DELINEATION OF IMPERVIOUS SURFACE AREA IN ILIGAN CITY PHILIPPINES USING LIDAR DATA

Carmel B. Sabado[1], Ma. Teresa T. Ignacio[1,2], Shara Grace C. Astillero[1], Ruben C. Tudio[1]

[1]Phil-LiDAR 2 Project, College of Engineering, Mindanao State University-Iligan Institute of Technology
Tibanga, Iligan City, 9200 Philippines
E-mail: carmelsabado@yahoo.com

[2]Department of Ceramic, Mining & Metallurgical Engineering, College of Engineering, Mindanao State University-Iligan Institute of Technology Tibanga, Iligan City, 9200 Philippines
E-mail: materesa.ignacio@g.msuiit.edu.ph

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ABSTRACT: Impervious surface or man-made surface is an important factor in the hydrologic cycle and water management of a developing city. Quantifying and understanding the extent of impervious surface area should be carried out to assess accurately water discharge during heavy rainfall, land use change detection, development and many other impacts on the community. Iligan City is one of the most devastated areas when tropical storm Washi hit Mindanao in December 2011.This research aimed to extract impervious surfaces like concrete and asphalt roads, buildings, parking areas and concrete pavement within a 7.05 km² city proper of Iligan. Utilizing Light Detection and Ranging (LiDAR) datasets and derivatives, an object-based image analysis (OBIA), support vector machine (SVM) classifier, and ground truthing, five classes were extracted. These classes were building, vegetation, impervious ground surface, pervious ground surface, and water. Building class and impervious ground surface were subsequently aggregated to a class of impervious surface. Furthermore, vegetation and pervious ground surface were assigned to a class of pervious surface. Results showed an overall accuracy of 0.83 with a Kappa Index of Agreement (KIA) of 0.78. Greater accuracy was attained when further refinement using rule-based classification approach was conducted to misclassified objects. Percent coverage of impervious surface area is greater than 50% of the total study area.

1. INTRODUCTION

Impervious surface is expressed as any materials on the earth surface that prevents the infiltration of water into the bare soil and is principally associated with habitation and anthropological activities like construction of transportation and buildings (Slonecker et al. 2001). Impervious surface area is considered as an important variable in urban environments affecting not only water quality and rainfall runoff but also air quality and urban development (Lu, D. and Weng, Q. 2009, Hung, M.C and Germaine, K, 2008). Due to its significance, extraction of impervious surface area has drawn a lot of attention in the field of remote sensing since the early 1970s. (Lu, D. and Weng, Q. 2009). According to Brabec et al. (2002), there are four ways of estimating impervious surface. One of which is conducting image classification. Image classification using object-oriented approach is gaining popularity in a number of disciplines especially in vegetation analysis and extraction of land cover classification.

It is the objective of this research to extract accurately impervious surfaces in the urbanized city of Iligan and calculate the percent coverage of the impervious surface to the total land area using remotely sensed Light Detection and Ranging (LiDAR) data. Measuring and understanding the total coverage of impervious surface area should be carried out to assess accurately water discharge during heavy rainfall, land use change detection, development and many other impacts on the community.

This study utilized LiDAR derived datasets. LiDAR is an active remote sensing system with an illumination source from laser lights. It can provide horizontal and accurate vertical information with high spatial resolutions. Currently, LiDAR technology have been rapidly developed and employed in vegetation analysis, estimating biomass, canopy height and closure (Lou, S. et al. 2015). Using LiDAR only derivatives in extracting buildings attained a high accuracy but with irregular boundaries of the buildings due to the lack of multispectral bands to support the segmentation and classification (Astillero, S. G. et al., 2016).

2. MATERIALS AND METHODS

2.1 Study Area

Iligan City is a highly urbanized city with a minimum population of three hundred thousand (300,000) residents in 2010, as qualified by the Philippines' National Statistics Office and is considered 1st class city in terms of capita income (NSO, 2016). Its population increased at a rate of 1.25% annually. With the increase in population, is the development of the areas with impervious surfaces. The location selected for this study is a 7.27 km^2 area, comprising ten (10) barangays.

