MAPPING THE STARCH-RICH SAGO PALMS THROUGH MAXIMUM LIKELIHOOD CLASSIFICATION OF MULTI-SOURCE DATA

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ABSTRACT

An approach to map Sago palms using multi-source datasets is presented in this paper. The approach consisted of applying the Maximum Likelihood Classifier (MLC) to a stack of calibrated and co-registered ALOS AVNIR-2 image, NDVI, Envisat ASAR image, and an ASTER GDEM of the study area located in Agusan del Sur, Mindanao, Philippines. The MLC was applied to eight combinations of the ALOS AVNIR-2 reflectance bands, NDVI, Envisat ASAR and ASTER GDEM to derive classification maps. Results indicate that more than 90% overall classification accuracy and more than 90% Producer's Accuracy for Sago Palm can be both achieved if MLC is applied to any of the 8 combinations. However, the User's Accuracy for Sago palm is only 77% when using the ALOS AVNIR2 image alone as input which indicates overestimation of Sago palm classification due to high commission errors. Better User's Accuracy of 91.37% was achieved when MLC was applied to a combination of ALOS AVNIR 2, NDVI, Envisat ASAR and ASTER GDEM. With this significant increase in User's accuracy, the approach of applying MLC to a combination of these multi-source datasets shows potential in mapping Sago palms in other areas in the Philippines.

Keywords: Sago palm, ALOS-AVNIR2, Envisat ASAR, ASTER GDEM, Philippines

INTRODUCTION

Background

The Sago palm (*Metroxylon sagu*), as shown in Figure 1, has a trunk which contains starch. It is reported to be the highest starch producer at 25 tons per hectare per year (Bujang, 2008). It is now grown commercially in Malaysia, Indonesia and Papua New Guinea for production of starch and/or conversion to animal food or fuel ethanol (McClatchey et al., 2006). Because of the Sago palm's significant economic benefits, there has been keen interest by the Philippine government for its mass propagation in order to develop and sustain a large-scale sago starch industry. For this to be realized, mapping the location of existing Sago palms is necessary in order to determine current supply as well as to characterize its habitat. Once these characteristics have been identified, it is then possible to locate other areas that have the same habitat characteristics for Sago palms to grow.

Figure 1. The sago palm in clusters. Shown in (a) are mature Sago palms, while younger ones are shown in (b). The Sago palms are similar in structure to coconuts and oil palms.

Large clusters of Sago palms have been reported to exist in marshlands and other wetlands of Mindanao in southern Philippines. Confirming the locations of these clusters is not only difficult due to in-accessability; it is also expensive especially when done using conventional field mapping techniques. The use of remote sensing data and techniques is considered to be the best alternative.

Earlier attempt to map Sago palms in Mindanao through remote sensing has been done through Maximum Likelihood classification of a Landsat ETM+ image (Santilan et al., 2012). While the approach was able detect actual locations of Sago palm stands, there was an overestimation in the Sago palm classification, with both the Producer's and User's accuracies less than 85%. The low accuracy was attributed to the similarities in the spectral characteristics of Sago palms with other palm vegetation, low spatial resolution of the Landsat ETM+ image, as well as the presence of water in Sago palm stands which may have affected their reflectance values.

Multi-source land-cover classification

For a given application it is often that spectral information acquired by a remote sensing sensor may not be sufficient to derive accurate information. Incorporation of additional or ancillary data sources in the process of remote sensing classification may result in better understanding and achievement of higher accuracy than utilizing spectral data from a remote sensing sensor alone (Watanachaturaporn et al., 2008). For forested wetlands, visible and near-infrared satellite data have generally not produced adequate results because these data do not provide the sensitivity to soil moisture or to relatively small areas of inundation necessary to distinguish wetland vegetation from upland vegetation (Lang et al., 2008). Synthetic aperture radar (SAR) data has proven its utility for mapping wetland and flooded forest extents not only because of its ability to penetrate the canopy and yield information about the ground but also because it is very sensitive to moisture which is a very useful characteristic for wetland mapping (Maillard et al., 2008). The integration of SAR data with visible and near-infrared satellite data has been found to bring a significant improvement to land-cover classification (Pereira et al., 2013). On the other hand, incorporation of a digital elevation model (DEM) and a normalized differenced vegetation index (NDVI) image as additional data sources has also been found to increase classification accuracy as these datasets account for the rugged topography so as to eliminate the presence or absence of certain classes in some elevation zones, and reduce the impact of shadows and to enhance the separability among various vegetation classes (Watanachaturaporn et al., 2008).

