WETLAND EXTRACTION USING RANDOM TREES CLASSIFIER ON HIGH RESOLUTION AERIAL IMAGERY AND LIDAR DATA

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ABSTRACT: Wetlands were mapped by employing the Random Trees (RT) classifier on a high resolution orthorectified digital aerial photograph (orthophoto) and LiDAR data of a 50 sq. km area of Toledo, Cebu, Philippines. The rule sets for wetland classification are developed in the eCognition Developer software. Two cases were investigated, namely; wetland extraction using (a) orthophoto and LiDAR data, and (b) LiDAR data only. The obtained producer accuracy for wetland extraction is 97% for both cases, while 91% and 81% user accuracies were obtained for cases (a) and (b), respectively. The overall Kappa values for classifying wetlands and non-wetlands in cases (a) and (b) are 0.89 and 0.78, correspondingly, indicating a reliable classification process. There are 600 wetlands extracted from (a) and 893 from (b). Only 23.5% (141) of the extracted wetlands in (a) and 17.3% (155) in (b) are actual wetlands, yielding to a percent difference of 9.9%.

1. INTRODUCTION

Both natural and human-made wetlands are significant and beneficial to the environment and society. According to Ramsar convention (Ramsar 2013), wetlands are cradles of biological diversity. They perform vital functions such as water storage, flood mitigation, and stabilization of local climate conditions. Economically, they are valuable for they supply water in fisheries and agriculture (maintaining water tables).

The Philippines has various wetlands ranging from lakes, rivers, ponds, inland and coastal marshes and swamps, estuaries, and mangrove swamps. Despite this diversity, very limited information about the wetlands can be extracted compared to forest and marine ecosystem, for only few studies have been undertaken (DENR-PAWB, 2005). In terms of their protection, there are many conflicting laws with overlaps in jurisdiction that cause confusion for many enforcement agencies. Thus, wetland degradation in terms of biodiversity loss continues to exist, directly affecting rural communities and indigenous people. Through the Philippine Biodiversity Conservation Priority-setting Program (PBCPP), which is implemented by the Protected Areas and Wildlife Bureau-Department of Environment and Natural Resources (PAWB-DENR), the Biodiversity Conservation Program of the University of the Philippines' Center for Integrative and Development Studies, and Conservation International-Philippines, priority wetland areas were identified for restoration, protection, and maintenance. (DENR-PAWB, 2005)

Wetlands occur across the range of climatic and landscape variation. An updated inventory of wetlands with accurate boundaries is essential; it would provide information necessary for decision making in terms of their protection, conservation, and restoration.

Using remote sensing data and techniques is a fast and effective method to extract wetland boundaries (Rampi *et al*., 2014, Islam *et al*., 2008, Sharma *et al*., 2012). There are two approaches to using remotely sensed data: traditional pixel-based methods, and the object-based approach. The former approach usually results in low accuracy estimates because of the existence of mixed-pixels. Though some research integrates high resolution optical and elevation data to eliminate the mixed-pixels, the limitation is on the utilized (low to medium) spatial resolution data (Baker *et al*., 2006). In contrast, the object-based approach is quite promising because it provides high accuracy estimates using high resolution data (Myint *et al*., 2011, Rampi *et al*., 2014). Mixed-pixel problems are eliminated, for it deals with homogeneous image objects - generated from image segmentation that uses pixel-based features. Furthermore, the approach has the ability to include contextual information, human knowledge, and experience to interpret the objects of interest (Rampi *et al*., 2014).

In this study, the latter approach is employed on a high resolution orthorectified digital aerial photograph and LiDAR data to extract wetlands. In addition, two cases are investigated, namely: wetland extraction using (a) orthophoto and LiDAR data, and (b) LiDAR data only. The supervised learning method employed in wetland feature extraction is a

Random Trees/Forests (RT) learning algorithm. There are a few comprehensive empirical studies comparing the learning algorithms such as using performance criteria to evaluate each learning method (Caruana and Niculescu-Mizil, 2006). According to the group of Caruana, RT ranked as second best learning algorithm. In addition, it also ranked second best in classification accuracy using an object-oriented approach (Li *et al*., 2014). It is also one of the algorithms that has the capacity to deal with contaminated information in low-quality training sets.

2. METHODOLOGY

The wetlands are mapped and automatically classified by utilizing Object-Based Image Analysis (OBIA) through the creation of rule sets in the eCognition Developer 9.0 64-bit software. A portion of Toledo with an area of 50 sq. km is used in this study as shown in Figure 2(a). Subsections in this section describe data preparation, and rule set creation and classification.

