MAPPING OF FOREST COVER EXTENT AND CHANGE IN THE PHILIPPINES USING DECISION TREE CLASSIFICATION ON ALOS-1/2 PALSAR-1/2 MOSAIC DATA

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ABSTRACT: The forest cover and change mapping methodology developed for the project “Reducing emissions from deforestation and forest degradation” (REDD) required manual processing of radar data and thus was very time and labor intensive. This methodology was enhanced to include advances and updates in data pre-processing such as use of multi-temporal speckle filtering, newer and better classification techniques like the decision tree classifier and latest practices on accuracy assessment like unbiased area estimation. Pre-processing steps were automated through Python scripts to speed up data processing and make the methodology easily replicable at the provincial, regional and/or national scale. To further allow the approach to be reproducible, the freely available 25-meter slope-corrected mosaic radar data from Daichi-1/2, also known as Advanced Land Observation Satellite (ALOS-1/2), acquired using the Phased Array type L-band Synthetic Aperture Radar (PALSAR-1/2) was utilized. Forest cover maps of the three field sites for 2007, 2010 and 2015, as well as the forest cover change maps from 2010 to 2015 were produced using decision tree classifiers (DTC). The thresholds used for the decision tree to map forest extent in the field sites worked best for the radar images of the site in Mindanao (Davao Oriental), which achieved unbiased measures of accuracy using Olofsson’s accuracy assessment techniques of at least 89% for all classes mapped. The forest cover maps for the sites in Luzon (Albay) and Visayas (Eastern Samar) over-estimated the actual forest cover, although the unbiased area estimation allows uncertainties to fall below 10%. The change map for Mindanao (Davao Oriental) achieved unbiased accuracy measures of at least 91% for stable forests and non-forest classes, while the deforestation class only had an accuracy of 50%. Better thresholds have to be re-identified to improve forest cover change mapping. The improved methodology has produced accurate results for forest cover mapping and thus can be applied to other sites in the Philippines, but unbiased areas estimation would have to be used to achieve error-adjusted estimates.

1. INTRODUCTION

1.1 Project Purpose and Relevance

The main purpose of the research was to improve a forest cover mapping methodology developed during the third phase of the Kyoto and Carbon Initiative (KC) Phase 3, and prepare it for up-scaling (Estomata, 2014a-b). This was part of the project “Reducing emissions from deforestation and forest degradation” (REDD) (GIZ, n.d.-a; DENR-FMB, 2016b). Under the KC Phase 4, the Earth Observation Research Center (EORC) of the Japan Aerospace Exploration Agency (JAXA) provided the ALOS-1/2 PALSAR-1/2 images (JAXA-EORC, n.d.) that were used to map forest cover and change in the three study sites of the National REDD+ System Philippines project (GIZ, n.d.-b).

A robust and replicable forest cover and change methodology will be valuable to the Philippines in order to contribute to two Cancun Agreements prerequisites: 1) the Forest Reference Emission Level and/or Forest Reference Level (FREL/FRL), and 2) the National Forest Monitoring System (NFMS) (UNFCCC, 2008). An NFMS concept note has been prepared for the Philippines and discusses data, methods and services needed to operationalize national level forest monitoring and reporting of REDD+ activities (Seifert-Granzin, 2015). According to UNFCCC (2009, Decision 4/CP.15), developing countries should utilize both remote sensing and ground-based forest carbon inventory to calculate forest-related greenhouse gas (GHG) emissions and removals and to identify changes in forest carbon stocks and forest areas.

1.2 Study Area

To represent the three regional areas of the Philippines, municipalities in the province of Albay in Luzon, Eastern Samar in Visayas and Davao Oriental in Mindanao were selected as study sites (Seifert-Granzin, 2014; DENR-FMB, 2016a). Table 1 provides the total land area of the provinces and the municipalities selected as study sites. Figure 1 shows the location of the study sites in the Philippines relative to the other South East Asian countries.

