ASEAN Engineering Journal

Full Paper

INVENTORY OF HIGH VALUE CROPS USING LIDAR DATA AND GIS IN LANAO DEL NORTE PHILIPPINES

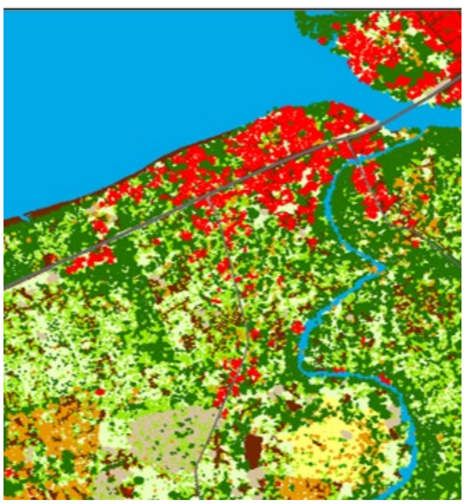
Article history
Received
27 July 2018
Received in revised form
08 December 2021
Accepted
09 December 2021
Published online
28 February 2022

Carmel Sabado-Burlat[a]*, Ma. Teresa T. Ignacio[b], Jaime Guihawan[b]

[a]Department of Civil Engineering, College of Engineering and Geosciences, Caraga State University, CSU, Butuan City, Philippines
[b]Phil-Lidar 2, College of Engineering, Mindanao State University- Iligan Institute of Technology, Iligan City, Philippines

*Corresponding author
csburlat@carsu.edu.ph

Graphical abstract



Abstract

One of the objectives of Republic Act 8435 or Philippines Agriculture and Fisheries Modernization Act of 1997 is to modernize the agriculture and fisheries sectors by developing it into a technology –supported division. In the Philippines, about 32% of the country's total land areas were agricultural lands. Mapping and delineating the agricultural crops are significant in the implementation of this Act. Moreover, having an updated and accurate inventory of the agricultural resources in an area is critical in the assessment, planning, and development specifically in providing the necessary government support to improve the agricultural system, like Farm-to-Market Roads (FMR), irrigation system, pre- and post-harvest facilities, among others. This study extracted agricultural crops like rice, corn, coconut, banana, and mango present in the province of Lanao Del Norte using Light Detection and Ranging (LiDAR) technology and Geographic Information System (GIS). LiDAR is an active remote sensing system with an illumination source from laser lights. Object-based image analysis (OBIA), multi-level support vector machine (SVM) classifier, and ground truthing were the general procedure in extracting and validating these crops. OBIA allows the segmentation of images derived from LiDAR datasets into meaningful objects. SVM classifier analyzes and identifies the pattern in the attributes of the segmented objects and classifies these objects based on its analysis. 71% of the extracted agricultural areas are planted with coconut, followed by banana with 13%, corn with 8%, rice constitutes 5%, and lastly mango with 3% of the total agricultural area. These extracted crops can now be utilized in updating the agricultural resource accounting of the province. Accuracy assessment was performed using 3,300 validation points gathered from the field and from orthorectified photos. Result of evaluating the accuracy shows that 80-90% of the crops were extracted and classified correctly. The accuracy assessment records an overall accuracy of 0.915 and a Kappa Index of Agreement (KIA) of 0.89147

Keywords: Agricultural Resources, Land Classification, Object-Based Image Analysis (OBIA), Remote Sensing, Support Vector Machine (SVM)

1.0 INTRODUCTION

Agriculture plays a significant role in the Philippine economy with coconut oils and fresh bananas contributed to 37% of the total agricultural exports of the country. In Lanao del Norte, agriculture is considered the lifeblood of the people being the second principal source of livelihood [9]. According to Philippine Statistics Authority [9], agriculture in the Philippines had an 8.55% drop in production of high value crops for the first three months of 2016. This negative change was due to the prolonged dry season and damages brought about by typhoons [8]. For quite some time, the Philippines have had an increasing negative agricultural trade balance for past 15 years. However, the nation still acquires most of its food from the domestic production by currently making a renewed effort to increase the production rice [3].

Detailed inventories in agriculture have implication on food security and economic stability of a developing country especially with agricultural exports dependent on crops and crop products [5]. High value crops in the province are not limited to coconut, mango, banana, rice, and corn only. Other high value crops are present, however, extraction of these crops are not covered in this study.

