# Potential Wetland Detection Using IfSAR-Derived Digital Elevation Model and Landsat 8 OLI Images

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**Abstract:** Wetland features, as defined by Ramsar Convention, are inundated or saturated by surface or ground water that support a prevalence of vegetation. Wetlands provide vital ecosystem services but anthropogenic disturbances such as land development, climate change and pollution threaten these resources, thus, the need to map these features. This study proposes the use of Stochastic Depression Analysis (SDA) to detect surface depressions on IfSAR-derived digital elevation models and to map surface water through image classification using Landsat 8 OLI to identify wetlands. Potential depressions are flagged by the SDA algorithm and verified if they contain water using the Normalized Difference Water Index (NDWI) computed from Landsat 8 imagery. The Normalized Difference Water Index (NDWI), which uses the reflected visible green light and near-infrared radiation, is used to detect wet areas. NDWI-derived datasets show wet areas upon achieving a set threshold but contains a lot of false positives attributed by season changes. By combining multi-temporal NDWI-derived rasters with SDA-derived depressions, wetland features can be isolated effectively. Using multi-temporal images also addressed the issues arising from cloud covers by considering the same scene on a different date. To semi-automate the process, a python script was developed to aggregate detected depressions and surface water raster datasets. Input rasters must satisfy the following criteria (SDA $\geq 6$ and NDWI $> 0$) to be considered a wetland. These values were derived from observation of some known wetlands. The final rasters demonstrated the ability of the algorithm to delineate wetlands with area $\geq 10,000 \text{ m}^2$.

Keyword: Wetlands, Stochastic Depression Analysis, NDWI, IFSAR-derived DEM, Python

## 1 INTRODUCTION

### 1.1 Background of the Study

The University of the Philippines Training Center for Applied Geodesy and Photogrammetry (UP TCAGP) is tasked to undertake a research program entitled "Nationwide Detailed Resources Assessment Using LiDAR" (Phil-LiDAR 2) funded by the Department of Science and Technology thru its Grant-in-Aid (DOST-GIA) program. The research project is monitored by the Philippine Council on Industry, Energy and Emerging Technology Research and Development (DOST-PCIEERD). One of the projects under the Phil-LiDAR 2 program is the Development of the Philippine Hydrologic Dataset for Watersheds from LiDAR Surveys (PHD) that aims to develop methodologies in extracting hydrologic features from LiDAR and other remotely-sensed data. One of the hydrologic features is the extraction of inland wetlands. Wetlands in general are areas where the environment, animals and plant life are controlled by water. The Philippines bio-geographical setting is home to wetland areas such as marshes, peatlands and swamps. These areas may be natural or artificial, permanent or temporary, with water that is static, flowing, fresh, brackish or salt. Wetlands are ecosystems that provide vital services which includes production of fishes and grains as source of food, and storage and retention of water for domestic, industrial and agricultural use. They also prove useful in natural hazard regulation by controlling flood and regulate soil erosion. They are also home to recreational and educational activities which are necessary in understanding the importance of these features. Conservation of these ecosystems is necessary to preserve biodiversity which makes inventory a significant task to manage our wetlands. [1]

In the Philippines, the Biodiversity Management Bureau-Caves, Wetlands and Other Ecosystems Division (BMB-CAWED) under the Department of Environment and Natural Resources (DENR) is the government agency tasked to establish and manage protected areas, coastal biodiversity and wetland ecosystems. In 2014, the agency published an Atlas of Inland Wetlands in Mainland Luzon which is intended to be a user-friendly reference of existing wetland features displayed in thematic and composite maps. The atlas is limited to inland wetlands in mainland Luzon but it provides an initial structure to build on a complete nationwide wetland database and mapping system. The information in the Atlas was generated from existing BMB list of wetlands, interview results, and published and unpublished literature. The location of the wetland sites were mapped using Geographic Information System. Data validation was

done through consultation workshop, coordination with concerned agencies and site visit. [2] This atlas served as the basis to determine the accuracy of the proposed method.

## 1.2 Objectives

The PHD project is tasked to develop workflows and methodologies which utilize remotely-sensed datasets that are effective in the detection of wetland features in a national scale. With this, it is the goal of this study to develop a method to extract inland wetlands using IfSAR-derived digital elevation model and Landsat 8 images. To operationalize the extraction procedures, a Python script was developed to automate the process.

