USING REMOTE SENSING AND GIS TECHNIQUES TO MONITOR AND ANALYSE LAND USE LAND COVER CHANGES IN BAYUGAN CITY, PHILIPPINES

Mark Lawrence Alonde[1] and Arturo G. Cauba Jr.*[2]
[1]Geodetic Engineer, PrimeWorld Builders & Development Inc.
Quezon City, Philippines
Email: marklawrencealonde@gmail.com

[2]Faculty member, Caraga State University
Ampayon, Butuan City 8600, Philippines
Email: agcauba@carsu.edu.ph

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ABSTRACT: The rapid development of cities in developing countries results in deteriorating of forest areas. The majority of these forest areas are converted to built-up areas, which affects the ecosystems. In this research, land cover classification of three different years was applied to simulate urban land use changes and to understand the development trend in Bayugan City, Philippines. In this study, supervised classification and post-classification change detection techniques were applied to Landsat images acquired in 1998, 2008 and 2018 to map LULC changes in Bayugan City. Landsat images were radio-metrically and geometrically corrected, and then, multi-temporal post-classification analysis was performed to detect LULC changes rates of the Bayugan City. Five classes including water, built-up, forest, cropland and barren were selected to evaluate their temporal changes by comparing the processed images. The objective of this study is to map and analyse the rate of changes in the LULC in Bayugan City which can help the decision makers to replan the use of natural resources efficiently. By applying Remote Sensing (RS) and Geographic Information System (GIS) techniques, areas of rapid change were identified and targeted for more detailed monitoring in the field. Changes among different LULC classes were assessed.

1. INTRODUCTION

1.1 Background of the Study

Land cover data shows how much of a region is covered by forests, wetlands, impervious surfaces, agriculture, and other land and water types. Water types include wetlands or open water. Land use shows how people use the landscape, whether for development, conservation, or mixed uses(Duranton & Puga, 2015). The major consequences of rapid population increase in the world are the speedy land use change, the alarming global change of the environment and the transformations of fertile lands to urbanized lands (Wu et al., 2006). The urban land use expansion process is a very complicated dynamic phenomenon. The urban land change is characterized and affected by interactions of many factors in time and space at various scales, for instance, political, economic, social and cultural factors and so many other factors (Barredo & Demicheli, 2003). The study of land use land cover (LULC) changes is very important to have proper planning and utilization of natural resources and their management. Since many problems often presented in environmental issues, we required technologies like RS and GIS. These technologies provide data to study and monitor the dynamics of natural resources for environmental management. To perform an effective investigation, monitoring and tracking of LULC change, a substantial amount of data about the study area is considerably required. Hence, the use of remote sensing technology provides an updated LULC data which can be used further to extract, analyse and simulate land use change spatially and efficiently (Dadhich & Hanaoka, 2011). In this research, Bayugan City was chosen as a case study, which has experienced a very rapid dispersed urban sprawl over the last decades. This urban sprawl phenomenon leads to the rapid conversion of forested areas into built-up urban areas. Hence, the objective of this study is to leverage remotely sensed data and Geographic Information System (GIS) tools to analyze LULC changes in Bayugan City. The primary goal is to detect and assess changes in the area over a three-year period by comparing images from different years. Specifically, this study aims to classify Landsat images of three different years by using Maximum Likelihood Classification (MLC), to detect the change in LULC in Bayugan City of the year 1998, 2008 and 2018, to generate LULC map of the year 1998, 2008 and 2018 and to understand the urban growth pattern and its developmental trend.

1.2 Study Area

The study area (Figure 1.1) is Bayugan City, Province of Agusan Del Sur, Island of Mindanao in the Philippines. Bayugan City is a 5th class city in the province of Agusan Del Sur. It is a developing and semi-urbanize area and has a total land area of 68,877 hectares and has an average elevation of 610.16 m. Bayugan City is comprised of 43 barangays and a total population of 103,202 as of 2015. This area is classified into timber lands and alienable and disposable (A&D) lands which includes settlements, agricultural, protected and underdeveloped. A&D has a total area of 17,085 hectares.