Table 1, Total Land Area Information Of The Three Study Sites

Province / Area (km^2)	Albay	Eastern Samar	Davao Oriental
Province	2,575.77	4,660.47	5,679.64
REDD+ site	498.09	799.03	1,278.28

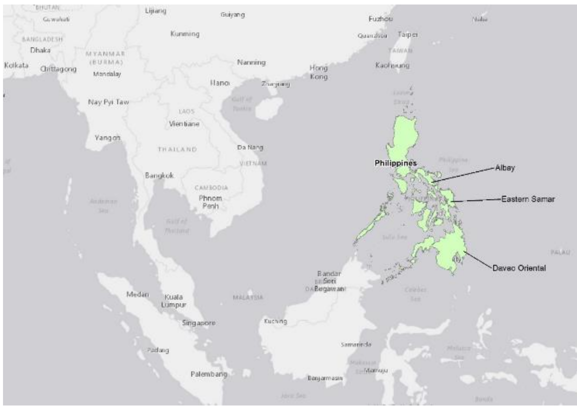

Figure 1. REDD+ study sites © Open Street Map, ESRI

2. DATA

2.1 Satellite Data

The satellite data used in this work was the radar data acquired by JAXA's PALSAR-1/2 sensors on board the satellite ALOS-1/2. The European Space Agency's Sentinel C-band data were not used because a baseline forest cover map for 2010 was needed in this research, and ESA's satellite was launched only in 2014 (ESA, n.d.-a). The 25-meter slope-corrected mosaic products from EORC were utilized in this research instead of the standard products so that the data used in this research is freely available.

The Philippines is covered by 93 25-meter mosaic scenes (longitude: 116–126 East, latitude: 5–21 North) and each study site is covered by one mosaic scene (1x1 degree tile). Figure 2 shows the mosaic scenes covering majority of the province of Albay (Figure 2a), the mosaic scenes partly covering the provinces of Eastern Samar (Figure 2b) and Davao Oriental (Figure 2c). The acquisition dates of the radar images from 2007 were between June to July, for 2010 between July to September and in 2015 between June to October.

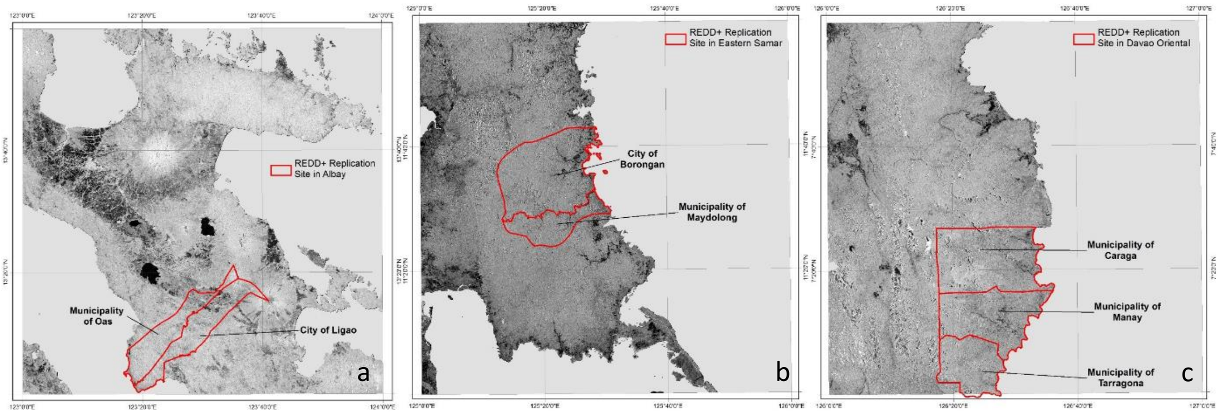

Figure 2 (a-c) The 2015 ALOS PALSAR HV Mosaic Scene (© JAXA) Covering The Study Site In The Provinces Of Albay [Scene ID: N14 E123] (a), Eastern Samar [Scene ID: 12 E125] (b) And Davao Oriental [Scene ID: N08 E126] (c).

2.2 Secondary Data

Secondary data used for this research were the satellite images from the Landsat archive, data from Google Earth (GE), 2010 land cover (LC) map of the Philippines from the National Mapping and Resource Information Authority (NAMRIA) and field data from the Forest Resources Assessment (FRA) of the National REDD+ System Philippines project (Lennertz, 2016a-b). These additional data were needed for the following purposes:

1) Landsat data were used as reference images to georeference all available radar data,
2) 2010 LC Maps were utilized to generate a sampling design for the three study sites,
3) Field data from the FRA were used as forest samples for the analysis, and
4) Google Earth images were used to verify the actual land cover as compared to the 2010 LC Maps from NAMRIA and the field data from the FRA.

The 2015 land cover map of the Philippines, also generated by NAMRIA, was not yet available during this research.