Objective

In this paper, a multi-source classification approach of mapping Sago palms by incorporating NDVI, Envisat ASAR and ASTER GDEM datasets to an ALOS AVNIR-2 image is presented. The study aims to investigate if the addition of these external datasets, either as an individual or as combined datasets, can improve the accuracy of classifying Sago palms in an ALOS AVNIR-2 image using the Maximum Likelihood Classifier (MLC).

MATERIALS AND METHODS

The multi-source classification approach

The stacked vector approach (Watanachaturaporn et al., 2008) is adapted to incorporate multi-source data into the Maximum Likelihood (ML) classification process. It is a straightforward approach where the data from each source are treated as augmented dimensions of an input data vector. In the stacked vector approach, a dataset consisting of four bands of ALOS AVNIR-2, an NDVI, a single-date Envisat ASAR, and an ASTER GDEM can be stacked together to form the input to the MLC.

Study area and multi-source datasets

The classification approach was tested to multi-source datasets (Table 1) of an area in Agusan del Sur, Mindanao, Philippines (Figure 2). A portion of the study area is within the Agusan Marsh Wilderness Sanctuary.

The study area was chosen because of the availability of multi-source datasets as well as ground truth datasets and high resolution Worldview-2 images (Figure 3) of Sago palm clusters that can be used to extract information necessary for classifier training and accuracy assessment. The areas with confirmed Sago palms are located in the municipalities of Bunawan and Veruela, Agusan del Sur.

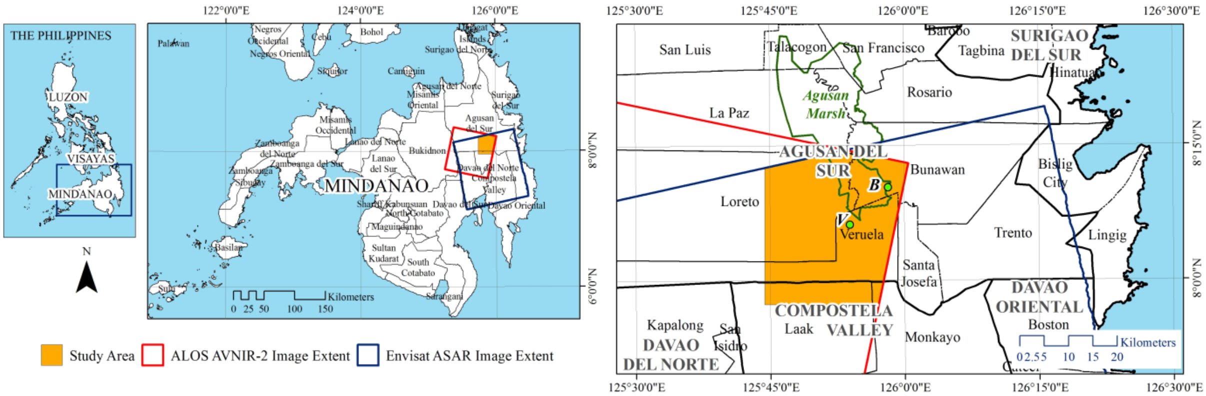

Figure 2. The study area in Agusan del Sur, Mindanao, Philippines. Points B and V are the locations of Sago palm clusters in Bunawan and Veruela municipalities, respectively.

Figure 3. Worldview-2 images acquired on 29 March 2012 showing Sago palm clusters in Bunawan and Veruela, Agusan del Sur.

Table 1. Datasets used in the multi-source classification of Sago palms.

Dataset Name	Description
ALOS AVNIR-2	Acquisition date: 14 September 2009; Level 1B (in digital numbers, DN) consisting of four bands (Blue, Green, Red and Near-infrared); Spatial resolution: 10 m. (Source: National Mapping and Resource Information Authority(NAMRIA))
NDVI	Normalized Difference Vegetation Index computed from radiometrically calibrated and atmospherically corrected ALOS AVNIR-2 bands 3 and 4 (Red and Near-infrared)
Envisat ASAR	Acquisition date: 15 November 2010; Level 1P, *C*-band (5.6 cm) SAR data acquired in image mode (IM), with HH polarization; Spatial resolution: 12.5 m. (Source: European Space Agency)
ASTER GDEM	30-m resolution elevation dataset, resampled to 10-m to conform with the resolution of ALOS AVNIR-2. (Source: NASA and METI; downloaded from http://reverb.echo.nasa.gov)

It can be noticed from Table 1 that the dates of acquisitions of the ALOS AVNIR-2 and Envisat ASAR are different, with the Envisat ASAR acquired one year later. This is because during the conduct of this study, neither of the two datasets are available that were acquired in the same dates, or even in the same months or years.