This paper has two main objectives. First, to extract accurately high value crops like rice, corn, coconut, banana, and mangoes planted in Lanao Del Norte using remotely sensed Light Detection and Ranging (LiDAR) data. Second, is to have an inventory in terms total area planted with these crops. Having an updated and accurate inventory of the agricultural resources in an area is critical in the assessment, planning, and development of the province specifically in providing the necessary government support to improve the agricultural system, assist and educate farmers, and provide irrigation, among others.

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 [10, 11]. Using LiDAR derivatives and orthophotos in mapping high value crops in Agusan Del Norte with an object-based image analysis and optimized support vector machine (SVM) model, attained a high overall accuracy [7,10,13]. Image classification using object-oriented approach is gaining popularity in a number of disciplines especially in vegetation analysis and extraction of land cover classification [6, 7, 10-14].

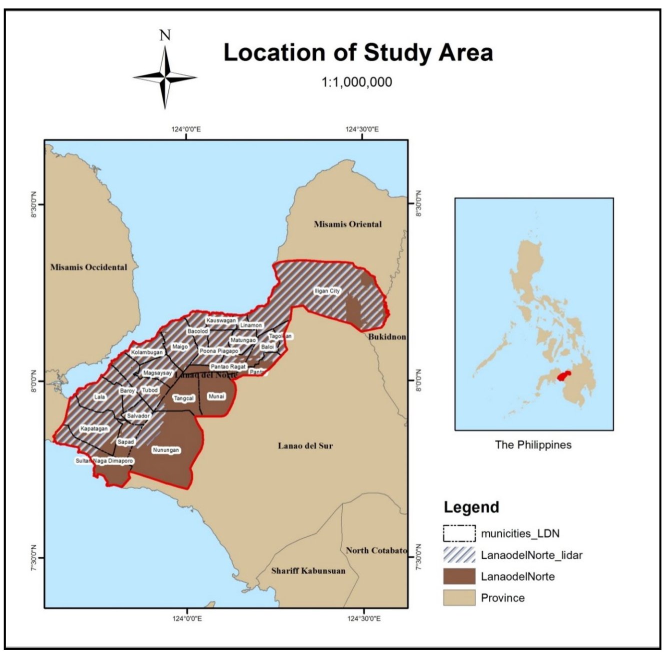


Figure 1 Location of study area with available LiDAR data

2.0 METHODOLOGY

Lanao Del Norte is in the northwestern part of Mindanao approximately 7º30' north latitude and 123º47' east longitude. It has a total land area of 3,800 km^2. The province prides itself as a major contributor to the overall development of Mindanao, Philippines. It hosts three of the seven Agus Hydropower Plants, which generates 80% of the Mindanao power grid [3]. There are more than 70,000 hectares of coconut land found in Lanao del Norte, and is the second largest producer of coconut oil in the region. Other major products include rice, fruits, corn, and aquaculture products [4].

Shown in Figure 1 is the map of Lanao Del Norte with its adjacent provinces in the island of Mindanao. Areas within the province with LiDAR footprint equal to a total of 1843.88 km^2. Only those areas with LiDAR data are discussed and processed in this research. The total LiDAR coverage is 69% of the total land area of Lanao Del Norte. The twenty three (23) municipalities under the province of Lanao Del Norte are: Bacolod, Baloi, Baroy, Iligan City, Kapatagan, Kauswagan, Kolambugan, Lala, Linamon, Magsaysay, Maigo, Matungao, Munai, Nunungan, Pantao Ragat, Pantar, Poona Piagapo, Salvador, Sapad, Sultan Nage Dimaporo, Tagoloan, Tangcal, and Tubod. But only 22 municipalities have LIDAR data. Excluded from the list of municipalities and cities mentioned above is the municipality of Munai.

Field measurement was done through field work and ground validation survey. It was performed on different dates starting from April 2015 up to June 2016 across the municipalities of the province of Lanao Del Norte to collect training points and validation points which were used in the supervised classification in eCognition software.

Due to the vastness of the area considered in this study, and due to security restrictions in areas where there are insurgencies, some portions of the study areas are not accessible for validation. With this, additional points were collected and gathered from available high- resolution orthophotos were also utilized instead. A total of 1286 fields points of different classifications were gathered in 2015, and 2,014 points were collected in 2016 for an overall of 3,300 training and validation points.

The airborne LiDAR and orthorectified photographs (orthophotos) were obtained with several different flight missions from August 2013 to November 2014 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 software with object-oriented modular approach and integrated LiDAR points processing environment [8].