2.1 Pre-processing: Data Preparation and Image Processing

Prior to the wetland extraction process, derivatives or raster layers listed in Table 1 are prepared, where the italicized derivatives are to be computed using ArcMap of ArcGIS 10.2.2, and ENVI (Environment for Visualizing Images) softwares.

Table 1. Derivatives used in Wetland Extraction via eCognition Developer. Italicized derivatives are to be computed.

RASTER	MEANING
RGB	Red, Green, and Blue bands; orthophoto
DTM	Digital Terrain Model
DSM	Digital Surface Model
INT	Intensity
nDSM	*normalized Digital Surface Model*
SLP	*Slope of DTM (in radians)*
CURV	*Curvature of DTM*
CTI	*Compound Topographic Index*
GRVI	*Green Ratio Vegetation Index*
HSV	*Hue, Saturation, Value layers*

The *nDSM*, the difference between *DSM* and *DTM*, provides the height of each object. This is generated using the Raster Calculator tool in ArcMap. The *SLP* derivative, which contains the slope of the *DTM*, is created using the Slope tool in ArcMap. The *Curvature* raster layer which is merely the second derivative of the *DTM* surface is generated using the ArcMap Curvature tool. In this layer, we can distinguish depressed areas (with upward concavity) with defined boundaries. The *CTI* is created in ArcMap using the *SLP* and flow accumulation grid, *fac* (Arc Hydro Tools>Terrain Preprocessing>Flow Accumulation). It represents the potential distribution of water movement and accumulation across the landscape, and identifies the areas with sufficient wetness. It is computed using the expression

$$\ln\left[\frac{Fac+1}{\tan SLP}\right] \quad (1)$$

via Raster Calculator in ArcMap. The *GRVI* is generated in ENVI using Band Math tool by inputting the expression

$$\frac{float\ (Green) - float\ (Red)}{float\ (Green) + float\ (Red)} \quad (2)$$

where *Green* and *Red* are bands in the *RGB* raster. This derivative is used to distinguish wetlands from upland classes. The *HSV* derivative is created using the Transform tool in ENVI (i.e. RGB to Hue, RGB to Saturation, and RGB to Value). The *Hue* in this derivative is used in distinguishing land~~s~~ from water and other upland classes.

The *DTM*, *DSM*, *INT*, *CTI*, *SLP*, and *Curvature* rasters are chosen because of the topographic information they contain, which is useful in differentiating wetlands from other classes. If the orthophoto is unavailable, the raster inputs will be reduced to the *DTM*, *DSM*, *INT*, *nDSM*, *SLP*, *Curvature*, and *CTI*, resulting to a different classification.

2.2 Wetland Extraction: Rule Sets Creation and Classification

Figure 1 shows the work flow in extracting wetlands via the RT classifier.

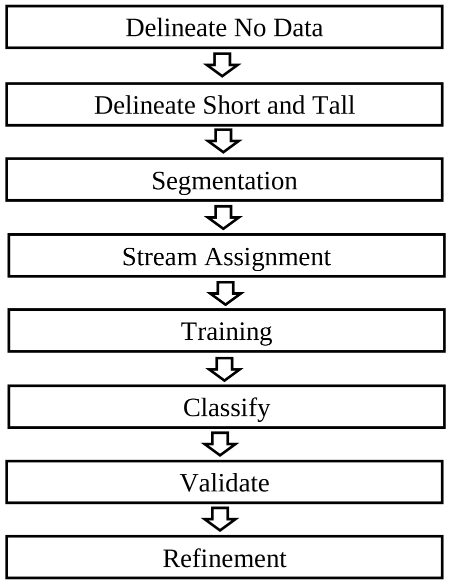

Figure 1. Flow chart for wetland extraction.

Delineate No Data
The first step is to delineate "no data" in the *DTM* via a multi-threshold segmentation algorithm with a minimum object size of 10. Pixels with a zero *DTM* value are assigned to the "no data" class, while the remaining pixels with nonzero *DTM* values are assigned as "unclassified".

Delineate Short and Tall Objects
Then, the "unclassified" pixels are grouped into "short" and "tall" classes based on a multi-threshold segmentation algorithm applied on the *nDSM* derivative. "Short" objects have height ≤ 2m while the "tall" ones have height > 2m.