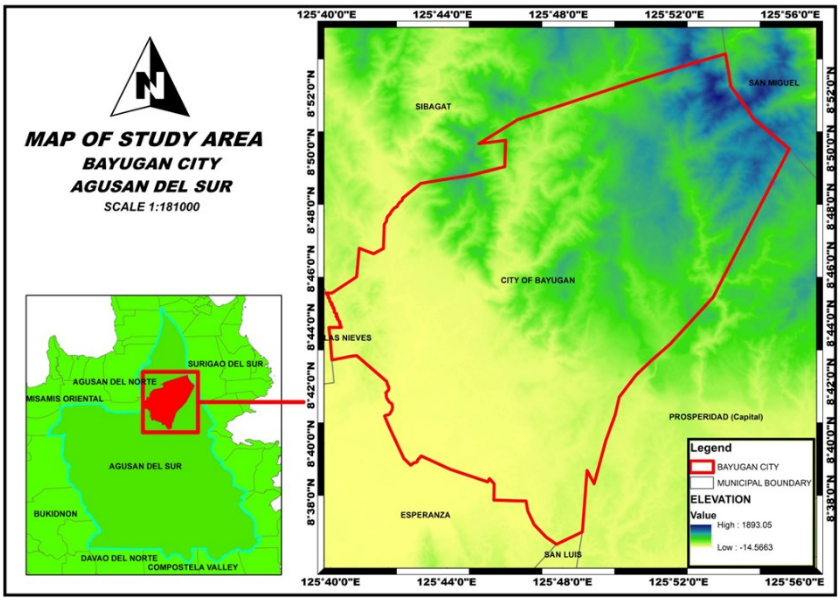

Figure 1.1 Map of the Study Area

2. MATERIALS AND METHODS

2.1 Datasets

The datasets used involved Landsat 5, Landsat 7 and Landsat 8 OLI images, which were downloaded from United States Geological Survey (USGS) Earth Explorer. This study utilized 3 scenes/ images in Bayugan City from year 1998, 2008 and 2018 obtained by Landsat 5, Landsat 7 and Landsat 8 OLI, respectively. The Landsat images were downloaded in GeoTIFF format.

2.2 Methods

The study's methodology (Figure 2.1) consists of six major activities namely, 1) Image Pre-processing, 2) Image Preparation, 3) ROI Collection, 4) Image Classification and Accuracy Assessment of three images 5) Comparison and Accuracy Evaluation of Classification, and 6) Land Cover Change Detection.

2.2.1 Image Pre-processing

The downloaded Landsat images have undergone radiometric calibration where the Digital Numbers (DN) were converted into radiance, and the radiance to Top of Atmosphere (TOA) reflectance. Radiometric calibration was processed in ENVI 5.1. After the images were radiometrically processed, atmospheric correction was then applied which used Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) as tool in the ENVI 5.1 software. This technique was used to compensate for atmospheric effects and it used hyper spectral radiance data to estimate land surface reflectance. The images that were radiometric calibrated and atmospheric corrected were subjected to image classification mask and cloud and shadow digitizing. The pre-processed images were used to manually digitize cloud and cloud shadow in ArcMap. The output of the cloud and cloud shadows that have been digitized was used in generating image classification mask. In image classification mask generation, the digitized image in cloud and cloud shadow and Bayugan City shapefile were used to generate project area mask band. Then, Band Math was employed in the image to create classification mask band. The image was used in layer stack with two sets of added data which are the Normalized Difference Vegetation Index (NDVI) and 30-m Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global DEM .