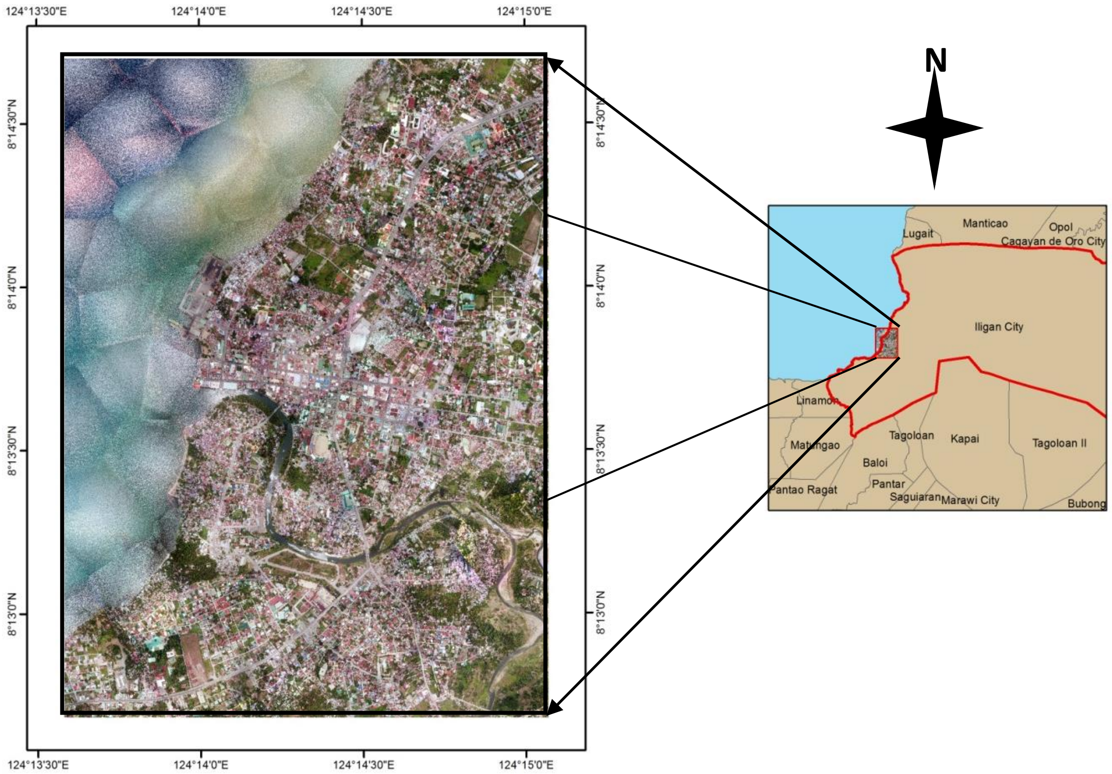

Figure 1. Study Area in Iligan City, Lanao Del Norte, Philippines. The image is an orthophoto is a true color composite (Red, Green and Blue) with 0.5m resolution was used for additional validation

2.2 Field Measurements

Field work and ground validation was performed from August 30 to 31, 2015 across Iligan City to collect training and validation points which were used in the supervised classification. In addition to the ground collected points, sample points gathered from orthophotos were also utilized. A total of 340 points for training samples and 190 points for the validation of the classified objects (Figure 2).

