitoring capability that covers extensive geographical areas while capturing irreplaceable information on the Earth's land, atmosphere and oceans. RS classifications of an image are the procedure of converting remotely sensed imageries to practical products. LU/LC classification using remotely sensing satellite data is significant research and generally used in RS applications. Nowadays, Remote Sensing technology has become one of the promising tools to measure the LU/LC changes. Data collection of two different time periods 2005 and 2017 are taken from Google Earth Image and are downloaded using Smart GIS 2019. In the pre-processing stage Geo-Referencing, sub-setting is implemented using an ERDAS version 9.2. For the data 2005, about 76.19 percent of accuracy is obtained, for the data 2017, about 77.24 percent of accuracy is obtained. From 2005-2017 there is a significant decrease in Grassland, Open land, Water body and Trees, there is a significant increase in the built-up, Highway and Tiled roof. About 33.85 percent of changes in land use are identified from 2005-2017 and about 25.06 percent of changes in the land cover is identified from 2005-2017.

Index Terms— Supervised Classification, Maximum Likelihood Classifier, Remote Sensing, LU/LC Dynamics, Google Earth Images.

I. INTRODUCTION

Land Use and Land Cover monitoring has two major subfields like change detection and classification. In the past few decades, it has become successful in the field of environmental monitoring, urban studies, forest monitoring, damage assessment and agricultural surveys. Soft computing methods for LU/LC are used for monitoring multi-spectral remote sensing Imageries. The numerous soft computing method and extraction of features are analyzed and summarized using LULC change detection and classification. Multi-spectral RS images are the key source in LU/LC monitoring. This is accomplished using LU/LC change detection and LU/LC classification. The LU/LC change detection may include detecting forest degradation, agriculture areas, water bodies and forest fire monitoring etc. The necessity for Land Use/Land Cover monitoring is three branched viz., 1. To identify and track the obtainability of every land cover class, up to date. 2. To allow the changes happening by identifying differences among two or more-time intervals for all land cover classes. 3. To permit the protective act in contradiction of destruction and degradation of natural resources [8].

For sustainable environmental and urban planning plans, comprehensive and accurate LU change statistics are necessary. Therefore, estimation of LULC change based on pattern, rate and type using RS helps to predict any further changes in urban growth [10]. Multispectral (MSP) and Hyperspectral (HSP) satellite data are used for various remote sensing applications. A review on LU/LC change detection is determined as important research in the area of remote sensing. The review paper aims to classify the numerous LU/LC applications such as pre-processing techniques, remote sensing satellites, landscape change models, geospatial software, LU/LC classification, spectral unmixing, evaluation metrics and clustering. Based on information obtained from LU/LC change, it will support Government officials for planning land resources taking protective measures of LU/LC environment [15]. Change Detection of LU/LC using Remote Sensing Methods aimed to study Land Use/Land Cover (LU/LC) changes for preparation of future map and to analyze the LU/LC changes in the Muthukur Mandal, Nellore District. In order to monitor land changes in LU/LC, the satellite data that has been used is LISS-III digital data (10th March 2005 and 18th March 2012). From the map 2005-2006 and 2011-2012, the prediction of 2016-2017 map was generated. Using the driver dataset was used in order to classify the suitability of LU classes [6]. The study based on LU/LC changes and drivers in the region of Muga watershed, Upper Blue Nile basin, Ethiopia was intended to detect patterns and the magnitude of LU/LC changes and to assess the changes in drivers over the previous three decades from 1985–2017 in the region of Muga watershed. The experimental results had a significant increase in the urban areas and cultivated land by 270% and 12% accuracy. Whereas Grasslands, Forest lands and Shrub-bush lands results decreased by about 40%, 21% and 12% accuracy. The author recommended integrating watershed management to include suitable LU planning and management with active contributions to local communities, by taking necessary precautions to LU/LC changes in the watershed [2]. NDVI trajectory can be used to detect the land cover dynamics in major parts of Beijing using Google Earth Engine for every Landsat imagery. The overall accuracy achieved for map classification is 86.61% and for change detection, it was 86.13% majorly based on three types that are vegetation gain related to a positive change of NDVI, vegetation loss related to a negative change of NDVI and no further changes [7]. Analysis of LU/LC change in Nadowli District, Ghana is done. Due to the illegal and legal influx of mining is carried in Ghana, it requires the latest technologies for LU/LC assessment using satellite RS data and GIS in that area. This study demonstrates that amid the 1991 and 2000 years there were no significant changes are seen in the LULC as shown in the 2014 year which resulted to decrease in closed Vegetation and Water but whereas Open Savannah has been marginally increased. Through satellite images, it was not able to prove the main reason for depleting of closed savannah wood, felling of trees (fuelwood) and Illegal mining [11]. LC/LU classification and assessment in southern Ghana was carried on using Landsat 7 ETM+ imagery as an objective to estimate an innovative method named “Dense Stack” to classify the images with multi-temporal Landsat 7 ETM+ imagery, map, extreme cloudy conditions, also to quantify and examine LC/LU changes in circa (2000 and 2010) of southern Ghana. From the experimental results, the study area revealed that the LC/LU change achieved was 26% indicating LC/LU maps for circa (2000 and 2010) during that study duration. For the year 2000, the results provided 62% changes with Agriculture, 26% for Savanna, 33% for Secondary Forest and 3% for Forest. During the year 2000, 18% of land was classified as Agriculture as abandoned or fallow through circa 2010. For LC/LU of circa 2000, Built-in change was represented to 6% involving 5% as Agriculture and 1% as Secondary Forest. Further monitoring of LC/LU change can be done by developing time-series classification methods and with freely accessible Landsat 7 ETM+ imagery throughout the world, mostly in the equatorial area [4].