Landsat

The Landsat datasets were downloaded from the United States Geological Survey's (USGS) Earth Explorer web tool (USGS, n.d.). The path and row information of the Landsat data downloaded for each site were as follows: Albay (114, 051), Davao Oriental (111, 055) and Eastern Samar (113, 052).

Land Cover Map

NAMRIA generated the 2010 LC map of the Philippines, which initially had 21 land cover classes aggregated into 14 classes: closed forest, open forest, shrubs, fallow, mangrove forest, marshland/swamp, fishpond, inland water, wooded grassland, grassland, annual and perennial crop, built up, and open/barren land. 116 ALOS Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) scenes, 40 Satellite Pour l'Observation de la Terre (SPOT) 5 scenes, and 29 Landsat-7 scenes were visually interpreted to generate the land cover map. According to NAMRIA, ground validation was implemented to assess the accuracy of the LC map (Santos et al., 2014).

Forest Resources Assessment

A forest resources assessment was conducted under the REDD+ project by the Deutsche Forstservice (DfS) GmbH. The reports contain the methodology of the FRA (Lennertz et al., 2017) and the results of the FRA in Davao Oriental (Lennertz, 2016a) and Eastern Samar (Lennertz, 2016b). 120 Sampling Units (SUs) were available for Eastern Samar while 81 SUs were available for Davao Oriental. The configuration of the SUs implemented on the field are discussed in the FRA report (Lennertz et al., 2017). A lot of information is contained in the FRAs but for this research, only the location of the sampling units and its land cover data were utilized. All plots were also compared with Google Earth images to check consistency and identify recent land cover changes.

3. METHODS

3.1 KC Phase 3 Methodology

ALOS PALSAR 25-meter mosaic data from JAXA were used for the KC Phase 3 methodology. A big portion of the processing required the commercial image processing software Environment for Visualizing Images (ENVI) (Estomata, 2014a-b). The study site was Leyte Island and this required mosaicking of 6 scenes then georeferencing them to a Landsat image. Other pre-processing was implemented such as land/sea masking, elimination of radar effects and speckle filtering using a 3x3 Lee filter. HH and HV bands were converted into radar-cross section values and 5 additional indices/ratios were calculated. Google Earth was the source of training and accuracy assessment samples, that had to be at least 4 hectares in area. A sampling scheme and design could not be employed because this depended heavily on the availability of Google Earth images. Since the goal of the research work in KC 3 was also to separate coconut palm from forest areas, the aim was to classify 3 classes – forest, non-forest and coconut palm. Three supervised classification algorithms were tested, and the Neural Network classification achieved the best results for the post-classified 2007 and 2010 forest cover maps of Leyte Island. Lastly, the 2007 and 2010 maps were used to detect changes in land cover classes through a post-classification change detection. The final change map was not assessed for its accuracy, while the forest cover map was assessed, and an error matrix was calculated.

3.2 KC Phase 4 methodology

The KC Phase 4 methodology follows the same approach implemented during KC Phase 3, but with some major modifications to improve the results of the analysis and incorporate advances in techniques for data pre-processing, classification and accuracy assessment based on the Methods and Guidance (MGD) (GFOI, 2016; GOFC-GOLD, 2016). Some of the major differences were the following:

1) a multi-temporal speckle filtering (MTSF) technique was applied;
2) a sampling scheme in selecting training and accuracy assessment samples was used;
3) the classification algorithm was tested;
4) the application of an unbiased area estimation; and
5) the direct classification for change analysis.

3.2.1 Data preparation and pre-processing

The mosaic images were downloaded from the JAXA-EORC website (JAXA, n.d.) as compressed folders ('.tar.gz'). Each study site was covered by one radar mosaic tile, therefore tile mosaicking was not necessary. The data preparation and pre-processing, excluding the speckle filtering and image registration, was automated using Python scripts and RSGISLib (Bunting et al., 2014).

Multi-Temporal Speckle Filtering

Multi-temporal SAR speckle filtering produces speckle filtered images with minimal radiometric accuracy loss and spatial resolution (Quegan et al., 2000 and 2001; Trouvé et al., 2003). For the process to be successful, input data/images must be perfectly georeferenced/geocoded, which was ensured for all the radar data used in this study. Images for the same area, taken at different dates were needed for the process and JAXA's L-band data provides images from 1996, 2007-2010 and 2015-2016. The process was implemented using the Sentinel Application Platform (SNAP) tool from the European Space Agency (ESA, n.d.-b).