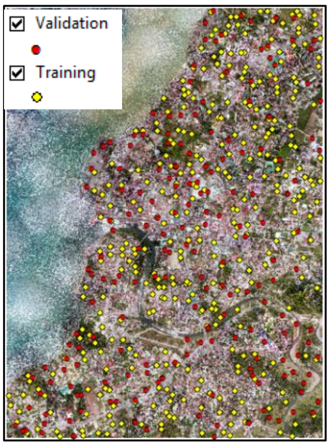

Figure 2. Training and Validation Points

2.3 LiDAR Data Derivation and Processes

The airborne LiDAR and orthorectified photographs were obtained with flight mission last August 2013 thru the DREAM program under the NOAH project of Department of Science and Technology led by Training Center for Applied Geodesy and Photogrammetry of University of The Philippines Diliman (UP-TCAGP). LiDAR point cloud has an average point density of 2 points/m^2 and an average spatial resolution of 1 meter. LAStools is a software with object-oriented modular approach and integrated LiDAR points processing environment (Hug, C. et al., 2012). LAStools software was used in obtaining the LiDAR derivatives like Digital Surface Model (DSM), DSM Hillshade, Digital Terrain Model (DTM), Intensity layer, and average number of returns (NUMRET). ArcGIS 10.2 spatial analyst was used to derive Normalized Digital Surface Model (nDSM), surface slope, slope of slope, rugosity, and curvature layers (Figure 3). eCognition version 9.0 edge extraction canny algorithm was used to output Canny Edge layer with a threshold of 0-0.5 on DSM hillshade layer.