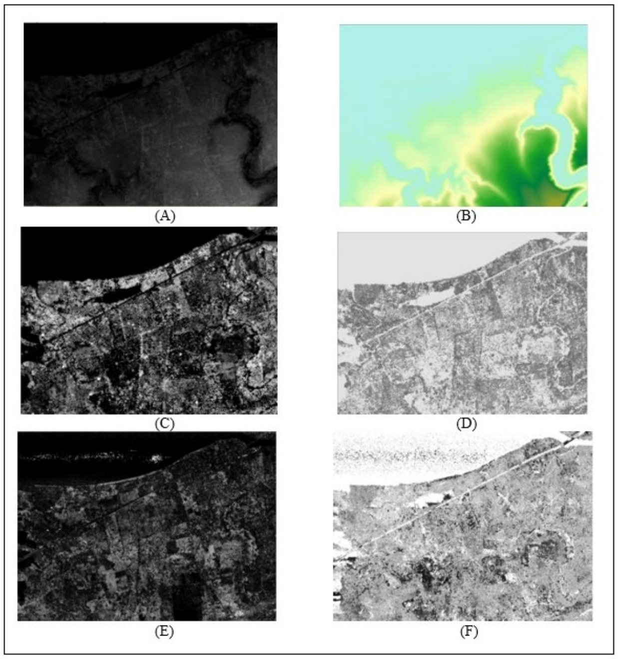


Figure 2 Image layers derived from LiDAR data used (A) DSM, (B) DTM, (C) Normalized DSM, (D) DSM Hillshade, (E) Intensity, (F) Slope

LAStools software was used in obtaining the LiDAR derivatives like Digital Surface Model (DSM), DSM Hillshade, Digital Terrain Model (DTM), and Intensity layer. ArcGIS 10.2 spatial analyst was used to derive Normalized Digital Surface Model (nDSM), and surface slope (Figure 2). 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. Shown in Figure 3 the flowchart of generating the Lidar derivatives and the operations used to derived it.

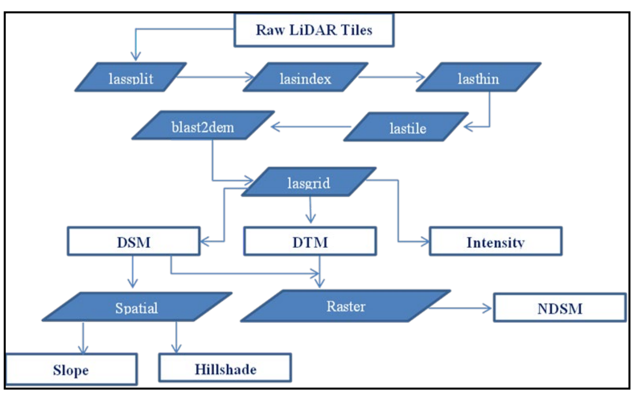


Figure 3 Flowchart of generating LiDAR derivatives

In Figure 4, an orthophoto of a portion of the studied area was shown. Orthophoto is a high-resolution aerial photo that is composed of red, green, and blue layer mosaic together. It was gathered simultaneously with the gathering of LiDAR points. However, due to the unfavorable weather during the flights, some of the areas does not have an aerial photograph.

The total land area covered with LiDAR data set is enormous that the researchers must divide it into different smaller projects within the same flight mission to accommodate faster processing and in consideration of the limitation of the software used.

Figure 4 Clipped orthorectified photos of the study area

Segmentation of an image into meaningful objects is the primary purpose of Object- Based Image Analysis (OBIA). [9,10] 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 with different parameters. O the other hand, 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 15 to 25 for non-ground and 30 to 50 for ground features but using the unique homogeneity criterion. Optimum combination of image layer weights and composition of homogeneity criterion was evaluated and tested thru different sets of permutation.

One powerful classifier in OBIA is support vector machine (SVM). SVM is a set of related supervised learning systems that analyze data and identify patterns, utilized for classification and regression analysis [2]. 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 [1, 10]. In eCognition environment, multi-level SVM was employed to classify objects from low elevation, medium, and high elevation into utilizing all the derived layers from LiDAR. Low elevation classes are grassland, bare/fallow, and rice. Medium elevation includes shrubland, corn, and banana, while high elevation features are coconut, mango, and other non-agricultural vegetations. Exploiting the objects' features like mean and standard deviation of all 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.