Data preparation

The raw ALOS AVNIR-2 dataset was calibrated to top-of-atmosphere radiance by applying gain and offset values. It was then subjected to atmospheric correction using the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) as implemented in the ENVI 4.8 image processing software. FLAASH creates an image of surface reflectance, scaled into signed integers with a scale factor of 10,000 (i.e., a reflectance of 0.05 or 5% is shown in the image as a pixel value of 500). The NDVI band was then computed using the FLAASH-corrected bands 3 and 4. The calibrated dataset and NDVI were then georeferenced to UTM 51 WGS 1984 using ground control points collected from 1:50,000 NAMRIA topographic maps (total RMSE < 0.5 pixel).

The Envisat ASAR IM-HH Level 1P data product was processed using the Next ESA Tool Box

(NEST) version 4C-1.1 in order to generate a radiometrically calibrated, orthorectified and normalized sigma nought (σ^0) image in linear scale and projected in UTM 51 WGS 1984. The order of the steps employed are: (1) refining the orbit state vectors in the product's metadata through application of the DORIS precise orbit file generated by the Centre for Traitement Doris Poseidon and Delft University; (2) radiometric calibration to convert the DN values (amplitude) to radar backscatter or sigma nought (σ^0) in linear scale; (3) de-speckling using the Enhanced/Refined Lee filter; (4) terrain correction using rigorous SAR simulation where a 3-arcsecond SRTM DEM was utilized; and (5) radiometric normalization. The equations used in each step and other details are available in the NEST documentation available at http://nest.array.ca/web/nest/documentation. The resulting image was then co-registered to the ALOS AVNIR-2 dataset using 9 ground control points common to both images (total RMSE < 0.5 pixel). It was necessary to re-sample (using nearest neighbor) the processed Envisat ASAR image to 10-m to be compatible with the ALOS AVNIR-2 dataset.

The ASTER GDEM was also resampled to 10-m using bilinear interpolation.

Layerstacking

Although the stacked vector approach is straightforward and easy to implement, Watanachaturaporn et al. (2008) pointed out that all data need to be normalized to bring them into the same scale especially if the approach is to be used with a parametric classifier such as the MLC. Unfortunately, in this study, normalization of the four datasets to a common scale - i.e., data stretching/shrinking such that dataset values are within a common range (e.g., 0 to 1) - seems to greatly degrade the pixel values especially for Envisat ASAR. Hence, normalization was not done and instead, a set of factors were chosen and multiplied to the NDVI (x10,000), Envisat ASAR (x10,000) and ASTER GDEM (x10). In this manner, the ranges of pixel values in these datasets are not very far from that of the calibrated ALOS AVNIR-2 dataset (which is in a scale of 10,000). After applying the scale factors, the four datasets were then stacked. The portion of the study area was extracted and used as input to the MLC. All these and subsequent processes were done in Envi 4.8. Figure 4 shows each band of the stacked datasets as well as their R-G-B combinations.