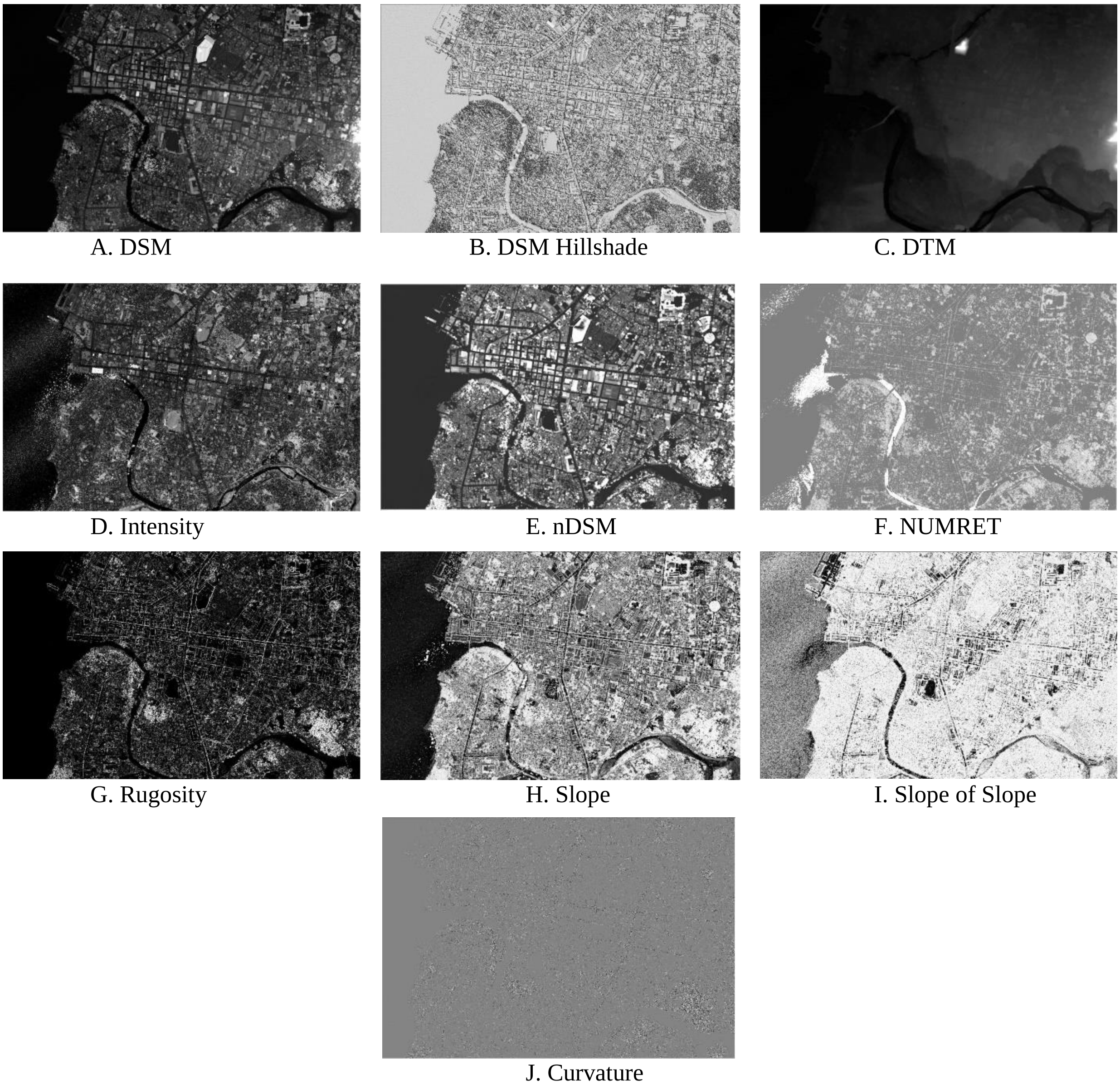

Figure 3. Image Layers Used (A) DSM, (B) DSM Hillshade, (C) DTM, (D) Intensity, (E) Normalized DSM, (F) Average Number of Returns, (G) Rugosity, (H) Slope, (I) Slope of Slope, (J) Curvature

2.4 Segmentation

Segmentation of an image into meaningful objects is the primary purpose of Object- Based Image Analysis (OBIA). Blaschke, T. et al., (2011) and Candare, R.J. et al. (2016), pointed out that OBIA workflows can be easily manipulated, allowing for the inclusion of human semantics and hierarchical networks. It permits the exploitation of neighboring information and attributes. Multi-threshold segmentation and multi-resolution segmentation in eCognition 9.0 software were used in this study. Multi-threshold segmentation was performed to create classes of water and land. It was also implored in separation of land to ground and non-ground classes utilizing the layer of nDSM. Multi-resolution segmentation optimizes the procedure of segmentation by diminishing average heterogeneity of image objects for a given resolution locally. Multi-resolution segmentation was done on both ground and non-ground features with scale parameter of 16 for non-ground and 30 for ground features but using the same homogeneity criterion. Optimum combination of image layer weights and composition of homogeneity criterion was evaluated and tested thru different sets of permutation.

2.5 Classification

One powerful classifier in OBIA is support vector machine (SVM). A SVM is a set of related supervised learning systems that analyze data and identify patterns, utilized for classification and regression analysis (Tzotsos, 2008). The SVM machine learning technique finds the optimal separating hyperplane between classes by focusing on the training cases that are placed at the edge of the class descriptors. In this study, SVM was employed to classify objects into building, impervious ground surface, pervious ground surface, and vegetation. Exploiting the objects' features like mean and standard deviation of layer values, geometry features, and textural values enables the classifier to use these features all at once. Also, radial basis function (RBF) kernel and a value of 100 for the parameter C to adjust the trade-off between large margins and classification errors were used.

Supplementary to SVM classifier, rule-based refinement was integrated to further classify objects that were misclassified in the SVM specially that part with problematic LiDAR intensity.

3. SUMMARY OF RESULTS

3.1 Classified Land Cover

Shown in Figure 4 is the classified land cover of the study site. With 5 major classes of building, impervious ground surface, pervious ground surface, vegetation, and water. However, building class and impervious ground surface were then aggregated to a class of impervious surface, and vegetation together with pervious ground surface was assigned to pervious surface in order to get the total area coverage of impervious surface.