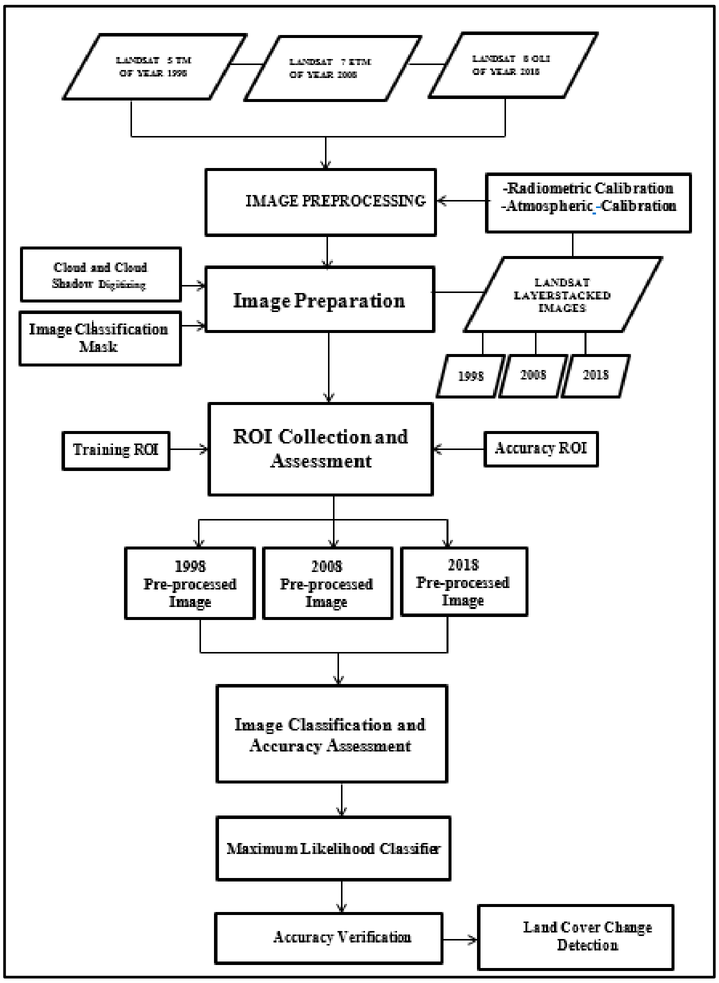

Figure 2.1 Methodology flowchart

2.2.2 Region of Interest (ROI) Collection and Accuracy Assessment

The Landsat layer stacked image was used in RGB combination to visually interpret and determine the land-cover classes present in Bayugan City. Moreover, Google Earth Pro was used to assist in collecting training ROI and to validate the land cover classes. The training ROI must be distributed throughout the area of interest and a minimum of 150 samples per class were collected. The ROI for the validation data has a minimum of 50 samples per class and must be distributed throughout Bayugan City. Also, Google Earth Pro was used to assist in determining land cover classes. Validation ROI must be different from training ROI to assess the accuracy and to classify the different classes present in the area. Moreover, the datasets were used to evaluate the accuracy of the classified image and its classifier which is the Maximum Likelihood Classifier.

Table 2.1 Training and Validation ROI per year

LAND COVER CLASS	TRAINING ROI			ACCURACY ROI		
	1998	2008	2018	1998	2008	2018
Built Up	186	160	153	65	55	53
Water	180	172	159	89	55	55
Forest	152	177	171	68	57	68
Cropland	166	164	151	56	56	55
Barren	150	156	156	53	74	52

Maximum Likelihood Classifier (MLC) takes into account the variance-covariance within the class distributions and for normally distributed area (Bruzzone & Prieto, 2001). The generated layer stacked image including the training ROI was used in the classification. The pre-processed images from year 1998, 2008 and 2018 were classified to determine the land cover change each year. Moreover, validation ROI was used to measure the accuracy of MLC, which was determined by error matrices, such as the User's Accuracy (AC), Producer's Accuracy (PA), Overall Accuracy (OA) and Kappa Coefficient.

2.2.3 Land Cover Change Detection

Change Detection is the process of identifying differences on successive images of the same area (Asokan & Anitha, 2019). These differences are based on land cover classification and are used to determine urban development in the area. Change detection is conducted by assessing the total land area of different classifications to differentiate land cover classes. Land Cover Maps generated using MLC for the years 1998, 2008, and 2018 were employed to visually distinguish changes in classification, categorize various land cover classes, and quantify changes within these land cover classes.

3. RESULTS AND DISCUSSION

3.1 Accuracy of Land Cover Classification

Based on the classification accuracies using MLC, land cover classification for three years namely, 1998, 2008 and 2018, shows high overall accuracy and Kappa Coefficient. In 1998, the overall accuracy and Kappa Coefficient are 96.2069% and 0.9523, respectively. In 2008, the overall accuracy and Kappa Coefficient are 90.4762% and 0.8792, respectively. And in 2018, the overall accuracy and Kappa coefficient are 95.7596% and 0.9469, respectively.

3.2 Land Cover Change Detection of Land Cover Map using MLC

Change Detection is the process of identifying differences between successive images of the same area. These differences are based on land cover classification. The MLC classifier was employed to assess changes in land cover between 1998, 2008, and 2018 in Bayugan City. Land cover changes represent differences in the area covered by various land cover classes from 1998, 2008, and 2018. Figure 3.1 illustrates the different land cover classifications for the years 1998, 2008, and 2018, which include built-up, forest, water, barren, and cropland

