Pixel Based Land Cover Change Detection Analysis and Prediction Using Remote Sensing and GIS Techniques A Case Study of Mandalay City, Myanmar

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ABSTRACT: In this paper, Land cover change detection, change type, and prediction are investigated by using Remote Sensing and Geographic Information Systems (GIS) in Mandalay city, Myanmar over a period of 20 years. The land cover changes by using maximum likelihood algorithm and support vector machine algorithm for land cover change classified with four classes including Water, Buildup, Vegetation, and Bare land from the year (2000-2020). The Mandalay city was lost 16.12 % of water, 60.1% of its vegetation land, and 67.87 % of its bare land. Significant distant amounts of these losses have been absorbed by the expanding urbanized areas, which have gained 70.27 % of the land. And then calculate the overall accuracy assessment of the classified land cover maps was analyzed by estimating the kappa value and overall accuracy. Finally, predictions of land cover change detection for 2030 show that the water, vegetation, and bare land to decrease by an additional 21.70 %, 10.76 %, and 9.30 % respectively. The highest gain in 2030 is predicted for urbanized areas at 5.54 %. This study can provide suggestions and a basis for urban development planning in Mandalay City, Myanmar.

KEY WORDS: land cover, change detection, prediction

1. INTRODUCTION

This research is supervised classification technique is applied to achieve this, satellite data of Landsat 7 (ETM) and Landsat 8 (OLI) have been obtained and preprocessed using ArcGIS software and for prediction of land cover changes are used QGIS software. This research investigated the prediction of future land cover change analysis in the year 2030 using version MOLUSCE plugin (ANN-Multi layer perception) model the QGIS 2.18.24. The pixel-based classification for land cover analysis for years 2000, 2013, and 2020 will be carried out by using the maximum likelihood algorithm, and support vector machine algorithm. To calculate the overall accuracy assessment of each land cover class for maximum likelihood algorithm and support vector machine algorithm. Change type and change detection use the Land cover map of the support vector machine algorithm because it has better accuracy assessment than the maximum likelihood algorithm. As a result of the land cover map to continue the processing and then land cover change type map and change detection map of Mandalay city from 2000 to 2020. Land cover change detection map is divided are three classes Positive Change, Negative Change, and No Change. This study attempts to detect and predict land cover change in the Mandalay City of Myanmar by using remote sensing and GIS application.

2. STUDY AREA

The study area of Mandalay city is located in the central dry zone of Upper Myanmar at 21.98° North, 96.08° East, 80 meters (260 feet) above sea level and on the riverbank of the Ayeyarwady River in the west, the Myint Nge River in the south and Shan Mountainous area in the east, and (Figure 1). Mandalay city is located in the middle of Myanmar and is the second-largest capital city hosting the biggest commercial center and industrial in the Central dry zone of Myanmar. The middle dry zone of Mandalay city population has increased from about 500,000 in 1998 to over a million in 2002 and to 1.4 million in 2014. In Upper Myanmar of Mandalay City is including five townships known as Aung Myay Thazan, Chan Aye Thazan, Maha Aung Myay, Chan Mya Thazi, and Pyi Gyi Ta Khun Townships.