Segmentation
After separating "tall" from "short" objects, the "short" objects are segmented to delineate wetlands from non-wetlands. The multi-resolution segmentation is employed on the *Curvature, CTI, DTM, INT*, and *SLP* derivatives with layer weights of 2 for *Curvature* and *CTI*, and 1 for the remaining layers. A scale parameter of 20, and homogeneity criterion of 0.3 for shape and 0.5 for compactness were used, the aforementioned parameters determined after several trial-and-error experiments.

Stream Assignment
After segmentation, the loaded stream line shapefile (as thematic layer) is used to assign the stream in the processed area by using "assign class by thematic layer" algorithm.

Training
A feature array is created that contains object features of training set[*] (for wetlands and non-wetlands) based on the statistical analysis on the layer values (mean and standard deviation), and Haralick texture features (GLCM homogeneity, entropy, and angular second moment).
In this study, two cases are investigated: wetland extraction using (a) orthophoto and LiDAR data, and (b) LiDAR data only. Thus, two feature arrays are generated with the following settings:

(a) **Layer values**. The layer features are computed from the mean and standard deviation of each derivative listed in Table 1.

[*] The number of training points in a training set for each class is 70% of the total selected points while the remaining 30% is for validation set.

Haralick Texture. The textural features are from GLCM homogeneity, entropy, and angular second moment in all directions of *Curvature, CTI, INT, GRVI*, and *nDSM* layers.

(b) **Layer values**. Similar to (a) except that *RGB, GRVI*, and *HSV* are excluded.
Haralick Texture. Similar to (a) except that *GRVI* is eliminated.

Then an RT classifier is trained based on the extracted object features from wetland and non-wetland training sets. Similarly, two RT classifiers are created and trained with respective feature arrays. Optimal parameters are used for the RT classifier which results in better classification.

Classification

The trained RT configuration is then applied to “short” objects only. Thus, the “short” objects are assigned as either wetland or non-wetland.

Validation

The classified wetlands and non-wetlands are validated internally by using the selected validation points. A confusion matrix is utilized to assess the accuracy in classifying wetlands and non-wetlands.

Refinement

The wetlands are then refined by employing the merge region algorithm to merge all the wetland segments. Then, the merged wetlands are exported to a shapefile and loaded into ArcMap. The wetlands with areas less than $50m^2$ are deleted, as well as the wetlands along the stream and in rice fields.

3. RESULTS AND DISCUSSION

Figures 2(b) and 2(c) show the extracted wetlands after applying the RT classifier on (a) orthophoto and LiDAR data, and (b) LiDAR data only, respectively. Table 2 shows a full error matrix, accuracy, and kappa estimates for wetland