The research paper intended to monitor urban LC/LU change using Landsat Image in Algiers City for the duration 1987-2016. The study focused on monitoring and predicting annual growth of urban changes over the past 29 years by mapping the urban areas in Algiers City. The results obtained depict the strategy of urban land trailed in the Algiers City, where established areas generally were extended to South, West and East Central Regions [3]. The present study used RS and GIS for monitoring the deforestation and LU changes by mapping forest cover (1975, 1990, 2001 and 2012) and topographical maps (1925) in Idukki district, Kerala, India. The satellite dataset was collected from WGS 84 datum and Lambert Conformal Conic (LCC) projection. For the year 1925, 93.2% of landscape for about 4675.7 km² were under forest. For the year 2012, 52.1% was estimated as forest cover for 2613.4 km² [12]. Supervised Classification and change detection approaches are used to monitor desertification in Biskra, Algeria region with the help of Landsat Imagery. The results achieved 95.15% overall accuracy and a Kappa coefficient of 0.90. As a further study, establishment of a natural barrier can be considered as a better plan with important aids for the residents in that area [1]. The LC classification and change detection protocol for apprising Alaska NLCD from 2001-2011 developed a comprehensive method called and offer a 10-year cyclical apprise of the state's LC/LU changes. The overall accuracy obtained for detection of change and no change was 90% for pilot study and 86% for 2011 updated land cover label. Further, it is unable

to regulate change the status of 30m pixel using photointerpretation for two ages of Landsat images [9]. LULC dynamics and assessment of deforestation in West Singhbhum, Jharkhand, India with geo-spatial methods analyzed the LULC change dynamic and deforestation of West Singhbhum in the date 1997 to 2017 via MLC and post-classification using change detection method. The percentage achieved for the settlement, agriculture land and mining area are positive by values 120.00%, 27.99% and 78.95%. Similarly, the accuracy obtained for classes like a dense forest is -0.45%, spare vegetation is 14.70%, water is 38.46%, bare soil is 20.94% and barren land is 27.74% have revealed negative progress with the values. Due to increasing demand in agricultural land and development in settlement areas and mining, it is observed that higher damage of sparse vegetation cover has occurred for the study area [13].

The research paper for Muga watershed, Upper Blue Nile basin, Ethiopia was on LULC dynamics and drivers intended to detect the pattern and magnitude pattern of LULC changes and since last three decades (1985 to 2017) is focused on evaluating drivers change in the Muga watershed. For years 1985, 2002 and 2017, Landsat images were detected based on changes and drivers of change using Synergy, focus group discussion, household survey, field observation and key informant interviews were used to detect changes and drivers of changes. The experimental results showed significant growth in case of urban areas and cultivated land by 270% and 12%, respectively. Whereas, forest lands, shrub-bushlands and grasslands were decreased by about 21%, 12% and 40% [2]. Geospatial datasets and Landsat series are extracted for LC change detection and classification analysis in Nepal for the period of 1980-2010 to develop land cover maps with the use of ancillary spatial datasets. In the year 2010, the overall accuracy obtained for land cover maps is 83%. Based on the available ground truth data, different land cover types achieved is about 46% - 94%. As further work, the experimental results can be improved by creating new datasets or validation sources that are free of cost [5].