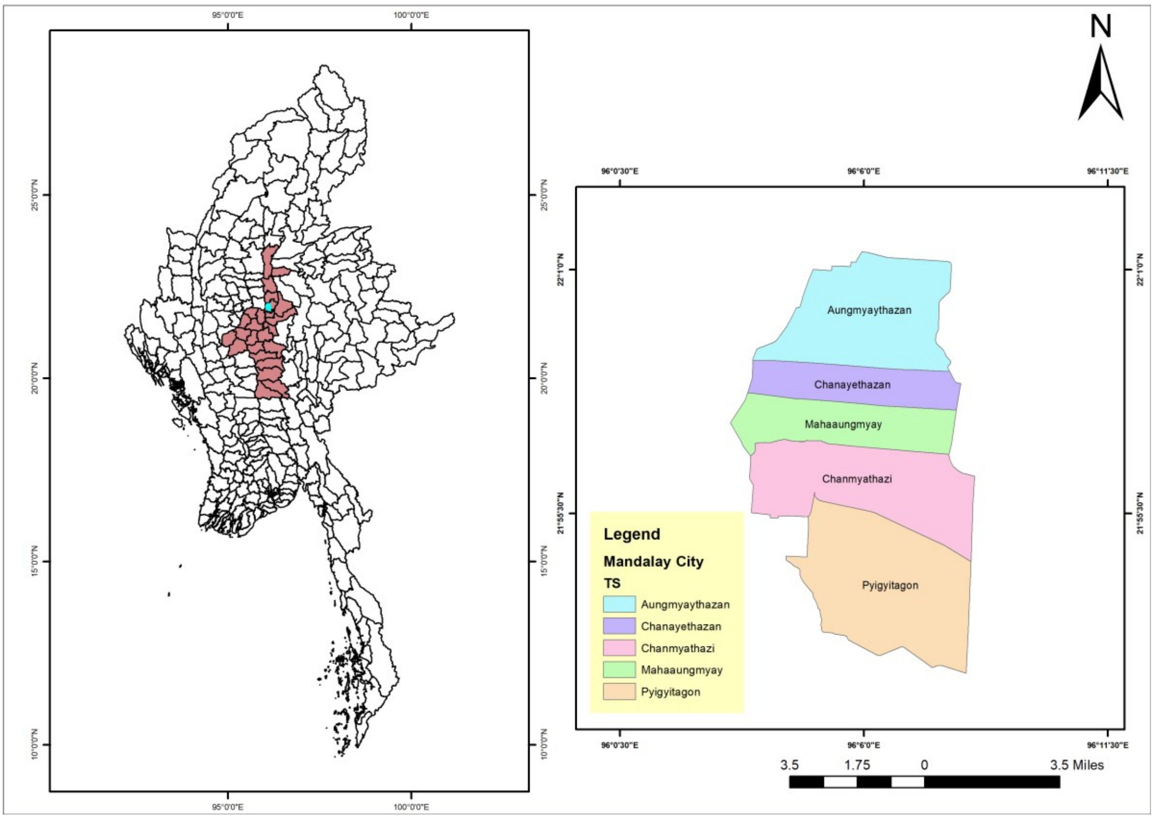


Figure 1. Study Area

3. METHODOLOGY

3.1 Data Description

These images with Landsat-7 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) images at a resolution of 30 m were acquired for the years 2000,2013 and 2020 respectively, from the United States Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) found at http://glovis.usgs.gov/ and show the Table 1. Landsat imagery data processing is done using software ArcGIS 10.7.1, QGIS 2.18.3 have been used to analyze image processing and classification the road maps were obtained from the open street map website (https://www.openstreetmap.org). The whole research methodology is shown in Figure 2.

Table 1. Characteristics of data collected

Sensor	Month/Day/Year	Resolution	Path/ Row
Landsat 7 ETM+	2000 and 2013	30 m	133/45
Landsat 8 OLI	2020	30 m	133/45

(Source: http://glovis.usgs.gov)