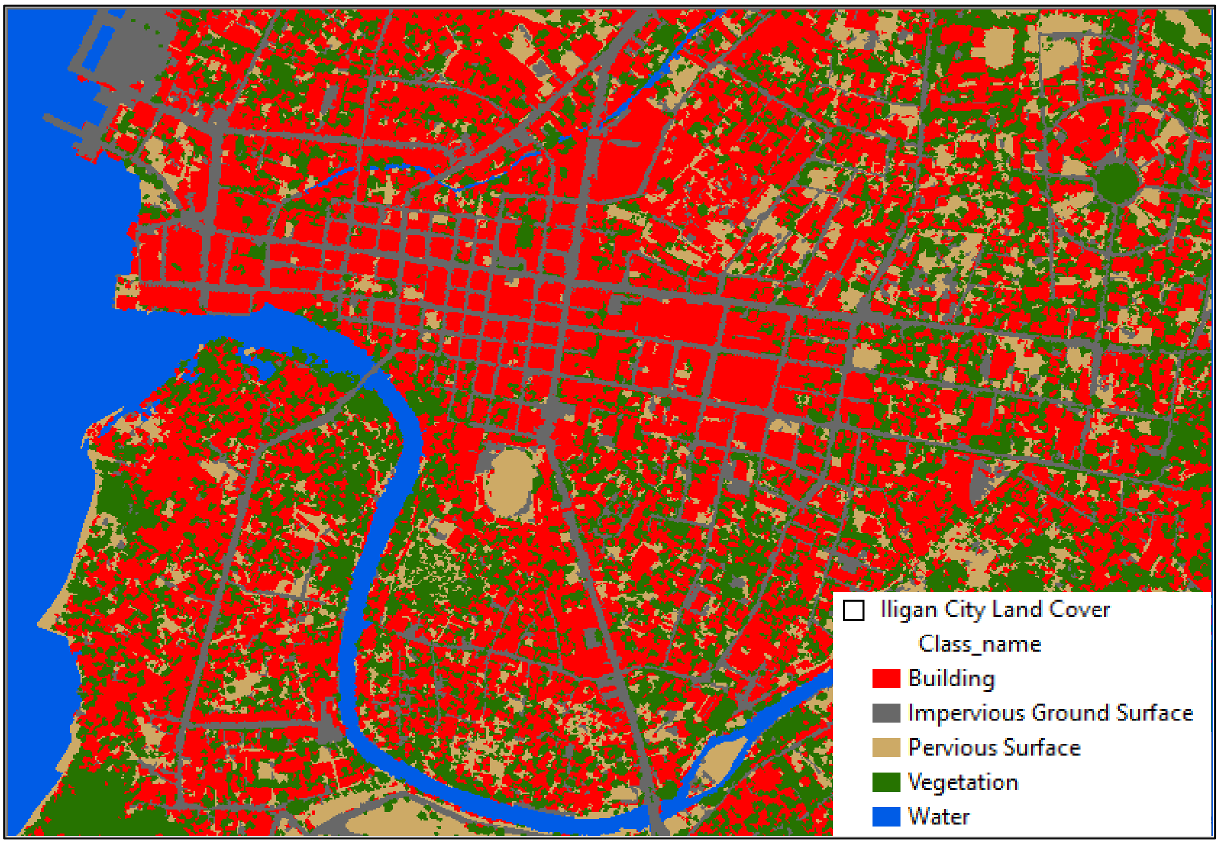

Figure 4. Classification of Objects in a Portion of the Study Area

3.2 Percent Coverage of Impervious Surface

The need of measuring the extent of impervious surface area should be carried out to assess accurately water discharge during heavy rainfall, land use change detection, development and many other impacts on the community. Shown below in Table 1 is the total percentage of impervious surface area in Iligan City.

Table 1. Percent Cover of Impervious Surface

Class	Area, km^2	Percent Cover, %
Impervious Surface Area	3.74173	53.11
Pervious Surface Area	3.303921	46.89

When compared to the total land area of the whole territory of 7.05 km^2, this result shows that 53% of the Iligan City territories can be classified as ISA. The resulting ISA map of Iligan City is displayed in Figure 5.