To simplify the process and focus on the extraction of agricultural features, thematic layers of rivers, roads, and buildings, were used in the delineation and extraction. 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.

After classifying the objects into respective classes, accuracy assessment was done. Validation data for this project relied on the imagery, knowledge of the study area of the researchers, and from ground truthing conducted by the researchers to all the different municipalities within the province of Lanao del

Norte. Accuracy assessment is performed by comparing the result of classification after SVM algorithm against validation points acquired from the field and from the orthophotos. Another object level is created below the current user level. Assigning all objects to unclassified class is required to clear out all the classes. This is followed by assign class algorithm using validation points as thematic layer and then turning the classified objects as samples. From these samples, a TTA mask is generated by accessing the Classification menu, selecting Create TTA mask from samples, and then choosing the current/ last object level. All object samples are shown in a TTA mask while others are in black. Accuracy assessment is then accessed from Tools menu. The last SVM object level is compared against the TTA mask, selecting all classes indicated in validation points. The Error Matrix based on TTA (Test and Training Area) Mask method was used to assess the accuracy of the project using the points gathered from the field and from the orthophotos.

After evaluating the accuracy of the classified land cover, all the specified classes of high value crops were exported from eCognition and viewed in the ArcGIS software wherein the projected coordinate system of the polygon raster was defined to WGS 1984 UTM Zone 51N. Spatial analyst in ArcGIS software was utilized to compute for the area of each polygon and then summarized to get the total area planted with coconut, banana, rice, corn, and mango.

3.0 RESULTS AND DISCUSSION

Shown in Figure 5 is a not drawn to scale but labeled accordingly with classified land cover of a portion of the study site. With 11 major classes of banana, bare/fallow, built-up, coconut, corn, grassland, mango, other vegetation, rice, road, and water. However, in this sample area, dominant crops are coconuts, mango, and corn. Using the points gathered from the field, the accuracy assessment of the areas with orthophotos have precisions ranges from 85-90%. This is evident in the results of the classifications using SVM. On the other hand, those areas without orthophotos are 80-85% accurate.

Having an updated and accurate inventory of the agricultural resources in the municipality is critical in the assessment, planning, and development of the province specifically in providing the necessary government support to improve the agricultural system, assist, and educate farmers, and provide irrigation, among others.

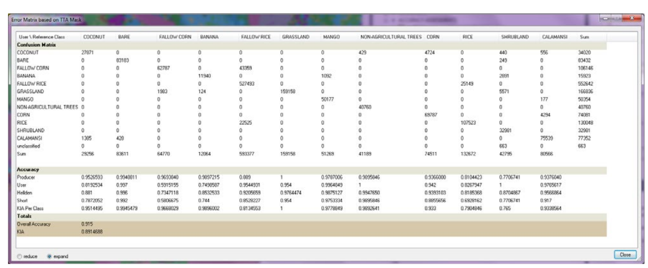
Figure 5 Classification of objects in a portion of the municipality of Bacolod, Lanao del Norte

In Table 1, areas planted with high value crops are presented. In can be observed from the table that 28% of the total land areas in Lanao Del Norte with LiDAR data are planted with banana, coconut, corn, mango, and rice. Out of this 25%, areas planted with coconut are the largest with a percentage of 71% followed by banana at 13%, corn with 8%, rice with 5% and lastly mango with 3%. With this, Lanao del Norte is considered an agricultural province in the island of Mindanao.

Table 1 Area Planted with Agricultural Crops

Crops	Area Planted, km^2	Percent Planted
Rice	23.89	4.70%
Corn	40.48	7.96%
Coconut	363.61	71.48%
Mango	13.50	2.65%
Banana	67.22	13.21%

Accuracy assessment was done using the Error Matrix method based on TTA mask. This was selected for the statistical analyses since it delivers both the overall accuracy and the opportunity to assess the producer accuracy, user accuracy, and Kappa analysis of the results. The accuracy assessment records an overall accuracy of 0.915 and a Kappa Index of Agreement (KIA) of 0.8914688. In Figure 6, the error matrix based on TTA mask of a particular project in the municipality of Lala, Lanao del Norte was shown.