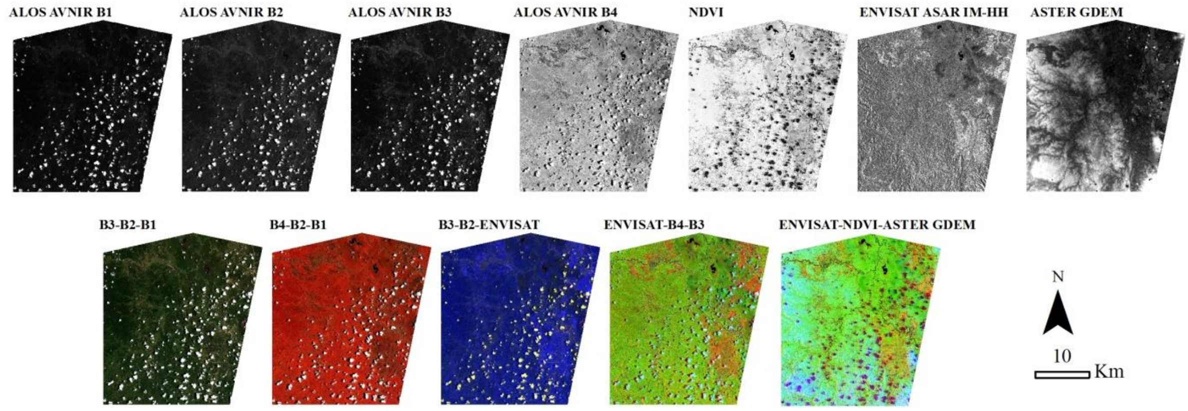

Figure 4. The 7 bands of the stacked dataset and some of their R-G-B combinations.

Maximum Likelihood Classification

Regions of interests (ROIs) of four vegetation classes namely, Sago palm, Shrubs & Trees, Marshland and Grassland, were collected in the stacked datasets for the estimation of the MLC parameters (class means and covariance matrices). The collection of this training dataset was done through image interpretation aided by information from field surveys (conducted on February-April 2012) and Worldview-2 images. For Sago palms, all the training ROIs were collected in the Bunawan area and none in the Veruela area. During ROI selection, class statistics and test for divergence (using the Jeffries-Matusita Distance) were computed as initial assessment of the statistical separability of each vegetation class according to eight combinations of the stacked datasets.

An independent validation set to be used for accuracy assessment was also collected randomly from the stacked datasets. Majority of the validation ROIs for Sago Palms were collected from the Veruela area and a few in the Bunawan area. Table 2 summarizes the training and validation sets.

Prior to classification, non-vegetation as well as cloud and shadow-covered areas were maskedout from the image by simple thresholding of the NDVI image. Only those pixels with NDVI > 0.3 were selected for classification. All results were subjected to 3x3 majority analysis to remove isolated pixels and smoothen the classification map.

Table 2. Summary of training and validation sets for ML classification.

Set	Number of Pixels			
	Sago Palms	Shrubs & Trees	Marshland	Grassland
Training	699	1,499	1,316	872
Validation	187	1,246	309	745

RESULTS AND DISCUSSION

Class statistics and separability

Figure 5 shows the mean pixel values of training ROIs of the four vegetation classes in each band of the stacked datasets. Based on this figure, all classes have almost similar mean values in Band 1 while in Band 2, only grassland is distinguishable which could be due to the fact that Grassland is the greenest among the 4 classes. In Band 3, Marshland and Grassland are slightly distinguishable from Sago palms and Shrubs & Trees. It also appears that Sago palms' reflectance is very similar to that of Shrubs & Trees in Band 3. It is in Band 4 that all classes are distinguishable from each other due to greater differences in their class mean values. In terms of NDVI, Sago palm has the highest mean value followed by Shrubs & Trees, Marshland and Grassland. There is a big difference in NDVI values between Sago palm and Grassland. Looking at the Envisat ASAR class mean values, Shrubs & Trees has the highest backscattering coefficient and is distinguishable from the other classes. The mean backscattering coefficient of Sago palm is similar to that of Marshland and Grassland. In terms of elevation with the ASTER GDEM as basis, it shows that all four classes have distinct mean elevation values. As expected, Marshland has the lowest mean elevation while Shrubs & Trees have the highest mean elevation.

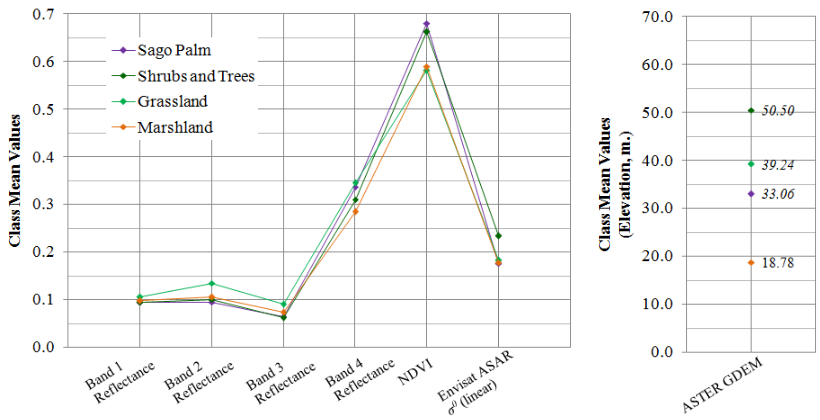

Figure 5. Class Mean Values of the four vegetation classes in each band of the ALOS AVNIR-2, NDVI, Envisat ASAR and ASTER GDEM stacked dataset. Note that the mean values are in their proper units.