Radar cross-section and additional ratio calculations

Digital Number (DN) amplitude values of the polarization bands (HH and HV) of the ALOS PALSAR data were converted to decibel (dB) values through the radar cross-section calculation and as provided by JAXA, the calibration factor (CF) for both ALOS-1/2 PALSAR-1/2 is -83.0 dB (JAXA-EORC, 2012; Rosenqvist, 2016). Additional ratios/indices were calculated from the original HH and HV bands as it was observed to aid in improving the class separability in the previous study (Estomata, 2014a-b) and was also expected to do the same for this study. It was observed in this study that the Normalized Difference Index (NDI), also known as the forest degradation index (RFDI) (Almeida-Filho et al., 2010), provided additional separability of classes compared with the NL ratio of Li et al. (2012).

Mask Band

The radar effects mask that accompanied the polarization bands were utilized to mask out pixels of the polarization bands that had radar effects (Rosenqvist, 2016).

Image to Image Registration

All features on the radar mosaic datasets geocoded by JAXA had an offset of 100 meters compared with same features found on Landsat images. Therefore, the pre-processed radar mosaic data had to be georeferenced to the respective 30-meter Landsat data. At least 10 well-distributed ground control points (GCPs) were selected for each site, and a root mean square error (RMSE) of less than 0.45 was achieved for the radar datasets of Albay and at least 0.35 for the radar images of Davao Oriental and Easter Samar.

3.2.2 Sampling Scheme and Selection

Classes to be sampled

The 14 classes of the 2010 LC map of NAMRIA were aggregated into the 6 Intergovernmental Panel on Climate Change (IPCC) classes (IPCC, 2003; Santos, 2014). An additional class of "coconut palm" was also included, to assist with separately classifying coconut palm and forest areas. Since the class "other land" was not found in all sites, only 6 classes had to be identified namely forestland, wetland, grassland, cropland, settlements and coconut palm. A sampling scheme was implemented, and all samples taken from the land cover map were cross-checked on Google Earth to check for consistency. The normalized Jeffreys-Matusita distance/ROI separability of coconut palm, cropland and grassland were very low, therefore the classes were aggregated into a single "non-forest" class (Richards et al., 2006). The thresholds for the decision tree classifier were then developed to identify only four classes – forestland, wetland, non-forest and settlements. After the images were classified, the classes were aggregated into forest and non-forest.

Forest training samples (from FRA)

The samples of "forestland" from the 2010 NAMRIA LC map for Davao Oriental and Eastern Samar were replaced by the more updated (~2014-2016) forest cover information from the FRA. 50 plots were used for training, and the rest were used for accuracy assessment. The FRA plots were also cross-checked with Google Earth as the fieldwork was conducted between December 2014 and March 2016, which differed from acquisition dates of the 2015 PALSAR images (July and October 2015). Google Earth did not have any available images for the forests of Eastern Samar. Therefore, the 50 training samples from the FRA of Eastern Samar could not be cross-checked and were rather assumed to be correct and consistent with the reality on the ground. However, Google Earth images were abundant for Davao Oriental and the FRA samples were checked for consistency. Out of the 81 FRA samples, only 61 were consistent with the images in Google Earth. The training samples for Davao Oriental were expanded and composed of 6 to 9 PALSAR pixels that corresponded to the location of the FRA samples.

Sampling for Accuracy Assessment

Cochran's (1977) equation for a stratified random sampling was used to get the total sample size for the accuracy assessment. Olofsson's (2014) technique was also implemented to obtain information on the confidence interval/uncertainties of estimates and for this research the following assumptions were provided for all the forest cover maps: 1) there will be 20 errors of omission of forest in non-forest per 100 units, 2) user's accuracy for forest will be 90%; and 3) the target standard error for the forest estimate is 2.5% (at 95% confidence interval (CI)). The total number of samples varied depending on the area classified as forest and non-forest in each of the study sites. It required around 230 samples for Albay, 200 samples for Davao Oriental and 170 for Eastern Samar. The major limitations to achieve the minimum number of forest samples were: a) the limited number of FRA data left for Davao Oriental and Eastern Samar because other FRA data were used as training samples; and b) limited availability of satellite images and/or aerial photos that clearly showed forest areas in Albay and Eastern Samar.