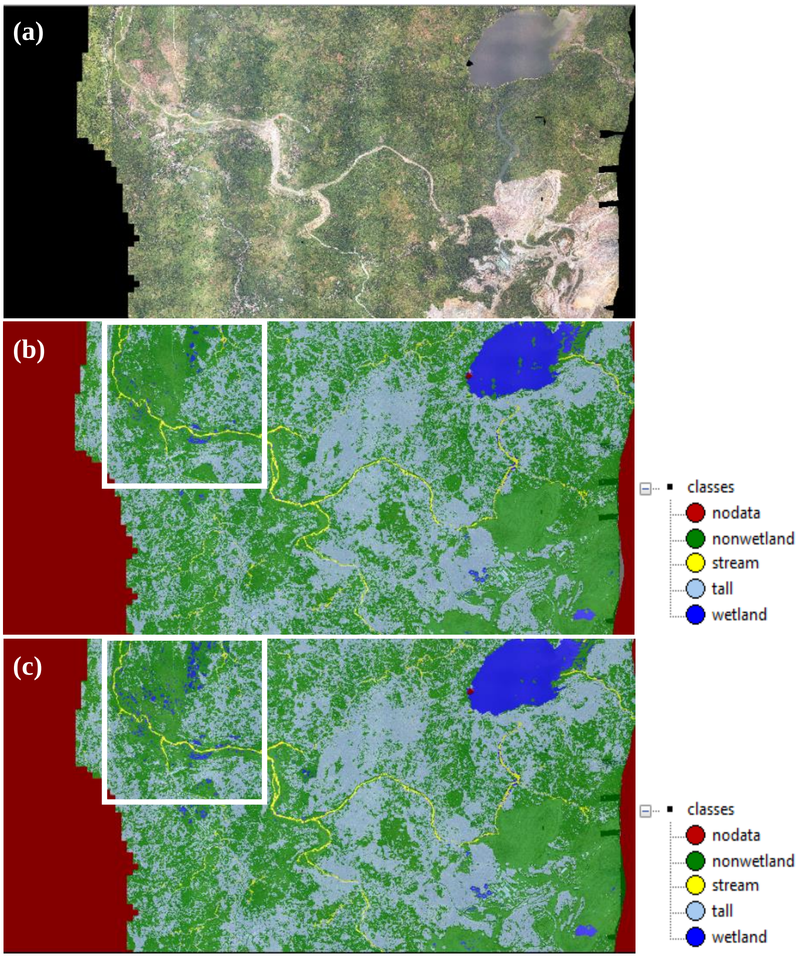

Figure 2. (a) Orthophoto (b) classified wetlands using orthophoto and LiDAR data (c) classified wetlands using LiDAR data.

and non-wetland classes. The obtained producer accuracy for wetland extraction is 97% for both cases, while 91% and 81% user accuracies were obtained for cases (a) and (b), respectively. The low user accuracy value from case (b) indicates the existence of numerous misclassified wetlands. Nevertheless, the overall Kappa values for classifying wetlands and non-wetlands in cases (a) and (b) are 0.89 and 0.78, respectively, indicating a reliable classification process.

Table 2. Full error matrix with corresponding accuracy and Cohen's Kappa for both cases (a) and (b).

Case (a). ORTHOPHOTO AND LiDAR DATA

A.1 Confusion Matrix

CLASSIFICATION \ *VALIDATION/REFERENCE*			
CLASS	**Wetland**	**Nonwetland**	**Total**
Wetland	13577	1400	**14977**
Nonwetland	386	16185	**16571**
Total	**13963**	**17585**	**31548**

Note: The indicated numbers are pixels, not object.

A.2 Accuracy

Accuracy	Wetland	Nonwetland
Producer	0.9724	0.9204
User	0.9065	0.9767
Overall	**0.9434**	

A.3 Cohen's Kappa

Kappa	Wetland	Nonwetland
Per Class	0.9474	0.8323
Overall	**0.8861**	

Case (b). LiDAR DATA

B.1 Confusion Matrix

CLASSIFICATION \ *VALIDATION/REFERENCE*			
CLASS	**Wetland**	**Nonwetland**	**Total**
Wetland	13627	3136	**16763**
Nonwetland	336	14449	**14785**
Total	**13963**	**17585**	**31548**

Note: The indicated numbers are pixels, not object.

B.2 Accuracy

Accuracy	Wetland	Nonwetland
Producer	0.9759	0.8217
User	0.8129	0.9773
Overall	**0.8899**	

B.3 Cohen's Kappa

Kappa	Wetland	Nonwetland
Per Class	0.9487	0.6644
Overall	**0.7815**	

In case (a), 600 wetlands are extracted while 893 in case (b) as seen in Table 3. It is evident in Figure 2 that more wetlands enclosed in the white box are classified in case (b) than in case (a). However, some of these extracted features are false positives. In case (a), a total of 460 wetlands are deleted in which 306 (51%) have areas less than 50 sq. m. (considered as salt and pepper), and 154 (26%) are false positives; yielding a total of 140 (23%) actual wetlands. In case (b), 738 wetlands are deleted: 274 (31%) have areas less than 50 sq. m., and 464 (52%) are false positives, leaving 155 (17%) actual wetlands. The number of actual wetlands obtained from both cases have a percent difference of 9.9%, implying that they yield similar results.

Table 3. Summary of extracted wetlands using RT classifier for each case.

Case	Extracted Wetlands	Area less than 50 sq.m.	Misclassified	Actual Wetlands
(a)	600	306	154	**140**
(b)	893	274	464	**155**

4. CONCLUSION

More objects are classified when using LiDAR data only than with the additional orthophoto. The addition of the RGB orthophoto layer results in a lower incidence of false positives.

Orthophotos are costly and not always available. Despite this, high accuracy wetland extraction is possible using LiDAR data only. The overall accuracy of 89% and Kappa value of 0.78 indicate that the classification process is reliable.

The study is limited to an area of Toledo City, Cebu, with primarily mountainous terrain. The parameters for segmentation and classification may need to be optimized for different terrain types (i.e., flood plains, urbanized areas, etc.).

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