Using joint deep learning research paper made an attempt to unify the RS classification on LCLU. For land cover classification, the accuracy obtained was 90.18%. But for land use purposes, the accuracy was 87.92% based on two study areas is higher than the initial accuracies obtained and consistently outpacing the benchmark comparators. The author recommended extending JDL framework to other dataset sources such as SAR, Hyperspectral and LiDAR datasets and test them based on their model transferability and capability for various other regions [14]. The main objective of this present work is to assess Land Use/Land Cover dynamics by comparing the accuracy of two different time periods (2005-2017) with Maximum Likelihood classification using Google Earth Imagery. This study was analyzed based on Kushalnagar study area with LU/LC classification for semi-urban planning purposes. The rest of the research work are as follows, Section 1 includes the Introduction about LU/LC dynamics, Section 2 include Study area and its Data Characteristics, Section 3 consists of the proposed methodology, Section 4 comprises of Result Analysis, Section 5 concludes the final work done on the research paper.

II. STUDY AREA AND DATA CHARACTERISTICS

Kushalnagar is a town on the Kaveri River, in the southwest Indian state of Karnataka which covers an area of 10 km sq. The latitudinal and longitudinal extinction of this area is 12.47N, 75.97E. As per the 2011 census, the population in Kushalnagar is 26,487. Kushalnagar has an average literacy rate of 78 percent. The average annual temperature in Kushalnagar is 23 degrees Celsius and average rainfall is 42.8 inches. The Buddhist Namdrolling Monastery also called as the Golden Temple located in south of town, it is bounded by groves of sandalwood trees. Kaveri is the main river in this region, which originates at Talakaveri located on the eastern side of the Western Ghats with its tributaries as shown in Fig. 1.



Figure 1. Location map of the Kushalnagar

A. Data Characteristics

The study is based on using satellite imageries of Multi-spectral (Unsigned 8-bit of time periods from 10/04/2005 to 18/04/2017) with 1.25m spatial resolution as shown in Table I. These datasets are collected from

different time periods (2005 and 2017 Google Earth Pro images). Two images of different time periods are taken from Google Earth Pro version 7.32 and are downloaded using Smart GIS 2019 which are free of cost. In addition, such satellite images (Kushalnagar study area) have been processed using ERDAS version 9.2 for analyzing, image processing and preparing maps, respectively.

TABLE I. DETAILS OF THE DATA PRODUCTS USED

Sl. No	Data Type	Data of Acquisition	Spatial Resolution
1.	Multi-spectral (Unsigned 8 bit)	10/4/2005	1.25m
2.	Multi-spectral (Unsigned 8 bit)	18/4/2017	1.25m

III. PROPOSED METHODOLOGY

The proposed methodology implemented based on the purposes of the current work is depicted using a flowchart as shown in Fig. 2.

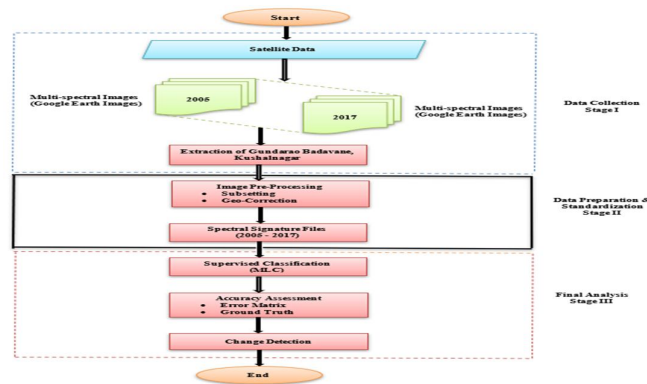


Figure 2. Proposed methodology to study change detection in Kushalnagar

A. Pre-Processing of Satellite Imagery

Dataset is collected from different time periods from 2005 and 2017 using Google Earth Pro images. Two images of different time periods are taken from Google Earth Pro version 7.32 and it is downloaded using Smart GIS 2019. The downloaded images are pre-processed by subsetting the image and by Geo correcting the images using ERDAS version 9.2. The classification of pre-processed data is processed using the Maximum likelihood classifier under Supervised classification.