## 1.3 Limitations of the Study

The definition of wetlands by Ramsar Convention were not satisfied as a whole in this study since the existing ecosystem in each detected wetland features were not considered. No actual field validation was done to determine the flora and fauna of the study area. In the study, two characteristics must be exhibited by the features to be tagged as potential wetland, these are, a.) The feature must be depressed and b.) It must contain water. Only the features with defined boundaries were considered in the study due to the limitation of the depression detection algorithm. Swamps and marshes which have no definite boundaries were not considered. The actual shape of the detected feature was not validated since existing inventories present these features as points instead of polygons. The wetland points by BMB-CAWED were the only basis in the computation of the method's accuracy.

## 1.3 Study Area

Cagayan River basin is located in the northeastern part of Luzon island and contains the largest river in the Philippines having a catchment area of 27,281 km$^2$. It is bounded by mountain ranges, the Sierra Madre in the East, Cordillera Central in the west and Caraballo-Maparang in the south. [3] Among the 109 features in Mainland Luzon, 28 are located inside the river basin boundary.
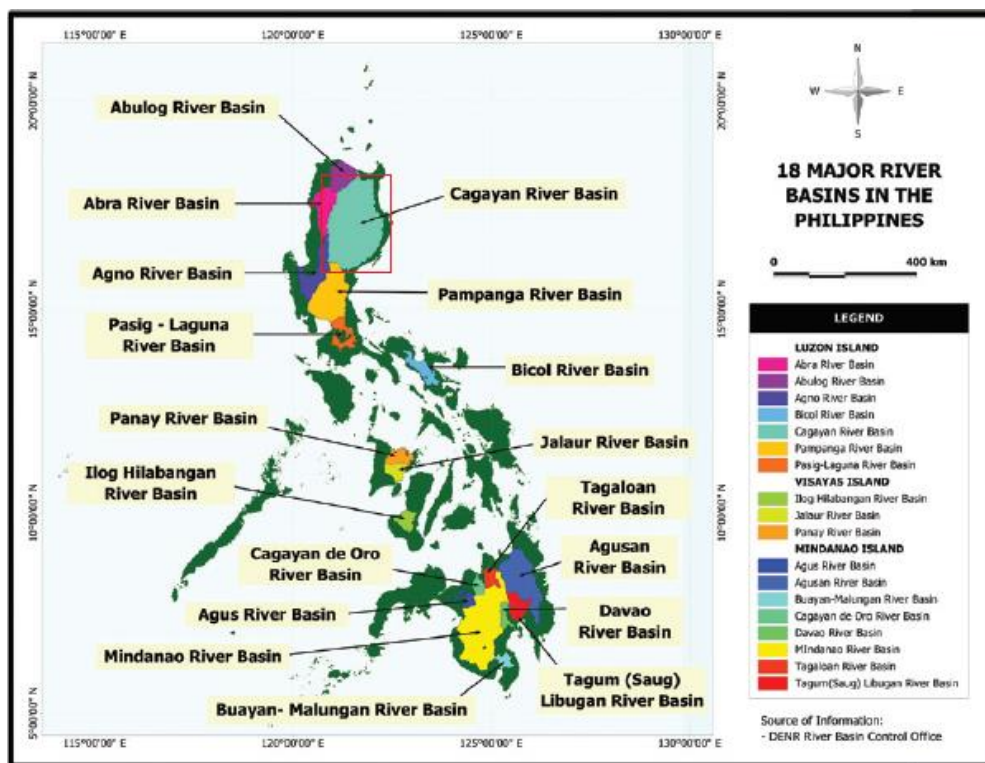


*Figure 1: Map of the 18 Major River Basins in the Philippines.*
*Source: National Wetlands Action Plan for the Philippines 2011-2016*

### 1.4 Data

### 1.4.1 IFSAR-Derived Digital Elevation Model

IfSAR or Interferometric Synthetic Aperture Radar is a new and effective approach in generating high-resolution data through the use of Digital Elevation Model (DEM) and orthorectified image. [4] Compared to other DEM generation methods, the biggest advantage of IfSAR is its weather and light independent capability. Radar remote sensing uses the wavelengths in the microwave region which passes through clouds and particles in the atmosphere. The ability to acquire data even with the presence of smoke and clouds makes IfSAR a useful tool. IfSAR signals interact with the terrain and measure distance to first surface features. It is a side-looking sensor and does not view nadir which makes the ground view of the target reduced. [5]