This simple graphical analysis of class mean values indicates that each data, in the exception of ALOS AVNIR-2 Band 1, has valuable information that could be used to distinguish the four vegetation classes. Clearly, Band 4 and ASTER GDEM have the most important information in distinguishing each class. While this is true, it could also be inferred that the use of other datasets will improve the discrimination as there are specific bands/data where one class is more distinguishable from one or more classes.

Since it is the interest of this study to accurately classify Sago palms from other vegetation classes, it is important to have basis on the statistical separability of Sago palm from other vegetation classes. Hence, Jeffries-Matusita Distances (JMD) were computed from 8 combinations of the ALOS AVNIR-2 bands, NDVI, Envisat ASAR and ASTER GDEM. The goal here is to determine if the addition of NDVI, Envisat ASAR and ASTER GDEM to the ALOS AVNIR-2 will have an effect on the separability of Sago palm from other classes. Depending on the combination, a JMD value nearer to 2 means Sago palm is highly separable to that class it is being compared to.

The results, shown in Figure 6, strongly indicates increase in separability of Sago palm with Shrubs & Trees as NDVI, Envisat ASAR and ASTER GDEM datasets are combined to the ALOS AVNIR-2 reflectance bands. There is very low separability between the two classes if relying only on the four ALOS AVNIR-2 bands. Individual addition of NDVI, Envisat ASAR and ASTER GDEM significantly increases separability. However, greatest separability is achieved when NDVI, Envisat ASAR and ASTER GDEM are all combined with ALOS AVNIR-2 dataset. What this imply is that when only the four ALOS AVNIR-2 bands are used in classification there is greater possibility that Shrubs and Trees will be confused by the classifier as Sago palm, and vice-versa. This will lead to high commission errors and consequently overestimation in the classification of Sago palms. But with the combination of additional datasets, confusions between Sago palm and Shrubs & Trees will decrease which may indicate better classification.

On the other hand, the JMD distances of Sago Palm with Marshland and Grassland are higher than those with Shrubs & Trees in all 8 combinations. This means that Sago palms are highly separable with Marshland and Grassland regardless of the combination of the datasets. But just like in the case of Shrubs & Trees, greatest separability is achieved when NDVI, Envisat ASAR and ASTER GDEM are all combined with ALOS AVNIR-2 dataset.

At this point, it can be asserted that the use of all the stacked datasets will have better accuracy in the classification of Sago palm than using the ALOS AVNIR-2 image alone. This assertion is confirmed by the results of the ML classification as discussed in the next section.

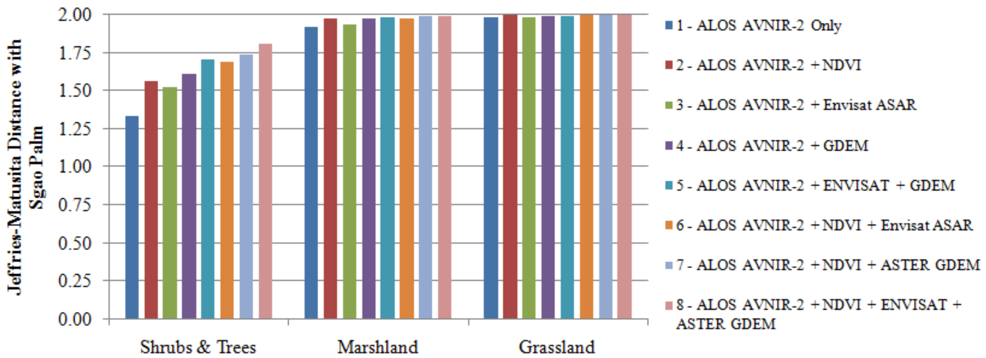

Figure 6. Separability of Sago palm with other vegetation classes based on the Jeffries-Matusita Distance that were computed from 8 combinations of the stacked datasets.