B. Subset and Geo-corrected Data

Subsetting is a process to extract small-sized referential digits of data from a huge database. To subset an image, the image to be subsetted is viewed, the AOI tool is selected. The portion of the image which is required is selected using a tool and saved AOI layer in AOI format. In Data Preparation the subset image is selected. The input image name and output image name are given. Then the same AOI is selected for two data of the year 2005 and 2017. Subsetting of images for the years 2005 and 2017 has been shown in Fig. 3, 4, 5 and 6.

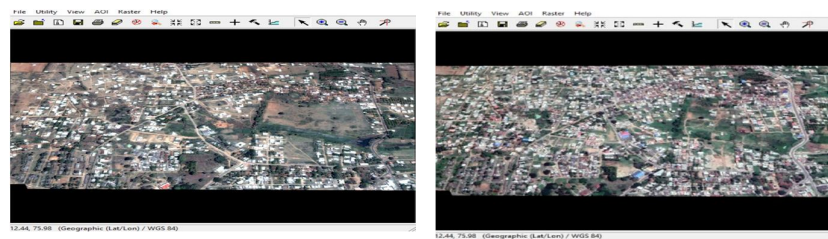


Figure 3 and 4. Subset image of 2005 and 2017

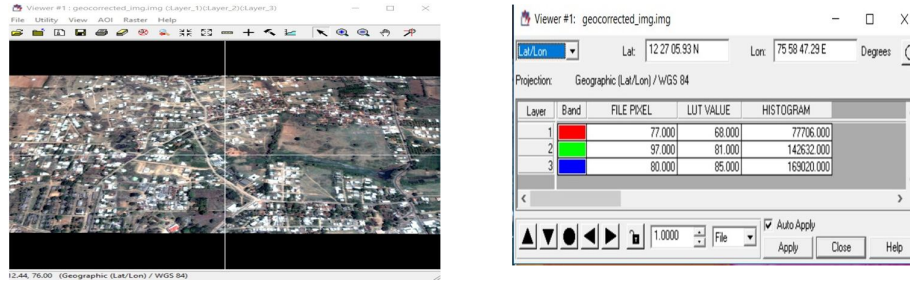


Figure 5. Geo-corrected image of 2005

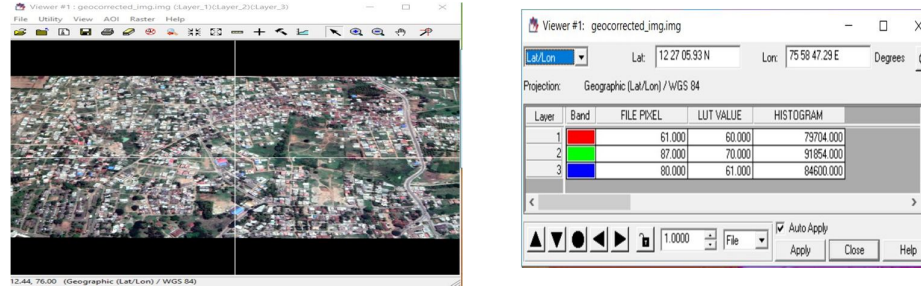


Figure 6. Geo-corrected image of 2017

C. Classification of the Pre-processed Images

LU/LC has been classified using Maximum Likelihood Classifier (MLC) under supervised classification which has been selected for the two various time periods at an interval of ~12 years, i.e., 2005 - 2017, respectively. Google Earth Images of the years 2005 and 2017 are used. Maximum Likelihood classification technique have been used to detect changes in the LU/LC dynamics. For classifying LU/LC dynamics, where 20 out of 140 spectral signatures is obtained for 2005, 40 out of 280 for 2005, 60 out of 420 for 2005, 80 out of 560 for 2005, 100 out of 700 for 2005, 20 out of 160 for 2017, 40 out of 320 for 2017, 60 out of 480 for 2017, 80 out of 640 for 2017 and 100 out of 640 for 2017, respectively, representing seven various categories of LU/LC classes.