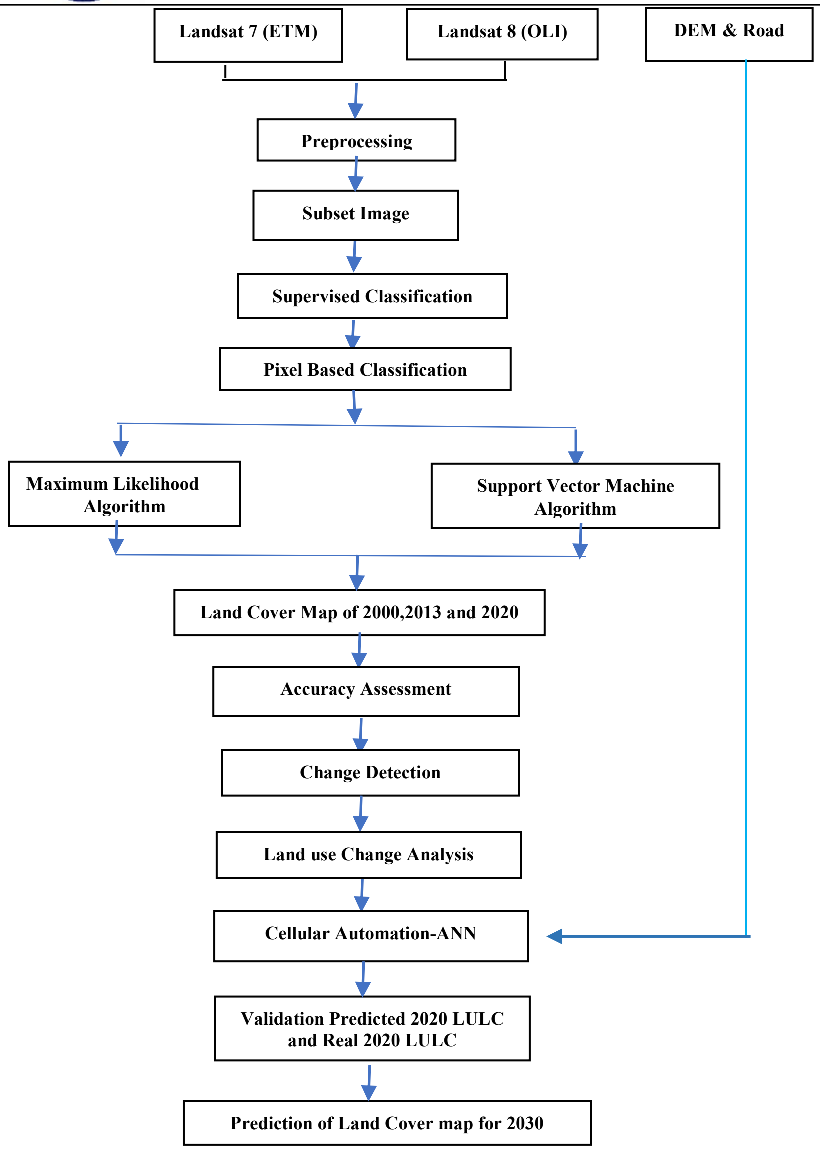


Figure 2. Overall research methodology

Table 2. Land cover classification scheme

LULC	Types Description
Waterbody	Areas had surface water including ponds, rivers, streams, ponds, lakes, reservoirs, and marshland
Built-up area	Areas associated with rural, Commercial areas, urban settlements, industrial areas, government and institutional buildings, roads, hard surfaces, parking areas, recreational areas, and golf courses
Vegetation	Areas used for crops cultivation Cropland (wetlands and drylands), such as rice & bean and orchards
Bare Land	Area covered with little or no vegetation on the ground surface, Exposed soils, landfills, and areas of active excavation

3.2. Methods

The pixel-based classification used supervised classification using the maximum likelihood algorithm & support vector machine algorithm to determine the land cover analysis through software ArcGIS 10.7.1 This method is the most widely used and easy to use and apply pixels to the land cover classification. The land cover change type and change detection analysis are based on four classes are Water, Buildup, Vegetation, and Bare land.

(a) Maximum Likelihood Algorithm (ML)

In ML, the distribution for each class in each band is assumed to be normal and the probability a given pixel belongs to a specific class [4],[27] is calculated based on this assumption. This algorithm is each pixel is then assigned to the class that has the highest probability. The Pixel-based Classification is performed by calculating the discriminant functions for each pixel in the image.

(b) Support Vector Machine (SVM)

The SVM classification algorithm is a binary learning technique is performed by making use of an efficient hyperplane searching technique that uses minimal training area and therefore consumes less processing time [3],[7]. SVM concept is based on statistical learning theory and has the aim of determining the location of decision boundaries that produce the optimal separation of classes (Vapnik 1995). The margin shows the distance between the classifier and the training points.