Error Matrix based on TTA Mask

User \ Reference Class	COCONUT	BARE	FALLOW CORN	BANANA	FALLOW RICE	GRASSLAND	MANGO	NON-AGRICULTURAL TREES	CORN	RICE	SHRUBLAND	CALAMANSI	Sum
Confusion Matrix													
COCONUT	27871	0	0	0	0	0	0	429	4724	0	440	556	34020
BARE	0	83183	0	0	0	0	0	0	0	0	249	0	83432
FALLOW CORN	0	0	62787	0	43359	0	0	0	0	0	0	0	106146
BANANA	0	0	0	11940	0	0	1092	0	0	0	2891	0	15923
FALLOW RICE	0	0	0	0	527493	0	0	0	0	25149	0	0	552642
GRASSLAND	0	0	1983	124	0	159158	0	0	0	0	5571	0	166836
MANGO	0	0	0	0	0	0	50177	0	0	0	0	177	50354
NON-AGRICULTURAL TREES	0	0	0	0	0	0	0	40760	0	0	0	0	40760
CORN	0	0	0	0	0	0	0	0	69787	0	0	4294	74081
RICE	0	0	0	0	22525	0	0	0	0	107523	0	0	130048
SHRUBLAND	0	0	0	0	0	0	0	0	0	0	32981	0	32981
CALAMANSI	1385	428	0	0	0	0	0	0	0	0	0	75539	77352
unclassified	0	0	0	0	0	0	0	0	0	0	663	0	663
Sum	29256	83611	64770	12064	593377	159158	51269	41189	74511	132672	42795	80566	
Accuracy													
Producer	0.9526593	0.9948811	0.9693840	0.9897215	0.889	1	0.9787006	0.9895846	0.9366000	0.8104423	0.7706741	0.9376040	
User	0.8192534	0.997	0.5915155	0.7498587	0.9544931	0.954	0.9964849	1	0.942	0.8267947	1	0.9765617	
Hellden	0.881	0.996	0.7347118	0.8532533	0.9205659	0.9764474	0.9875127	0.9947650	0.9393103	0.8185368	0.8704867	0.9566864	
Short	0.7872052	0.992	0.5806675	0.744	0.8528227	0.954	0.9753334	0.9895846	0.8855656	0.6928162	0.7706741	0.917	
KIA Per Class	0.9514495	0.9945479	0.9668029	0.9896002	0.8134553	1	0.9778849	0.9892641	0.933	0.7904846	0.765	0.9338564	
Totals													
Overall Accuracy	0.915												
KIA	0.8914688												

reduce expand Close

Figure 6 Error matrix based on TTA mask of a project in Lala, Lanao Del Norte

In Figure 7 is the summary of inventory in terms of land area in Lanao Del Norte with agricultural crops. Iligan City, and municipalities of Kolambugan and Magsaysay are the top three among all the municipalities in Lanao del Norte with the largest area planted with coconut based on the Figure 5.

It is also visible that rice which is a staple food of Filipinos are largely produced in municipalities of Lala and Kapatagan. Corn on the other hand were mostly planted in the areas of Kapatagan, Sultan Naga Dimaporo (SND), and Iligan City.

Due to the extent of the land area of Iligan City, it is also the largest region with planted crops like coconut and banana among the 16 municipalities. With almost 40 km^2 of its land are planted with different varieties of bananas.

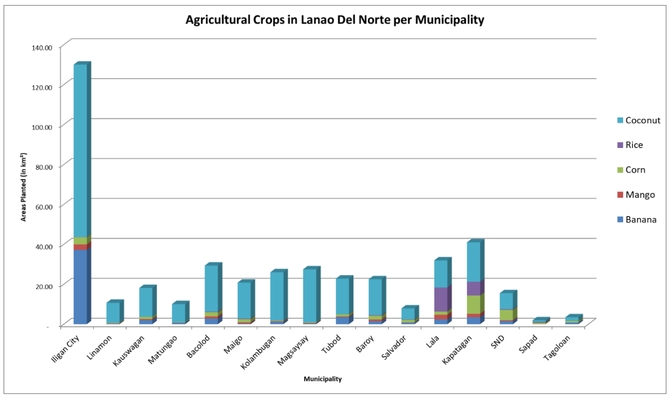


Figure 7 Inventory of agricultural crops in the municipalities in Lanao del Norte

4.0 CONCLUSION

In this paper, extraction of high value crops in the province of Lanao del Norte using LiDAR datasets was presented. Object-based image analysis (OBIA) can be a promising method in delineating areas planted with high value crops like banana, coconut, corn, mango, and rice especially when supervised classification (SVM Classifier) will be used.