D. Accuracy Assessment of Classified Images

Assessment of accuracy is carried based on how closely the outcomes are related to the true values and provides the qualitative gathering of evidence from the satellite data. Producer's accuracy: It is a map accuracy from the point of view of Producer. It expresses how fine the classification decides based on reference classification. Producer accuracy can be calculated in Equation (1):

$$\text{Producer's Accuracy} = \frac{a_{ii}}{\sum_{i=1}^N a_{ki}} \quad (1)$$

User's accuracy: It forecast how well the pixel probability are classified as class I, which are belonging to class I. User accuracy can be calculated in Equation (2):

$$\text{User's Accuracy} = \frac{a_{ii}}{\sum_{i=1}^N a_{ik}} \quad (2)$$

Overall accuracy: The overall percentage that are matched for number of areas to total number of areas has been calculated in the Equation (3), which are called overall accuracy (OA).

$$\text{Overall Accuracy} = \frac{\sum_{k=1}^N a_{kk}}{\sum_{i,k=1}^N a_{ik}} = \frac{1}{n} \sum_{k=1}^N a_{kk} \quad (3)$$

Kappa Statistics: Kappa Statistic is based on the difference between the actual agreement in the error matrix and the chance agreement which is calculated using Equation (4).

$$\hat{\kappa} = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \cdot x_{+i})} \quad (4)$$

In the Equation (4), where r = number of columns, rows in the error matrix, N = Number of pixels in the error matrix, x_{ii} = Belonging to class i diagonal element, x_{i+} = Belongs to total number of observations of row i , x_{+i} = Belongs to total number of observations of column i .

E. Change Detection using the results of accuracy assessment

The two different time points are measured with a periodic change over the landscape to extract change detection in LU/LC dynamics with its suitability and advantages by demonstrating the change of nature. In this work, seven dependent variables namely Built-ups, Water body, Highway, Tiled roof, Trees, Grassland, Open land is considered. LU/LC maps is measured as independent variables. MLC method has been performed to detect the changes of land use/ land cover over time period. To obtain seven different classes, huge number of signatures has been collected. The MLC model used has been validated in order to simulate LU/LC dynamics for the time period 2005-2017 using accuracy assessment and then LU/LC change analysis of estimated class and pixels are compared from 2005-2017 time period.

IV. RESULTS

A. LU/LC Change Analysis for Data 2005 and 2017

Experimental Results for Various Training Sites (2005)

For each class, 20, 40, 60, 80 and 100 signature are collected from the dataset of 2005. The LU/LC classification has been carried out for signature 140, 280, 420, 560 and 700 with validating points of 50,100, 200, 300 and 400 is as shown in Fig. 7, 8 and 9.

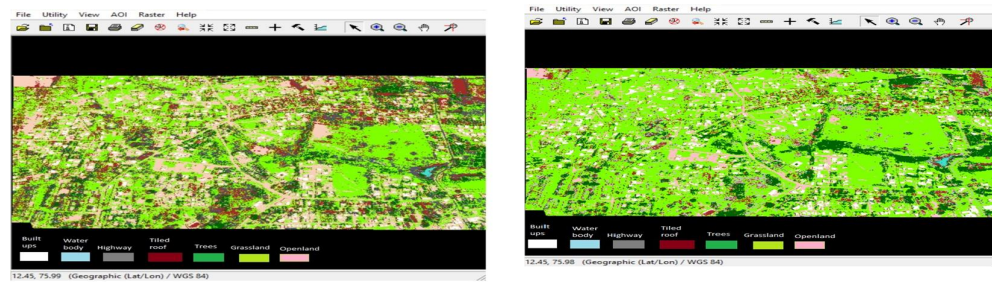


Figure 7. Classified image for training set 140, 280 with points 50 and 10

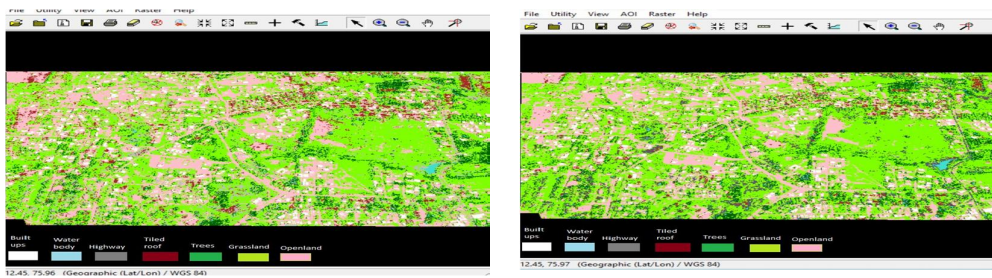


Figure 8. Classified image for training set 420, 560 with points 200 and 300



Figure 9. Classified image for training set 700 with validation points 400

Experimental Results for Various Training Sites (2017)