(c) Area Change

This stage calculates changes in the area between the initial year (2000) and final year (2020) of the Landcover. The changes in the land cover area are represented in sq. km and % (Ashaolu et al., 2019b; Rahman et al., 2017b).

(d) Transition Potential Modelling

There are so many methods for calculating transition potential maps, In QGIS software this plugin includes artificial neural networks (ANN), weights of evidence (WoE), logistic regression (LR), and Multi-Criteria Evaluation (MCE). For calibrating and modeling land use/cover changes, each methodology takes land use/cover change information and geographic factors as inputs. (Buğday and Erkan Buğday, 2019; El Tantawi et al., 2019b; Guidigan et al., 2019). The Artificial Neural Network (Multilayer Perception) technique was used for this research to Predict the Land cover map for the year 2030.

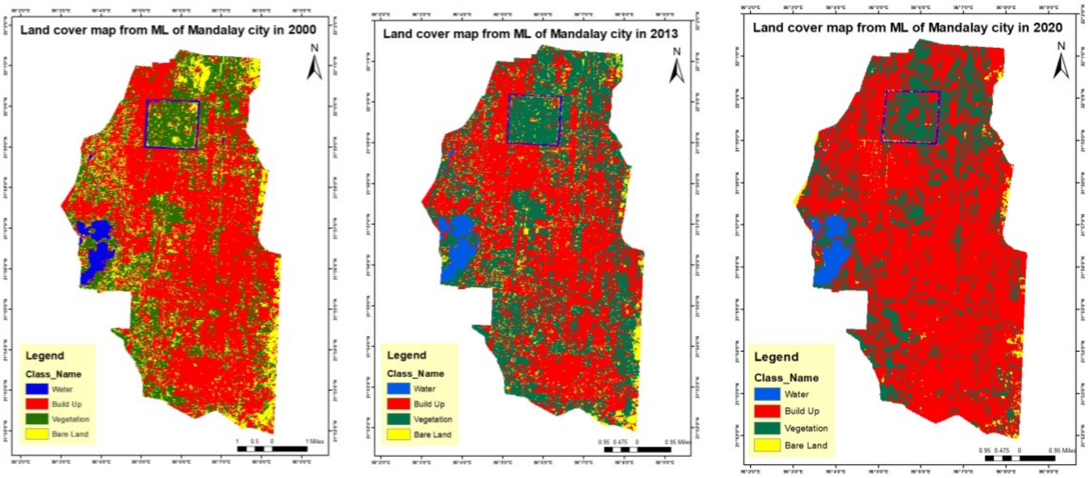
(e) Validation

The validation is carried out between the predicted and real Land cover maps of 2020. The result explains the agreement of every criterion of each cell (Saputra and Lee, 2019). Several simulations were done to predict the Land cover change map for 2030 utilizing various combinations of spatial variables factors, and for the analysis, two to three spatial variables were combined to create an ANN-Multi layer perception.