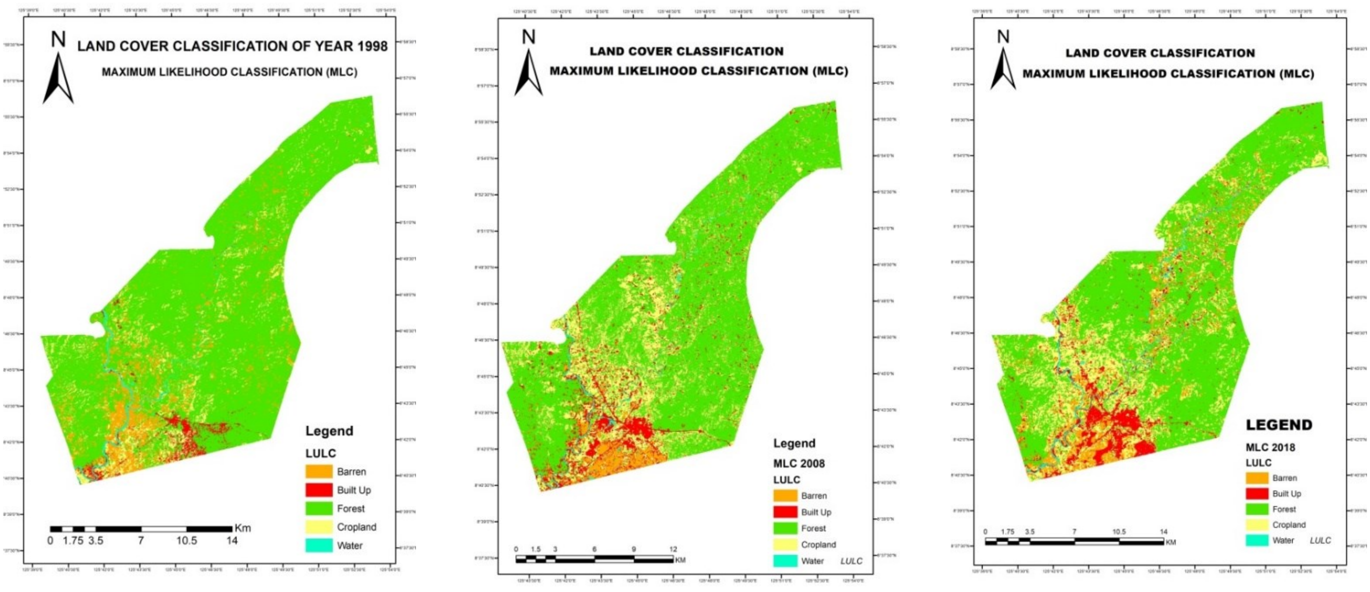

Figure 3.1 Land Cover Map of Bayugan City in 1998, 2008 and 2018

The classification results for the pre-processed images from 1998, 2008, and 2018 are presented in Figure 3.1. Table 3.1 displays the statistics for different land use areas and their proportions for these three years. It is evident that the forest area was the largest in the study area, covering 260,111,767.95 m² in 1998, 227,178,223.66 m² in 2008, and 201,383,636.87 m² in 2018. Over the 20-year period from 1998 to 2018, the built-up areas gradually increased, while the water area showed a declining trend. This decrease in water area can be attributed to developments and dredging activities in water bodies. The river's width became narrower in 2018 compared to 1998, leading to a sharp decrease in the water area. Forest changes were linked to urban expansion and deforestation. Additionally, forest covered more than half of Bayugan City's total land area in 1998 but decreased significantly from 2008 to 2018. Other land cover classes have also undergone changes and conversions. Built-up areas have a substantial impact, especially in 2018, indicating increased development within the region. The visualization of the land cover map from 1998 to 2018 illustrates the rapid development and urbanization of the area.

Table 3.1 Computed area in m2 of different land cover classification of Bayugan City

LULC CLASSES	1998 (m^2)	Area(%)	2008 (m^2)	Area (%)	2018 (m^2)	Area (%)
Barren	33,635,874.01	10%	14,214,742.61	4%	28,767,742.51	8%
Built-up	7,098,008.16	2%	26,148,999.46	8%	31,531,600.60	9%
Forest	260,111,767.95	78%	227,178,223.66	66%	201,383,636.87	59%
Cropland	27,639,189.92	9%	72,520,440.47	21%	78,977,188.42	23%
Water	3,686,110.66	1%	3,535,262.54	1%	2,889,188.26	1%