Classification results and accuracies

Figure 7 shows the results of the ML classification as applied to 8 combinations of ALOS AVNIR-2, NDVI, Envisat ASAR and ASTER GDEM. All the classifications were able to detect actual locations of Sago palms in both the Bunawan and Veruela areas. However, differences were found when accuracy of the classifications was assessed. The summary of overall classification accuracy, kappa statistic, Producer's and User's Accuracy for Sago Palm is shown in Figure 8. For convenience, the kappa statistics was plotted in percentage form.

Based on Figure 8, the use of MLC to all the 8 combinations produced more than 90% overall classification accuracies (OA). The highest OA of 96.42% was found when MLC was applied to the combination of ALOS-AVNIR2, Envisat ASAR and ASTER GDEM. When all the datasets are combined, a 95.82% OA was achieved. Lower OAs of ~92% were achieved when NDVI and ASTER GDEM are individually added to the ALOS AVNIR-2 image, as well as when both the NDVI and Envisat ASAR are added to it.

With regards to the classification of Sago Palm which is the interest of this study, all the 8 combinations produced more than 90% Producer's Accuracy which may indicate that more than 90% of all actual Sago palms in the study area has been correctly classified as such. Significant differences were found when the User's Accuracies (UA) of the classifications are taken into account. Only 77% UA was achieved when ALOS AVNIR-2 was used alone. This accuracy goes down to 69.72% when

NDVI is added. The addition of both the NDVI and Envisat ASAR also shows poor UA (70.66%). This means that for these classifications, commission errors are high and there are overestimations in Sago palm classification. When the error matrices of these classifications were examined, many Shrubs and Trees were incorrectly classified as Sago palms. However, the best result was achieved when incorporating NDVI, Envisat ASAR and ASTER GDEM datasets to the ALOS AVNIR-2 image. A UA of 91.37% for this classification results indicate low commission errors, and that overestimation in Sago palm classification is lower than when other datasets are used.