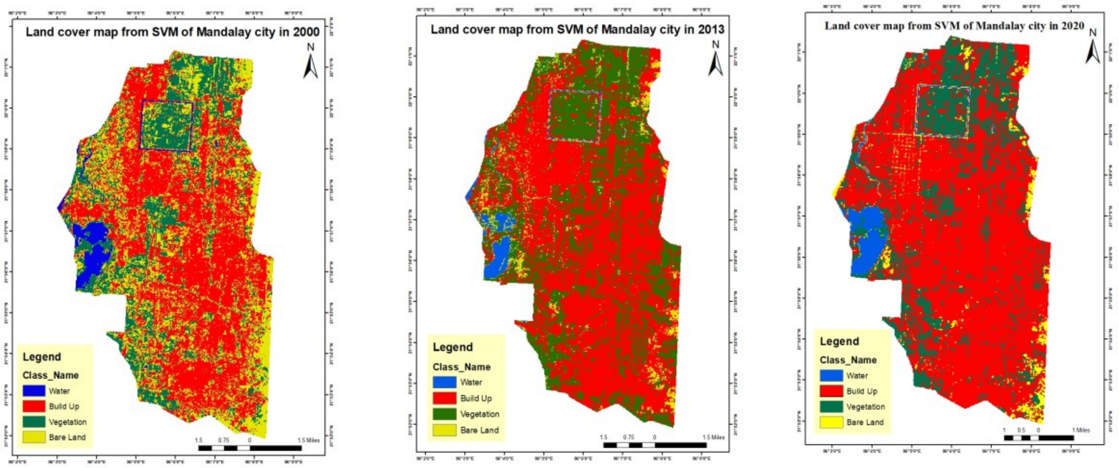
4. RESULT & CONCLUSIONS

4.1. Land Cover Change analysis for 2000,2013 and 2020

In Pixel-based classification, Landsat 7 (ETM) and Landsat 8 (OLI) for 2000, 2013, and 2020 were studied using the maximum likelihood algorithm and support vector machine algorithm. Based on remote sensing and GIS techniques, the images are classified as Water, Vegetation Buildup, and Bare land for land cover maps of (2000,2013, and 2020) are shown in Figures 3 & 4. According to classification results, the only built-up area is increased from 52.94 sq.-km to 90.175 sq.-km ,46.80 % to 79.69 %. Waterbody, vegetation, and bare land area are decreases respectively. In this study, the proportion of water bodies was dropping dramatically about change in 2.60 % change in vegetation 8.20 % change in bare land 9.49 % and build-up area is scientifically increase is build up 79.69 %. during the period of (2000-2020) are shown in Table.3.



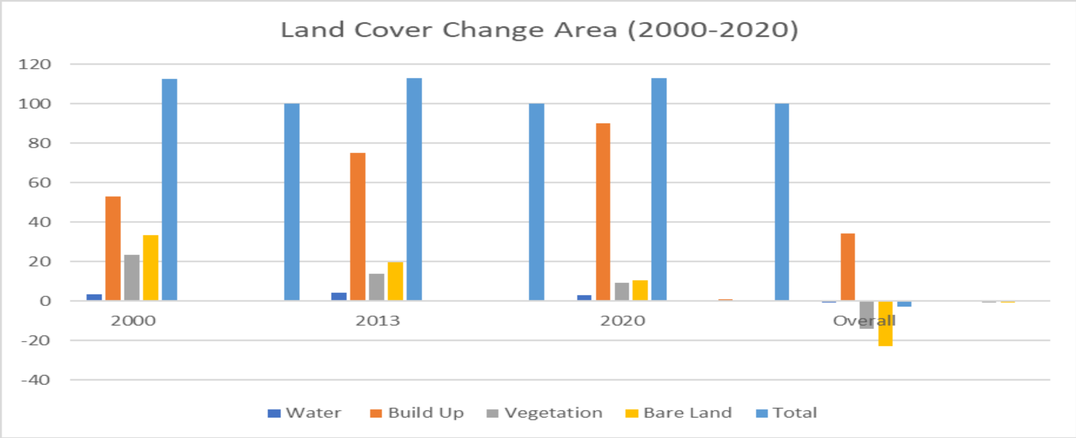
Figures 3. Land Cover map form Maximum likelihood algorithm of Mandalay City in 2000.2013 & 2020



Figures 4. Land Cover map form Support Vector Machine algorithm of Mandalay City in 2000.2013 & 2020

Table. 3 Composite table of area statistics of (sq.km and %) of the Mandalay City from 2000 to 2020.