### 1.4.2 Landsat 8 OLI-TIRS images

Landsat 8 is the latest of the Landsat projects which continuously acquire collection of space-based moderate resolution land remote sensing data. For four decades, it provided its users who work in the field of agriculture, forestry, geology, mapping, regional planning, education and global change research remotely-sensed images which contains various information. [6] Landsat 8 satellite images the entire Earth every 16 days in an 8-day offset from Landsat 7. Landsat 8 carries two instruments: the Operational Land Imager (OLI) sensor which includes refined heritage bands along with three new bands: deep blue band for coastal/thermal aerosol studies, a shortwave infrared band for cirrus detection and a quality assessment band. The other instrument is the Thermal Infrared Sensor (TIRS) which provides two thermal bands. These sensors provide improved signal-to-noise (SNR) radiometric performance quantized over a 12-bit quantization level which translates into 4096 potential grey levels in an image compared with the 256 grey levels in 8-bit instruments. [7] This study uses multi-temporal Landsat images with less than 10 percent cloud cover taken from April 25, 2013 to July 22, 2016 that covers the study area.

### 1.5 Implemented algorithms/techniques

### 1.5.1 Stochastic Depression Analysis

Stochastic Depression Analysis (SDA) tool in Whitebox Geospatial Analysis Tools (Whitebox GAT) can be used to derive surface depressions from DEMs by mapping topographic depression, taking into account the uncertainty in depression shape resulting from DEM error. Depressions are filled using Wang and Liu depression filling algorithm and the grid cells that are affected by the filling process are flagged and entered in a cumulative grid. In this way, the probability of a grid cell belonging to a depression feature, given the uncertainty in the DEM, can be mapped using an 80% probability as the true depression. For a depression to be delineated as a real depression, it must be flagged as a depression for at least 8 out of 10 iterations. [8] However, a different probability was used in this study because it was observed that pixels inside detected depressions are more clumped if a lower probability is used, thus, it is deemed sufficient to use 60% probability making a pixel a depression if it is flagged 6 out of 10 times.



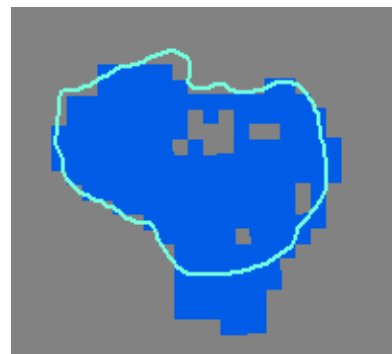*Figure 2: Detected Depression using 60% probability*



*Figure 3: Detected Depression using 80% probability*

### 1.5.2 Pre-processing of Landsat 8 Images

Landsat 8 images underwent pre-processing before the automation to convert raw digital numbers (DN) to top of atmosphere reflectance. The metadata of each Landsat tile contains the necessary corrections to be applied. The equations [9] used for conversion are shown below.

$$p\lambda' = M_p Q_{cal} + A_p \qquad (1)$$

where:

$p\lambda'$ = TOA planetary reflectance without correction for solar angle

$M_p$ = Band-specific multiplicative rescaling factor from the metadata

$A_p$ = Band-specific additive rescaling factor from the metadata

$Q_{cal}$ = Quantized and calibrated standard product pixel values (DN)

The equation for Top-of-atmosphere reflectance with a correction for the sun angle is:

$$p\lambda = \frac{p\lambda'}{\sin(\theta_{SE})} \qquad (2)$$

where:

$p\lambda$ = TOA planetary reflectance

$\theta_{SE}$ = Local sun elevation angle

### 1.5.2 Using NDWI to detect surface water

The Normalized Difference Water Index (NDWI) can be used to detect surface water features in remotely-sensed images. It uses the reflected near-infrared radiation and visible green light to enhance the presence of open water features while eliminating the presence of soil and vegetation features. [10] The equation used is shown below:

$$NDWI = \frac{Green - NIR}{Green + NIR} \qquad (3)$$

These Green and NIR bands were chosen to maximize the reflectance of water features in the green wavelength and to minimize the low reflectance of water features in the near-infrared region. It also takes advantage of the high reflectance of soil and vegetation in the NIR region to separate them from water features. Equation 3 returns a positive value when water features are encountered and negative values for soil and vegetation features. A threshold value of greater than 0 was chosen to isolate water from non-water features.