Accuracy Assessment Samples

The accuracy assessment samples for the forest cover maps were simplified to two classes: forest and non-forest where the latter was composed of cropland, coconut palm, grassland, settlement and wetland areas. At least 50 forest samples and 130 non-forests samples were obtained for Albay and used for accuracy assessment. Due to the abundance of Google Earth data in non-forest areas, 130 samples were collected for Davao Oriental and more than 200 were available for Eastern Samar. No Google Earth images were available for the forests of Easter Samar, therefore the 77 accuracy assessment samples from the FRA could not be verified using Google Earth and were instead assumed to be correct. 50 of the 61 FRA samples in Davao Oriental, that were consistent with Google Earth, were used to train the decision tree classifier. This leaves only 11 unused samples for accuracy assessment of the forest cover maps for Davao Oriental. To obtain more samples for accuracy assessment based on the FRA, 42 of the 50 samples used for training were expanded from 6-9 PALSAR pixels to 81 PALSAR pixels. The training samples of forest cover covered 28 hectares of forest while the accuracy assessment samples covered 125 hectares.

3.2.3 Threshold Identification

Severe under estimation of forests was observed when the thresholds for PALSAR-1 images were used to classify PALSAR-2 images, therefore two sets of thresholds were identified. A script that utilizes the "tree" package of the R statistical software used zonal statistics to automatically calculate the thresholds for the decision trees (Breiman et al., 1984; Ripley, 2015; R Core Team, 2015).

3.2.4 Decision Tree Classification

Knowledge-based decision tree classifiers have been used successfully to classify remote sensing data (Michaelsen et al., 1994; Reiche et al., 2013) and have outperformed other supervised classification algorithms and other linear discriminant function classifiers (Friedl et al., 1997). The classifier does not heavily rely on the distribution of input data (Friedl et al., 1997), which is the case in this study, where some training classes had limited samples available. The classifier is also able to specify clear rules that are required to distinguish classes (Simard et al., 2000). A multi-level hierarchy classification was implemented such that each pixel was initially classified as wetland/flooded crop or land. Pixels classified as land are then further disaggregated as settlement/bare soil or vegetation and the vegetation pixels are further identified as forest or non-forest (Estomata, 2018a). Post-classification steps were implemented until only two classes were left – forest and non-forest, excluding all radar-effects and isolated pixels.

3.2.5 Accuracy Assessment and Unbiased Area Estimation

As recommended by the MGD (GFOI, 2016; GOFC-GOLD, 2016), unbiased area estimation was implemented, and the process used was based on Olofsson et al. (2013 and 2014). Figures in the error matrices and the areas of each class, were used in the unbiased area estimation to obtain error-adjusted estimates of classes, with uncertainties at 95% CI.

3.2.6 Direct Classification of Change

Google Earth had limited data available for year 2007 for all three sites. Therefore, the focus of the direct classification was for the years 2010 and 2015. The backscatter values of each band (DN) of the 2015 radar images are subtracted from the respective bands of the 2010 radar images. This is referred to here as "difference change index" (DCI) (Reiche et al., 2013).

Deforestation Samples

Deforestation samples were identified from 2010 and 2015 Google Earth images. The images used ideally matched the acquisition dates of the radar images used (JAXA-EORC, 2012). Davao Oriental had sufficient Google Earth images that matched the acquisition dates of the radar imageries in both 2010 and 2015. Due to this, deforestation sample collection and analysis were only carried out for Davao Oriental. After a deforestation sample was identified from Google Earth, it was compared to the DCI image for the HV band (HV-DCI). A sample was at least 1 PALSAR pixel and the largest was 21 pixels. For the samples of the stable forests, the FRA data were used.

Analysis for the forest cover change classification and post-classification

To directly classify forest cover change on the radar images of Davao Oriental, samples of deforestation and stable forests were analysed through separability and zonal statistics. The acquisition dates of the radar images of Davao Oriental matched some of the images in Google Earth but finding enough deforestation samples to improve its separability from the stable forest class was difficult. In this study, the separability of the two classes for HV-DCI was only 1.45, while in Reiche et al.'s work (2013), they were able to achieve 1.98, which could be because they used the standard product instead of the mosaic dataset. Reiche et al. (2013) was able to identify a threshold of 2.2 dB, while in this study, the threshold for HV-DCI was 2.0 dB. This means that all change pixels with values greater than 2.0 dB were classified as deforestation, otherwise, as stable forests. To ensure that only deforestation within the forested areas of 2010 was accounted for in the analysis, post-classification processes were carried out.