The areas planted with high value crops is 25% of its total land area making Lanao del Norte an agricultural province. Of which, areas planted with coconut are 71.48%, different varieties of banana are 13.21%, and the fields planted with corn are 7.96%. These three crops are the commonly planted high value crops in the province.

These extracted agricultural crops can be used in updating the inventory made by the local government of Lanao del Norte in crafting its Comprehensive Land Use Planning (CLUP). Also, government will be guided as to what support will be provided to each specific area to improve the agricultural system, assist and educate farmers, and provide irrigation, among others.

Acknowledgement

This research is under the Phil-LiDAR 2 Program - Detailed Resource Mapping in the Philippines of Mindanao State University-Iligan Institute of Technology (MSU-IIT) with the supervision of Training Center for Applied Geodesy and Photogrammetry of University of The Philippines Diliman (UP-TCAGP). Appreciation is given to Department of Science and Technology (DOST) of the Philippine government for funding this research.

References

[1] Agricultural Transformation & Food Security 2040. *Centennial Group International. JICA. Philippines Country Report*. Access date: January 2013

[2] Angelos Tzotsos. 2008. A Support Vector Machine Approach for Object Based Image Analysis, *Lecture Notes in Geoinformation and Cartography*, 2008: 663-677. DOI: https://doi.org/10.1007/978-3-540-77058-9_36

[3] Department of Trade and Industry (DTI). (n.d.). Philippine Board of Investments. Lanao Del Norte http://www.boi.gov.ph/files/investment%20fact%20sheet/Lanao%20del%20Norte.pdf. January 2013.

[4] Provincial Government of Lanao Del Norte. 2013. Disaster Risk Reduction and Climate Change Adaptation (DRR-CCA) Enhanced Provincial Development and Physical Framework Plan: 2013-2018, Lanao Del Norte

[5] G. Lutero, E. Pizzoli. 2011. Inventories In Agriculture: Implications For Rural Development And Estimation Issues*, 4th Meeting on Statistics on Rural Development and Agriculture Household Income.*

[6] Shara Grace Astillero, Carmel B. Sabado, Maria Teresa T. Ignacio. 2016. Object-Based Urban Building Extraction Using Lidar-Derived Datasets. *International Symposium of Remote Sensing (ISRS).* ISSN 1598-6969

[7] M. Hung, and K. Germaine. 2008. Delineating Impervious Surfaces Utilizing High-Spatial Resolution Multispectral Imagery And Lidar Data. *American Society for Photogrammetry and Remote Sensing (ASPRS).* Portland, USA. 6

[8] Philippines Statistics Authority. 2016. Performance of Philippine Agriculture January To March 2016, Philippines Statistics Authority, 2016, ISSN 2012-0451

[9] Rudolph Joshua Candare, Michelle Japitana, James Earl Cubillas, and Cherry Bryan Ramirez. 2016. Mapping Of High Value Crops Through An Object-Based SVM Model Using Lidar Data And Orthophoto In Agusan Del Norte Philippines. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2016, III-7* DOI : https://doi.org/10.5194/isprs-annals-III-7-165-2016

[10] Stepane Dupuy, G. Laine, T. Tormos. 2012. OBIA for combining LiDAR and multispectral data to characterize forested areas and land cover in a tropical region. *4th International Conference on Geographic Object-Based Image Analysis (GEOBIA)*, 7 p. hal-00941801

[11] S. Luo, C. Wang, X.Xi, H. Zeng, D. Li, S. Xia and P. Wang, 2015. "Fusion of Airborne Discrete-Return LiDAR and Hyperspectral Data", *Land Cover Classification Remote Sensing* 8(1): 0003, DOI: https://doi.org/10.3390/rs8010003

[12] T. Blaschke, K. Johansen, D. Tiede, D. 2011. "Object-Based Image Analysis for Vegetation Mapping and Monitoring", *Advances in Environmental Remote Sensing: Sensors*, 2010: 241-271. DOI: https://doi.org/10.1201/b10599-13

[13] T. Blaschke, 2010 "Object Based Image Analysis For Remote Sensing", *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(91): 2-16. DOI : https://doi.org/10.1016/j.isprsjprs.2009.06.004

[14] NDRRMC (National Disaster Risk Reduction and Management Council) http://www.ndrrmc.gov.ph/ Republic Act 8435 or Philippines Agriculture and Fisheries Modernization Act of 1997 Access date: January 2013