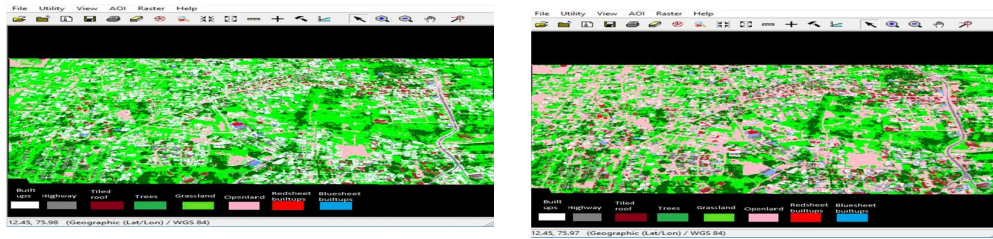


Figure 10. Classified image for training set 160, 320 with points 50 and 100

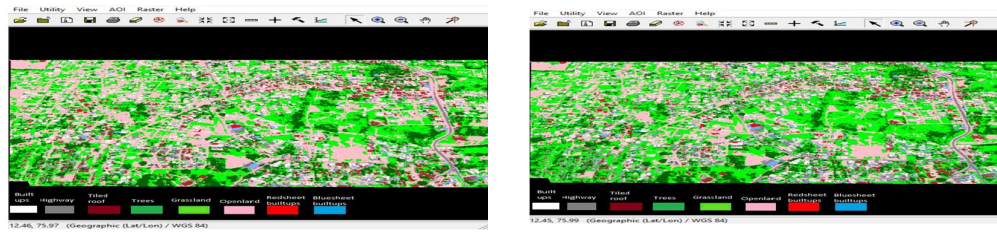


Figure 11. Classified image for training set 480, 640 with points 157 and 216

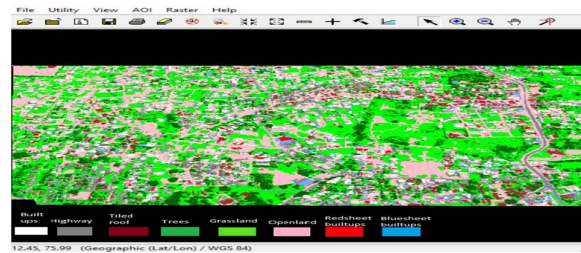


Figure 12. Classified image for training set 800 with validation points 268

For each class, 20, 40, 60, 80 and 100 signature are collected from the dataset of 2005. The LU/LC classification has been carried out for signature 160, 320, 480, 640 and 800 with validating points of 50,100, 157, 216 and 268 is as shown in Fig. 10, 11 and 12.