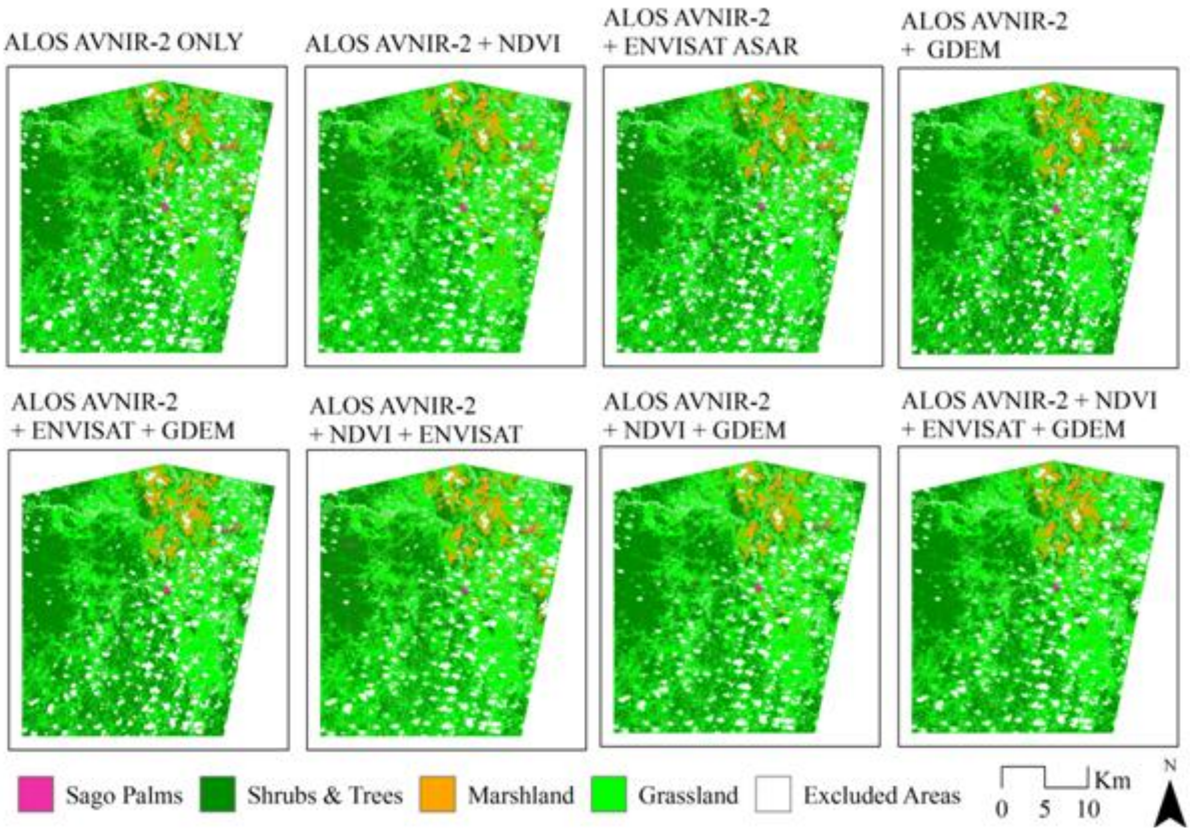

Figure 7. Results of the ML classification of 8 combinations of ALOS AVNIR-2, NDVI, Envisat ASAR and ASTER GDEM. (Due to the scale in which the above results are displayed, the classified Sago palms clusters may not be very visible especially that Sago palms in the study area are significantly fewer than other vegetation classes. Detailed classification maps can be requested from the author.)

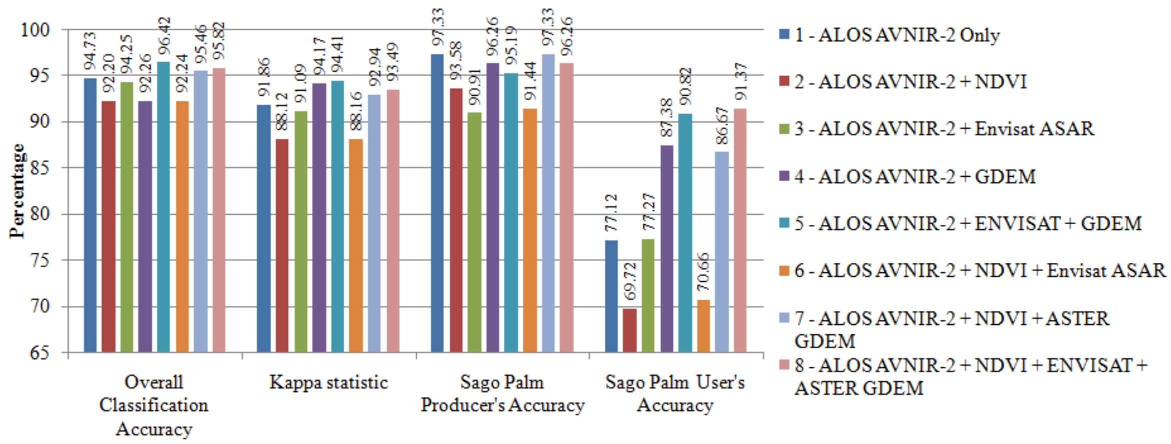

Figure 8. Summary of overall classification accuracy, kappa statistic, Producer's and User's Accuracy for Sago Palm.

Although not shown, it is also remarkable to note that the Producer's and User's Accuracy

(PA/UA) for the other vegetation classes in all the classifications are more than 85% with majority of them surpassing 90%. The lowest PA was found for Shrubs & Trees (87.56%) when the MLC was applied on the combination of ALOS AVNIR-2 and NDVI; the lowest UA was found for Marshland (88.82%) when the MLC was applied on the combination of ALOS AVNIR-2, NDVI, Envisat ASAR and ASTER GDEM.

Using the result of the classification incorporating NDVI, Envisat ASAR and ASTER GDEM datasets to the ALOS AVNIR-2 image, about 256 hectares of Sago palms were mapped in the study area.

CONCLUSION

In this paper, a multi-source classification approach of mapping Sago palms by incorporating NDVI, Envisat ASAR and ASTER GDEM datasets to an ALOS AVNIR-2 image was presented. Major results show that combination of all these datasets can improve the accuracy of classifying Sago palms using MLC. It was clearly shown by both the separability analysis and the accuracy of the classifications that in the study area, spectral information alone acquired by ALOS AVNIR-2 sensor was not sufficient to accurately map Sago palms in such a way that there is no overestimation. With significant increase in User’s accuracy, the procedure of applying MLC to a combination of these multi-source datasets shows potential in mapping Sago palms in other areas in the Philippines. For further studies, it is worth establishing the physical basis on the contribution of the *C*-band Envisat ASAR IM data and ASTER GDEM in the significant increase of User's Accuracy of Sago Palm when these datasets were combined with ALOS AVNIR-2 and NDVI.

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