### 2 METHODOLOGY

The SDA tool from Whitebox GAT is run to produce a depression raster from the IfSAR DEM. The resulting raster file is converted into tiff format and used as input in the Python script.

### 2.1 Automation

A python script is created to automate the process of overlaying the detected depression into the Landsat 8 images. The results are stored in an array with 0 values and have the same extents as the depression raster. A similar array (scene counter array) is also created to store the number of images analyzed per pixel of the depression raster. The script utilizes the geotransform of the depression raster to extract the information from each pixel. Geotransforms are lists of information used to georeference an image (based on an affine transformation). Below is a table of the equivalent geotransform of a particular index.

*Table 1: List of geotransform and their equivalent information*

| | |
|---|---|
| *geotransform[0]* | *top left x coordinate* |
| *geotransform[1]* | *west-east pixel resolution* |
| *geotransform[2]* | *rotation along x coordinates* |
| *geotransform[3]* | *top left y coordinate* |
| *geotransform[4]* | *rotation along y coordinates* |
| *geotransform[5]* | *north-south pixel resolution* |

The script determines the location of the detected depression using Equations 4 and 5.

$$x_{map} = geotransform_{SDA}[0] + \left(x_{pix} * (geotransform_{SDA}[1])\right) + \frac{geotransform_{SDA}[1]}{2} \qquad (4)$$

$$y_{map} = geotransform_{SDA}[3] + \left(y_{pix} * (geotransform_{SDA}[5])\right) + \frac{geotransform_{SDA}[5]}{2} \qquad (5)$$

The computed map coordinates are used to locate the corresponding pixels in the Landsat tiles using the Equations 6 and 7 then convert it back to pixel coordinates.

$$x_{pix} = \frac{x_{geog} - geotransform_{Landsat}[0]}{geotransform_{Landsat}[1]} \qquad (6)$$

$$y_{pix} = \frac{y_{geog} - geotransform_{Landsat}[3]}{geotransform_{Landsat}[5]} \qquad (7)$$

The script then scans the detected depression raster and the Landsat tiles to determine which pixels satisfy the condition (SDA > 6 and NDWI > 0). For each pixel in the depression raster, a value of 1 is added into the corresponding results array element every time the conditions are satisfied. The script loops until all the Landsat images are analyzed. The scene counter array is incremented by 1 for every image analyzed regardless if a potential wetland is detected or not. The percentage of occurrence of potential wetlands is computed based on Equation 8. The resulting array is then converted into a raster image.

$$\% \, occurence = \frac{Number \ of \ wetland \ occurence}{Number \ of \ scenes \ analyzed} x \, 100 \qquad (8)$$
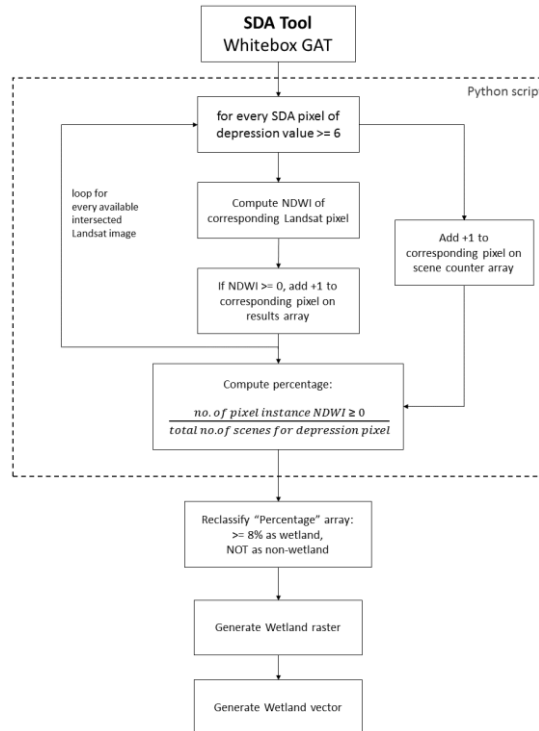


*Figure 4: Wetland Detection Flow Diagram*

## 2.2 Statistical Analysis of pixel values of the output raster

The output of the automation is a raster that contains the features that satisfied the conditions (SDA ≥ 6 & NDWI > 0). Since these values are not unique to wetlands, it can be observed that rivers, rice paddies, and other features are also detected by the algorithm.