B. Graphical Representation for the year 2005 and 2017

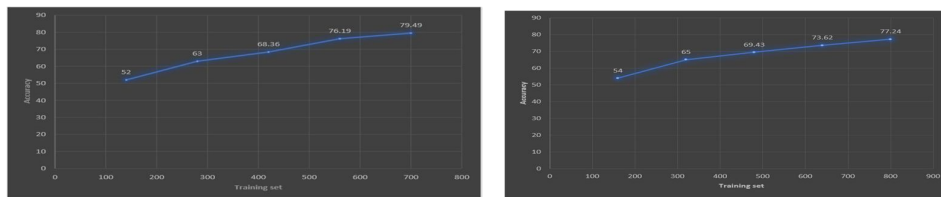


Figure 13. Graph of accuracy and training set for 2005 and 2017

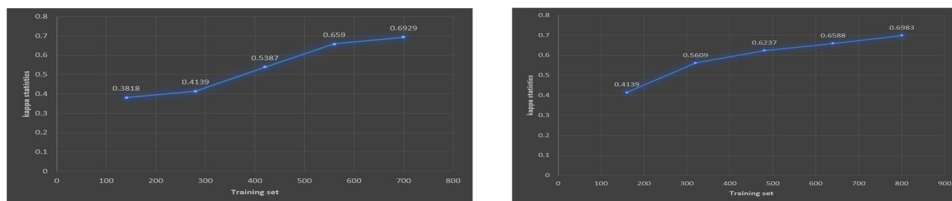


Figure 14. Graph of Kappa statistics and training set for 2005 and 2017

From Fig. 13. For 140, 280, 420, 560 and 700 training set (2005), 52%, 63%, 68.76%, 76.19% and 79.49% of accuracy is obtained for overall seven class of LU/LC. For 160, 320, 480, 640 and 800 training set (2017), 54 %, 65%, 82.569%, 73.62% and 77.24% of accuracy is obtained for all eight class. From Fig. 14. shows the plotting of kappa versus training set for year 2005 and 2017. For 140, 280, 420, 560 and 700 training set (2005), 0.3818, 0.4139, 0.5387, 0.6590 and 0.6929 of kappa is obtained for overall seven class of LU/LC. For 160, 320, 480, 640 and 800 training set (2017), 0.4139, 0.5069, 0.6237, 0.6588 and 0.6983 of kappa statistics is achieved.

C. Change detection from 2005-2017

Graphical Representation of Pixels and Classes

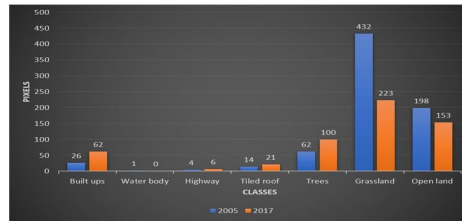


Figure 15. Graph of Pixels and Classes

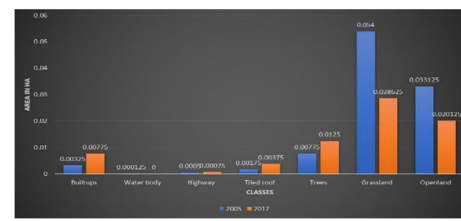


Figure 16. Graph of Area in ha and Classes

From Fig. 15 shows the graphical representation of changes in pixels values of 2005 and 2017 year. The comparison has been performed based on actual dataset and seven classes for two time periods. The graph interprets the periodical outcomes of LU/LC dynamics among two different periods has been analyzed. For the year 2005 to 2017, the maximum increased classes were Built up land, Highway, Tiled roof and Trees, whereas the lowest decreased classes were Grassland, Water body and Open land.

Changes in LU/LC from 2005 to 2017

Table V. shows the overall change difference from year 2005 to 2017. The overall percentage of changes in area for land use feature is 33.85% for Built ups, Highway and Tiled roof classes for year 2005-2017. In case of land cover feature, it is decreased to 25.06 % area from 2005-2017 for Water body, Trees, Grassland and Open land classes.

TABLE V. CHANGES IN LU/LC FROM 2005 TO 2017

Classes	LU/LC features	Change in pixels	Change in area (ha)	%
Land Use	Built ups	45	0.0675 ↑	33.85 ↑
	Highway			
	Tiled roof			
Land Cover	Water body	293	0.4395 ↓	25.06 ↓
	Trees			
	Grassland			
	Open land			

V. CONCLUSIONS

In this conclusion, the approach is used to solve the existing problem using Maximum Likelihood Classification Technique. In this work, its tracts the LU/LC dynamics using image processing techniques by extracting the feature using MLC and comparing the classified image to detect the changes in LU/LC. The experimentation is conducted on an image database developed for change detection using Google Earth image. The implementation of proposed methodology is carried out using ERDAS version 9.2 is an image processing software. From Data 2005 and 2017, the pixel changes for the land use are 45 and the pixel changes for the land cover are 293. It is noticed that there is a significant increase in pixels of Built ups, Highway, Tiled roofs from 2005 to 2017. In the case of Grassland and Open land, the pixels value is gradually decreased. There is a significant area increase of Built ups from 0.00325 ha to 0.00775 ha from 2005 to 2017. Highway from 0.0005 ha to 0.00075 ha. Therefore, the overall accuracy and kappa coefficient of the refined training samples obviously outperform those of the full training samples. It is Shown that more reliable results can be obtained by the refined training samples scheme in supervised image classification. Even though the current study displays good results, it is significant to note all misclassification problems and confusion used for change detection, as a further extension in this work. Proper selection of techniques, temporal and spatial properties of an images should be handled more systematically in the future to avoid factors causing such confusion. Several different change detection methods should be opted by selecting best suited approach for the consistent work to be done in the upcoming days.

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