3.2.7 Accuracy Assessment and Unbiased Area Estimation

The change maps had three classes: stable forest, non-forest and deforestation. The following assumptions (Olofsson et al., 2014) were provided for all change maps to determine the required total sample size for accuracy assessment: 1) there will be 1 error of omission of deforestation in non-forest and stable forest classes per 100 units, 2) user's accuracy for deforestation will be 80%; and 3) the target standard error for the deforestation estimate is 1% (at 95% CI). If deforestation samples are available for accuracy assessment, an error matrix and UAE may be applied on the change maps derived. Since deforestation samples were available for Davao Oriental, accuracy assessment and UAE could be implemented for the change maps of this study site.

4. RESULTS AND DISCUSSION

4.1 Forest Cover Maps

Table 2 provides the computed forest areas based on the forest cover maps (second column) and the corrected or 'unbiased forest areas' (third column) within a 95% CI. The fourth column shows the difference of the computed forest areas to the unbiased forest areas and shows that there is high over estimation of forest areas for the maps of Albay and Easter Samar (difference of more than 15%), while for the maps of Davao Oriental, the difference was below 4%.

Table 2, Results For Municipalities Of The Three Study Sites

Study Area Year	Computed Forest Area (ha) [A]	Unbiased Forest Area (ha) [B] ± 95% CI	Difference (%) [(A-B)/B]
2007	8,608	11,149 ± 12%	23
2010	16,076	12,188 ± 8%	32
2015	14,326	11,565 ± 8%	24
2007	63,696	55,271 ± 2%	15
2010	64,898	55,149 ± 2%	18
2015	65,869	52,522 ± 2%	25
2007	64,243	64,808 ± 1%	0.87
2010	69,020	66,516 ± 1%	4
2015	62,587	64,840 ± 2%	3

The forest area based on the maps of Albay had an unrealistic trend of doubling in area from 2007 to 2010. The unbiased estimates provide a more realistic trend of forest areas of 11,200 ha in 2007, an increase by 1,000 ha in 2010 and then back to 11,600 ha in 2015. The forest cover of the map of Eastern Samar was initially increasing from 63,700 ha to 65,900 ha. A consistent decrease in forest cover was observed after UAE with forests covering an area of 55,300 ha in 2007 and decreasing to 52,500 ha by 2015. The forest area estimates had 2% uncertainties. The map for Davao Oriental reflected corrected forest area estimates with 1-2% uncertainty. The forest area started at 64,800 ha in 2007, increase by 1,700 ha in 2010 and then back to 64,800 ha in 2015.

4.2 Accuracy of the Forest Cover Maps

The measures of accuracies (overall, producer's and user's accuracies) for the forest cover maps of Davao Oriental were observed to be better than the maps for the other two study areas (Table 3). This suggests that the thresholds used for the decision tree classifiers for both ALOS-1/2 PALSAR-1/2 worked better for the radar images of Davao Oriental than for Eastern Samar and Albay. The UAE procedure also computed unbiased overall and producer's accuracies for all classes. Table 3 shows the originally calculated accuracies followed by the unbiased accuracies. The user's accuracy did not change despite applying UAE.

Table 3, Measures Of Accuracies Of The Study Areas For Each Year

Study Area and Year		Classification Map			Forest Class				Non-forest Class			
		Overall Accuracy (%)			Producer's Accuracy (%)			User's Accuracy (%)	Producer's Accuracy (%)			User's Accuracy (%)
		Original [A]	Unbiased [B]	Difference [B-A]	Original [C]	Unbiased [D]	Difference [D-C]		Original [E]	Unbiased [F]	Difference [F-E]	
Albay	2007	86.37	87.43	1.06	70.66	60.74	-9.92	78.67	92.31	95.20	2.89	89.28
	2010	89.98	91.09	1.11	98.20	97.88	-0.32	74.21	86.88	88.86	1.98	99.22
	2015	90.97	92.29	1.32	96.41	95.42	-0.99	77.03	88.91	91.33	2.42	98.50
Eastern Samar	2007	89.97	87.80	-2.17	96.65	98.83	2.18	85.76	82.95	62.73	-20.22	95.95
	2010	89.74	86.83	-2.91	98.02	99.34	1.32	84.41	81.07	58.64	-22.43	97.51
	2015	86.35	82.71	-3.64	98.94	99.62	0.68	79.43	73.19	49.90	-23.29	98.50
Davao Oriental	2007	95.04	95.17	0.13	96.75	96.57	-0.18	93.88	93.27	93.80	0.53	96.52
	2010	93.83	93.93	0.10	98.95	98.90	-0.05	89.93	88.53	88.98	0.45	98.79
	2015	95.19	95.35	0.16	96.08	95.77	-0.31	94.82	94.26	94.95	0.69	95.88