LULC Types	**2000**		**2013**		**2020**		**Overall**	
Support Vector Machine Algorithm	**Area (sq.km)**	**Area (%)**	**Area (sq.km)**	**Area (%)**	**Area (sq.km)**	**Area (%)**	**Area (sq.km)**	**Area (%)**
Water	3.50	3.10 %	4.25	3.76 %	2.94	2.60 %	-0.56	-16.12 %
Build Up	52.94	46.80 %	75.24	66.51 %	90.175	79.69 %	34.24	70.27 %
Vegetation	23.27	20.56 %	14.06	12.43 %	9.2875	8.20 %	-13.98	-60.1%
Bare Land	33.42	29.54 %	19.57	17.30 %	10.7418	9.49 %	-22.68	-67.87 %
Total	112.63	100	113.12	100	113.144	100	-2.98	



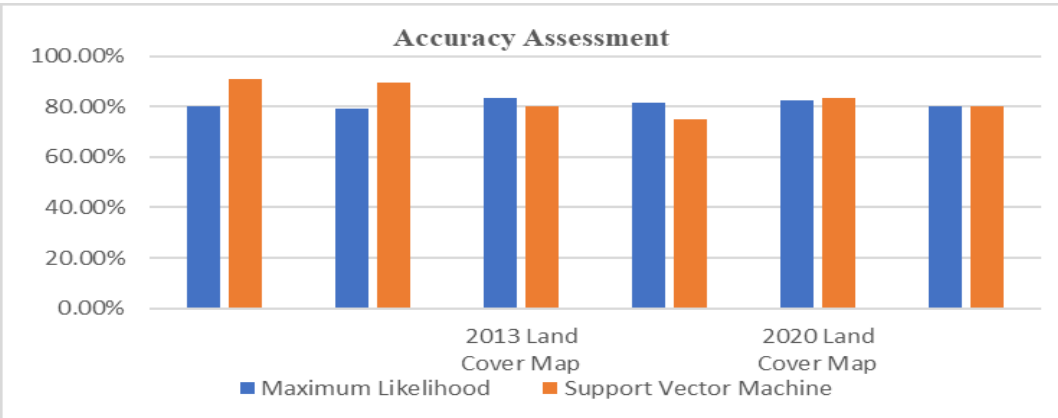
Figures 5. Change of Land Cover area of Mandalay City (2000-2020)

4.2 Accuracy Assessment

The comparison between landcover classification based on supervised pixel-based classification using maximum likelihood algorithm and support vector machine algorithm of kappa value and overall accuracy value for each other 80.12%and 79.12%in 2000 and 83.56%and 81.36% in 2013 and 82.45% and 80.34%% in 2020 and 90.89% and 89.33% in2000 and 85.11% and 82.34% % in 2013 and83.34% and81.23% in 2020. The support vector machine was the highest value of accuracy assessment is shown in Tables 4 and Figures 6.

Table 4. Overall Accuracy Assessment of Land Cover Classification

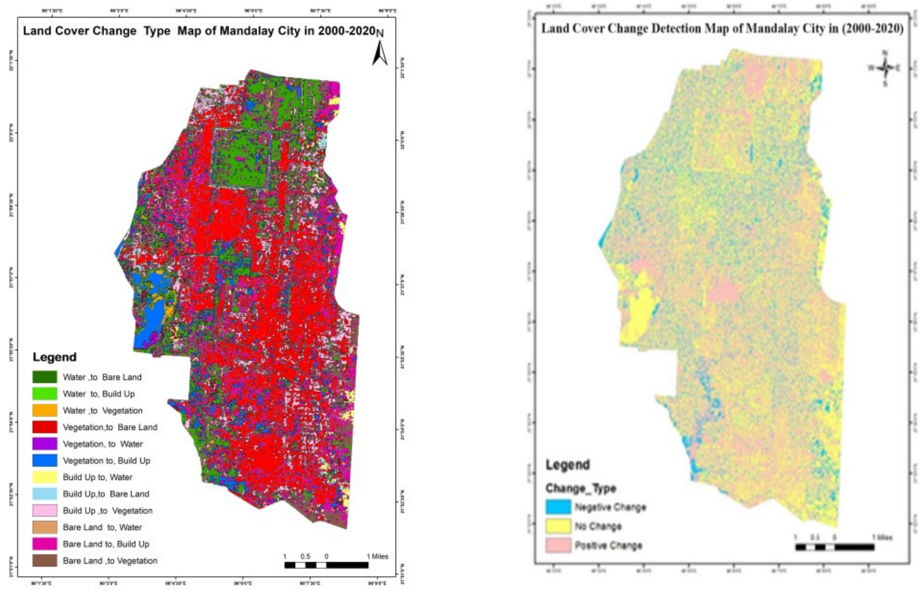
Year 2000 Land Cover Map			Year 2013 Land Cover Map		Year 2020 Land Cover Map	
Methods	Kappa Value	Overall Accuracy (%)	Kappa Value	Overall Accuracy (%)	Kappa Value	Overall Accuracy (%)
Maximum Likelihood	80.12%	79.12%	83.56%	81.36%	82.45%	80.34%
Support Vector Machine	90.89%	89.33%	85.11%	82.34%	83.34%	81.23%