*Figure 5: River detected by the algorithm*
*Source: Google Earth*



*Figure 6: Rice paddies detected by the*
*algorithm*
*Source: Google Earth*

From the 28 wetland features from the atlas found inside the study area, only 18 have areas greater than 10,000 square meters. The boundaries of the 18 known wetlands were digitized from a Landsat image. Six wetland features are selected as control and the remaining twelve as test areas. The percentage values generated by the algorithm that are within the controls were analyzed to determine the proper threshold for wetlands detection. It was found that pixel values greater than or equal to 8 percent comprises 99% of the control areas. The remaining pixel values are considered as noise.

## 3 RESULTS AND DISCUSSIONS

The points found in the atlas were used as the sole basis to account for the efficiency of the algorithm. The efficiency of the algorithm is based on whether or not it can detect the known wetlands. The results raster was reclassified into 1 for all the pixels with values greater than or equal to 8% and 0 for all the remaining values. Since there is a huge discrepancy in the spatial resolution of IfSAR-derived digital elevation models and Landsat 8 images, there may be

instances where the delineated features do not conform to the geometry of the digitized features. Since the primary goal of this study is to detect the existing features, it is deemed sufficient that clustered pixels that fall within the digitized boundary can be considered as a successful delineation. Among the 12 test areas, 10 satisfied the conditions which is equivalent to 83.33% success rate in detecting features.
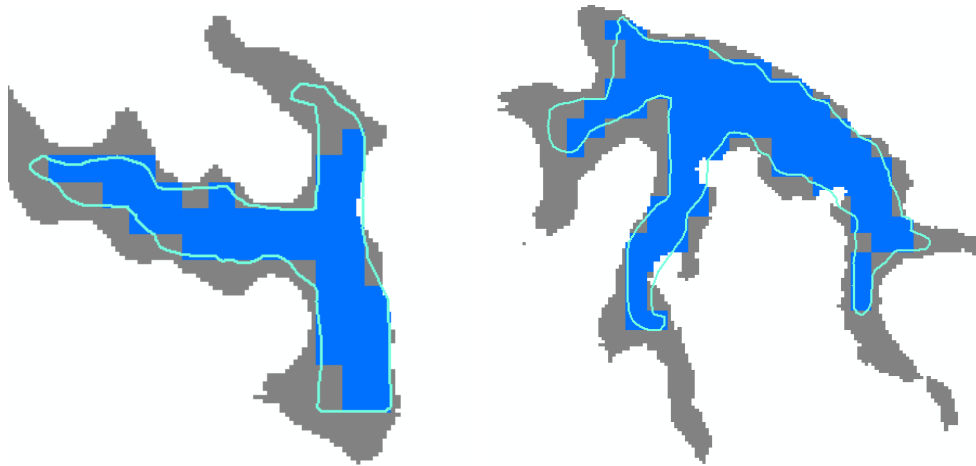


*Figure 7: Sample Delineated Outputs*

## 4 CONCLUSION

Inventory of existing wetlands is necessary in the conservation of these features. The method that was developed utilized IfSAR-derived digital elevation models and Landsat images for detecting depressions and for identifying surface water features, respectively. Using a python script allowed the use of large number of images that spans dry and wet seasons and eliminated the possibility of detecting intermittent water bodies. In the study, 83.33% of the wetland features identified by BMB-CAWED was detected by the algorithm. It was also demonstrated that wetland boundaries can be delineated based from combined IfSAR and Landsat imagery. Finally, since a python script was used to automate the aggregation process, various indices can be added to enhance the detection and improve the elimination of unwanted features. In conclusion, it was proven that using IfSAR-derived digital elevation models and Landsat 8 images are effective tools in delineating wetland features. The wetland database can be updated every 16 days due to high-temporal resolution of Landsat images which are available online. An effective inventory and timely update of the wetland database is valuable in the understanding and management of our wetlands.

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