Table 4, Accuracy Measures Of Forest Cover Classifications From Various Studies In The Philippines

Province	Albay	Davao Oriental	Eastern Samar	Southern Leyte	Sibuyan	Palawan	Southern Leyte	
Dataset used	ALOS PALSAR 25-meter Mosaic Data						FBD [a]	PLR [b]
Classification method	Decision Tree			Neural Network	Support Vector Machine (SVM)		Wishart	SVM
2007 Overall Accuracy (%)		95.04	89.97	83.96	90.70	87.28		
PA [c] Forest		96.75	96.65	91.83	99.54	96.77		
Non-forest		93.27	82.95	87.17	67.07	76.79		
Coconut palm		-	-	72.71	-	-		
2010 Overall Accuracy (%)	86.37	93.83	89.74	89.45	89.33	91.60	70.0	86.0
PA [c] Forest	98.20	98.95	98.02	90.98	94.95	96.83	61.0	84.3
Non-forest	86.88	88.53	81.07	89.32	74.39	85.71	-	-
Coconut palm		-		88.04			62.7	79.1
Built-up							85.3	95.8
Agriculture							82.6	82.5
Grassland							40.0	76.8
Water							86.1	98.9

[a] ALOS PALSAR Level 1.1 Fine Beam Dual Mode (HH & HV)
[b] ALOS PALSAR Level 1.1 Polarimetric mode (HH, HV, VH, VV)
[c] Producer's Accuracy

The forest cover maps of Albay achieved unbiased overall accuracies of at least 90%, except for the 2007 map. The unbiased producer's accuracies of the forest class in the 2010 and 2015 maps were at least 95% while for 2007, it was only 60%. Again, this could be due to the observed "diagonal lines" in the 2007 ALOS PALSAR 25-meter mosaic image of Albay. Although the forest class' unbiased producer's accuracies were relatively high, the user's accuracies were only around 75%, which suggests that the class has been 'over-mapped'. This also means that a high error of commission was achieved (Rossiter, 2014).

The overall accuracies of the forest cover maps of Easter Samar decreased by 2-4% after UAE was applied. The non-forest class achieved low unbiased producer's accuracies (50-60%), which means that a large area of non-forest on ground was classified as forest on the map.

The unbiased overall accuracy of the 2015 maps were as follows: 82% for Easter Samar, 92% for Albay and 95% for Davao Oriental. And only the forest cover maps of Davao Oriental achieved producer's and user's accuracies for both forest and non-forest classes of at least 89%.

Various studies have applied different forest cover classification methods using ALOS PALSAR data in the Philippines (Estomata, 2014a-b; De Alban, et al., 2015; Monzon, et al., 2015; Tumaneng et al., 2015). Table 4 shows the performance of these methods and, if only the results of the 2010 map for Davao Oriental (complete error matrices in Estomata, 2018a) are compared to the results of the 2010 map of Southern Leyte (mosaic data) and Palawan, it suggests that the methodology applied in this work may slightly improve the results of the forest cover classification using ALOS PALSAR. The last two columns of Table 4 show how Level 1.1 FBD and PLR ALOS PALSAR data can perform if more classes need to be identified (Monzon et al., 2015).

4.3 Forest Cover Change Map

Direct classification of change for all the three sites was implemented using decision tree classification. Table 5 shows the gross deforestation as calculated from the maps (column 2) which does not consider forest gain through reforestation, afforestation or any conversion of non-forest areas to forest areas. Since Davao Oriental had accuracy assessment samples for the deforestation class, UAE was implemented for this site. An unbiased area estimate for gross deforestation (column 3) for Davao Oriental is provided in the table.

Table 5, Gross Deforestation Analysis Results Based On Direct Classification And Net Deforestation Results Based On Unbiased Area Estimates Of The Forest Cover Maps

Study Area (2010–2015)	Gross Deforestation (ha)		Difference		Net Deforestation	
	Original [A]	Unbiased Estimate [B] ± 95% CI	ha [A-B]	% [(A-B)/B]	Original (ha)	Adjusted Net Deforestation (ha) ± Uncertainty (%)
Albay	3,350	-	-	-	1,750	623 ± 16%
Eastern Samar	5,650	-	-	-	-971	2,626 ± 5%
Davao Oriental	7,994	6,451 ± 769 (12%)	1,543	24	6,433	1,677 ± 3%