Figures 6. Overall Accuracy Assessment of Land Cover Classification

4.3 Land Cover Change Type and Change Detection

The land cover change type from 2000 to 2020 showed important trends in land cover transition from one class to another. The distribution of transition between land cover classes was mapped in Figure 7. Inland cover change detection map of Mandalay city from 2000 to 2020, there are divided into three classes Positive Change, Negative Change, and No Change. The yellow color is no change, this area is water body and bare land. The pink color is a positive change this area is a build-up area and the blue color is a negative change these areas are vegetation.



Figures 7. Land Cover Change Type Map and Change Detection Map of Mandalay City (2000-2020)

4.4 Predicted Land Cover Map

The Prediction of the land cover map for 2030 is shown in Figure 8. The Land cover categories from 2000 to 2013 and 2020 to 2030 showed an increase in built-up area by 46.80 %, and 66.51 %, 79.69 %, and 5.50 %respectively. From the analysis, it is learned that when the area of one classification increases, it decreases the area of other classes and vice versa.

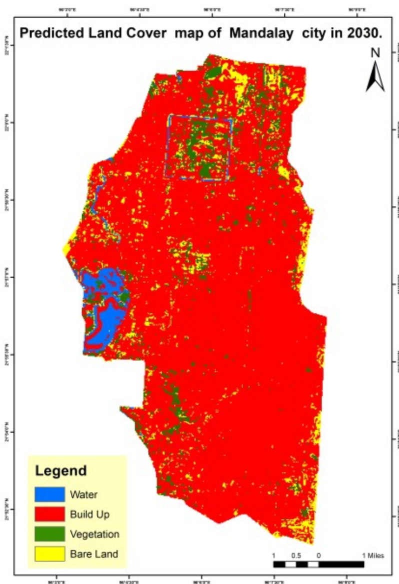


Figure 8. Prediction of Land Cover map of Mandalay city in 2030

Table 5. Prediction of Land cover area of Mandalay city in 2030

Year 2030		
LULC Types	**Area (sq.km)**	**Area (%)**
Water	2.30	-21.70 %
Build Up	95.175	5.54 %
Vegetation	8.2875	-10.76 %
Bare Land	9.7418	-9.30 %

5. CONCLUSION

In this research supervised classification of pixel-based classification and change type and change detection analysis in the Mandalay city using Landsat imagery was carried out and observed land cover change detection was analyzed (increase or decrease) over the two periods (2000-2020). Accuracy Assessment for Kappa Value of Mandalay City were 80.12%,83.56% and 82.45% using Maximum likelihood algorithm and 90.89%, 85.11% and 83.34% using Support Vector Machine algorithm to evaluate the performance of classification methods. Changes are mainly in built-up areas which was significantly increased in 2020, and significantly changed form (2000-2020) also prediction of land cover change detection for 2030, the buildup area had significantly changed as a result, it can be seen that water bodies, vegetation, and bare land were decreased from 2000-2020. The prediction of Landcover plays a vital role in creating plans for balancing conservation, competing users, and developmental pressures. The ANN Cellular Automation model is utilized to simulate and predict the future Land cover maps of the Mandalay city, Myanmar the three spatial variable factors viz., DEM, distance from the road and river, had a huge effect to predict the Land cover map of this research. This study demonstrates the ability of Remote Sensing and GIS in capturing high-resolution data changes in land cover analysis.

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