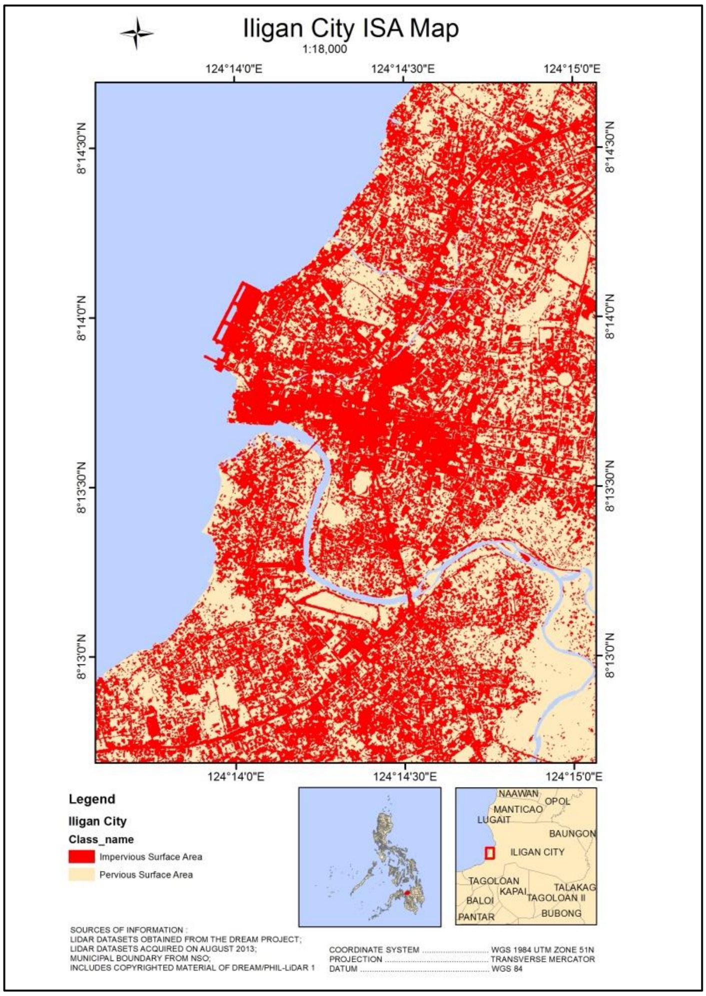

Figure 5. Impervious Surface Area Map of part of Iligan City

3.3 Validation and Accuracy Assessment

Ground truth data for this project relied on the imagery, knowledge of the study area of the researcher, and from field work. The Error Matrix based on TTA (Test and Training Area) Mask method was used to assess the accuracy of the project using the 190 validation points.

Shown in Table 2, is the assessment of the overall accuracy and coefficients of the classification. From the table, one can find that performing rule-based classification after using SVM classifier results in a more accurate assessment than utilizing SVM alone. It is also notable that the overall accuracy is close to the Kappa Coefficient (KIA) both for SVM alone, and SVM with rule-based classification.

Table 2. Assessment of the Classification in the Study

Accuracy	SVM					SVM and Rule-based				
	Water	Vegetation	Building	Pervious Surface	Impervious Surface	Water	Vegetation	Building	Pervious Surface	Impervious Surface
Producer	0.973	0.886	1.000	0.970	0.578	0.988	0.992	1.000	0.978	0.827
User	1.000	1.000	0.099	0.939	0.968	1.000	1.000	0.753	0.788	0.968
Hellden	0.986	0.940	0.181	0.954	0.723	0.994	0.996	0.859	0.873	0.892
Short	0.973	0.886	0.099	0.912	0.567	0.988	0.992	0.753	0.775	0.806
KIA Per Class	0.957	0.878	1.000	0.962	0.476	0.980	0.992	1.000	0.971	0.760
Overall Accuracy	0.837					0.934				
KIA	0.782					0.907				

4. CONCLUSION

Using object-based image analysis (OBIA) in delineating surface area (ISA) can be a promising method especially when supervised classification (SVM Classifier) is combined with rule-based classification for refinement. The ISA of Iligan City is more than half of its total territory encompassing exactly of 53%. This extracted ISA can be used in understanding the importance of impervious surfaces in hydrologic cycle and water management.

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