Change cannot be directly estimated for post-classification change analysis (GFOI, 2013). Rather, change is calculated by getting the difference between the forest cover estimated for two dates. This change is the Net Deforestation and is shown in last 2 columns of Table 5. The last column shows the adjusted net deforestation, which was calculated from the UAE of the 2010 and 2015 forest cover maps. This procedure requires a separate accuracy assessment to consider errors of post-classification change analysis (GFOI, 2016). This accuracy assessment was not done in this study because the focus of the work was to develop a direct change analysis methodology. The uncertainties in the last column were calculated by adding the uncertainties of the estimates of each year and could vary if the techniques of McRoberts (2014) are applied. Net deforestation considers both change from forest to non-forest and vice versa.

4.4 Accuracy of the Change Maps

Table 6, Measures Of Accuracy Of The Forest Cover Change Analysis Of Davao Oriental

Measures of Accuracies		Non-forest	Stable forest	Deforestation
Original (%)	OA[a] [A]		88.49	
	PA[b] [B]	88.49	91.50	63.76
	UA[c]	96.54	92.15	44.65
Unbiased (%)	OA[a] [C]		91.12	
	PA[b] [D]	94.23	91.93	55.33
	UA[c]	96.54	92.15	44.65
Difference (%)	OA[a] [A-C]		-2.63	
	PA[b] [B-D]	5.74	0.43	-8.43

[a] Overall accuracy, [b] Producer's accuracy, [c] User's accuracy

The forest cover change map for Davao Oriental was assessed for its accuracy and the results are reflected in Table 6. The original and unbiased accuracy measures are shown in the table and the deforestation class achieves very low accuracies. The area of deforestation was calculated with an uncertainty of 11.28%, which is even less than the most uncertain forest cover map in this report, the 2007 map of Albay with 10% uncertainty.

Several studies have also focused on mapping forest cover change in the Philippines using ALOS PALSAR data (Estomata, 2014a-b; Tumaneng et al., 2015; De Alban et al., 2019), as well as mangrove changes (Monzon et al., 2019). Most, if not all, of the existing research applied post-classification change detection and did not apply accuracy assessment due to the unavailability of historical datasets that could provide information on change from forest to non-forest from 2007 to 2010. MGD version 2 has elaborated how to assess the accuracy of post-classified change maps (GFOI, 2016; GOFC-GOLD, 2016).

5. CONCLUSION

The radar images of Davao Oriental resulted in a fairly accurate classification of forest using the decision tree classification thresholds. However, better thresholds would need to be identified for Eastern Samar and Albay. This effectivity of the thresholds was reinforced by a supplementary analysis (Estomata, 2018b) where high-resolution optical data (WorldView-2) for an area of Easter Samar (41.87 km^2) and Albay (40.13 km^2) were visually interpreted and affirmed that forest cover maps of Eastern Samar and Albay had more forest mapped than in reality. The radar-based forest cover maps showed 15-32% more forest areas compared to the visually interpreted maps. To compensate for the limitation of the classifier, additional procedure of unbiased area estimation provides better forest area estimates with uncertainties at 95% CI of below 10%. The area of forests as calculated from the maps differed from the unbiased forest area estimate with a range of 1 to 32%. Their accuracies also differed by 23% for the non-forest class, 2% for the forest class (excluding Albay 2007) and 3.64% for the overall accuracy. This further supports that the decision tree classification may not necessarily yield accurate results for all study sites. The results for the change classification show that better thresholds should be identified. Deforestation samples must be identified using high resolution data that match the acquisition dates of the radar images used for the change analysis. A corrected estimate of deforestation with uncertainties was calculated for Davao Oriental through UAE.

A country-level analysis is achievable because the radar data used in this research are freely available for the entire Philippines and the image processing used open source software only (RSGISLib, SNAP Google Earth and QGIS). Obtaining better thresholds that would effectively and correctly estimate forest at the national level may be quite challenging, therefore the new classifiers – Random Forest and Extra Trees Classifier of RSGISLib may be explored instead. These new classifiers can achieve comparable results to national level forest cover maps (Devaney et al., 2015) and was tested in the first part of this report (De Alban et al., 2019). Countries with limited resources have been given the opportunity to map their forests through free wall-to-wall coverage of L-Band SAR. FREL/FRL and the NFMS, two prerequisites under the Cancun Agreements, are achievable through forest cover and change information derived from analysis and classification of PALSAR-1/2 data, and at the same time contribute to the achievement of the K&C objectives.

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