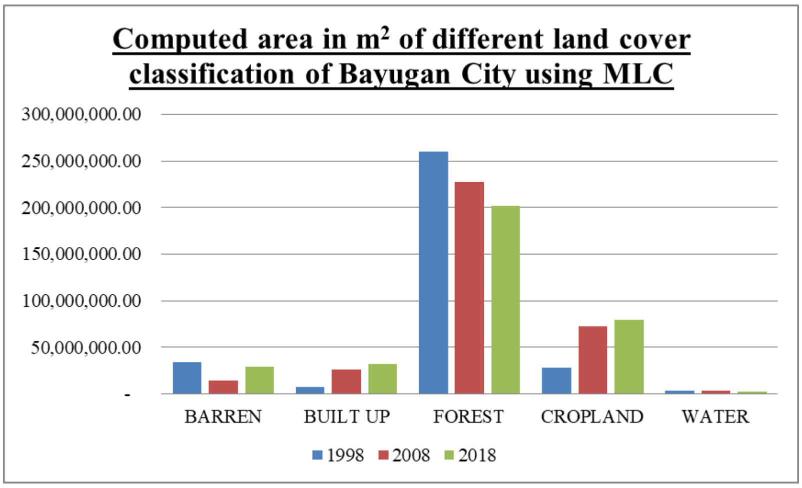

Figure 3.2 Computed area (in sq. m) of different land cover classes of Bayugan City

The Built-up area has experienced a net increase proportion of 17%, equivalent to a net increase in area of 24,433,592.45 m². This increase in Built-Up area is primarily attributed to the conversion of forest and barren land, with transfer-in areas of 15,031,985.49 m² and 7,225,672.13 m², respectively.

Table 3.2 Area Transfer Matrix from 1998 to 2018

LULC CLASS		LULC 2018 Built Up (m^2)
LULC 1998	Barren	7,225,672.13
	Forest	15,031,985.49
	Cropland	4,456,656.41
	Water	1,147,278.17
	GRAND TOTAL	27,861,592.20

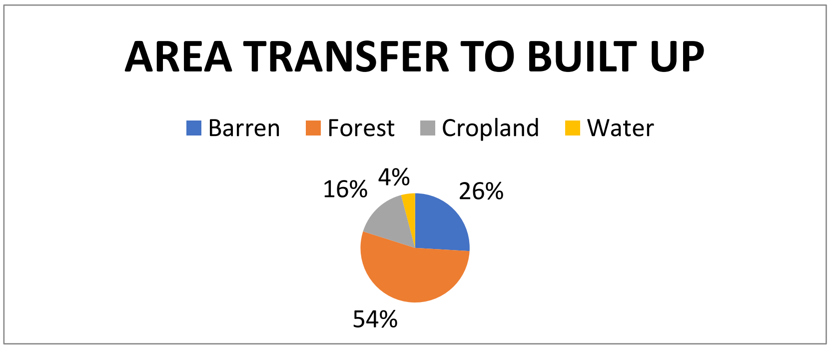

Figure 3.3 Percentage of Area Transfer of Built-up from 1998-2018

4. CONCLUSION AND RECOMMENDATION

In this study, Landsat 5 TM, Landsat 7, and Landsat 8 OLI image data were employed to create land use maps for 1998, 2008, and 2018. The land use structure of the study area was analyzed based on the classification results for each period. The accuracy of the land cover classification was assessed based on various metrics, including Producer's Accuracy, User's Accuracy, Overall Accuracy, and Kappa Coefficient. These land cover maps for 1998, 2008, and 2018 were utilized for change detection analysis, highlighting differences over a 10-year span. These changes are essential for understanding urbanization and area development in Bayugan City. Notably, the forest coverage in Bayugan City was substantial, with forest areas measuring 260,111,767.95 m^2 in 1998, 227,178,223.66 m^2 in 2008, and 201,383,636.87 m^2 in 2018. The built-up area consistently increased during this period. Changes in water bodies, barren land, and cropland were closely linked to human activities. The barren area exhibited fluctuations, mainly due to human interventions. Forest area changes were primarily associated with timber harvesting and urban expansion, leading to a significant reduction in forested land between 1998 and 2018. To preserve ecological functions, careful consideration of woodland harvesting in planning is recommended. Furthermore, to enhance the accuracy of future land cover mapping, it is advisable to incorporate image datasets with higher spatial resolutions, such as ortho-photo images. This improvement in input data quality and parameter settings can lead to more precise LULC scenarios. Additionally, this study lays the groundwork for further research, including the development of models to predict future land use changes in Bayugan City.

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