BIOMASS ESTIMATION AND MAPPING OF CAN GIO MANGROVE BIOSPHERE RESERVE IN SOUTH OF VIET NAM USING ALOS-2 PALSAR-2 DATA

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Abstract. In this study, we used radar data from the ALOS-2 PALSAR-2 satellite to build biomass estimation models and then create a biomass map in Can Gio Mangrove Biosphere Reserve. We used the single variable regression and multivariate regression method, in which 30 sample plots for training model and 15 sample plots for validation model, the coefficient of determination (R^2) and root mean square error (RMSE) were used as metrics for evaluating the biomass estimates. The regression analyses showed that the HV polarization was highly related to the biomass, linear model ($R^2 = 0.74$; RMSE = 28.16), exponential model ($R^2 = 0.69$; RMSE = 28.73), and polynomial model ($R^2 = 0.76$; RMSE = 28.03). However, the HH polarization did not show a high relationship with the above-ground biomass, linear model ($R^2 = 0.42$), exponential model ($R^2 = 0.46$), or polynomial model ($R^2 = 0.42$). We also tried multiple linear regression between the parameters extracted from radar image (HH, HV, and textures) and field biomass. The coefficient of determination (R^2) between the biomass and two independent variables (HH and HV) was 0.79, and RMSE was 29.78. However, the model with the combination of HV variable and eight texture variables provided a better result ($R^2 = 0.81$; RMSE = 27.76), in other word the model could explain 81% variation of forest biomass. This model was used to produce the aboveground biomass map in Can Gio Biosphere Reserve in South of Vietnam.

Keywords: *microwave data, HH polarization, HV polarization, backscattering, textures, model, mangrove ecosystem, Vietnam*

Introduction

Mangroves are unique ecosystems that occur along ocean coastlines throughout the tropics and are the most carbon-rich forests in those regions. The economic potential of mangroves stems from three main sources, namely, forest products, estuarine and near-shore fisheries, and ecotourism (FAO, 1994; Cannicci et al., 2008; Donato et al., 2011; Alongi, 2012).

Climate change has been one of the biggest challenges for most countries in the 21st century. (IPCC, 2001; Raghuvanshi et al., 2008), carbon dioxide (CO_2) is one of a primary interactant of global warming (IPCC, 2011; Rogelj et al., 2016). Forest sequestrate atmospheric (CO_2) in the form of plant biomass during photosynthesis (IPCC, 2003; Drégelyi-Kiss et al., 2008). Mangrove forest has great potential for CO_2 sequestration (Ong et al., 2004; Alongi et al., 2012). Mangrove forests account for only approximately 1% of the world's forests, but for about 10–14% of the CO_2 sequestration. Therefore, if the mangrove ecosystem is destroyed, the resultant amount

of gas emissions could be very high (Cannicci et al., 2008; Drégelyi-Kiss et al., 2008; Alongi, 2012).

In 1943, the mangrove forest area in Vietnam was 408,500 ha. It decreased from 400,000 ha in the 1960s to 73,000 ha in the 1990s, due to the use of herbicides during the Indochina War and conversion of mangroves for agriculture and aquaculture. In 2015, mangrove area increased to 270,000 ha due to government and donor-funded planting efforts and mangrove protection policies (Mai Sy Tuan, 2016).

Mapping and carbon stock data are important in determining conservation priorities for climate change mitigation efforts as well as implementing programs such as REDD + (Hutchison et al., 2014). However, until now, there is still uncertainty about the amount of carbon emissions caused by the loss of mangrove forests because there is insufficient data on carbon stocks in these ecosystems (Donato et al., 2011; Hutchison et al., 2014).

The estimation of forest biomass using remote sensing data has proved to be more advantageous than traditional method, because it has advantages such as technology, space, time and cost (Lu, 2006; Gibbs et al., 2007; Goetz et al., 2011). The main remote sensing data is available as; optical satellite, lidar and radar satellite (Lu, 2006).

Optical satellite data

Studies on the estimation of forest biomass using optical satellite images such as Tucker et al. (1973), Tucker (1977), and Sader et al. (1989) have been of interest since very early to this now-aday, and are usually about the use of plant indicators such as Normalized Difference Vegetation Index (NDVI) (Hamdan et al., 2013; Kamal et al., 2015; Wicaksono et al., 2016) and Leaf Area Index (LAI) (Wicaksono et al., 2016; Castillo et al., 2017). However, due to disadvantages of optical satellite data such as high saturation, clouds, especially in tropical regions, the applications of these indicators are limited.

Lidar data

Lidar provides an excellent source of data for estimating forest biomass because it has three-dimensional information about forests (Maclean, 1998; Chen, 2013). Hayashi et al. (2015) developed empirical models to estimate aboveground biomass (AGB) and canopy height from the Ice, Cloud, and land Elevation Satellite (ICESat)/Geoscience Laser Altimeter System (GLAS) data in Borneo. However, due to the trade off between cost, high processing capacity, and specialized software, the application of Lidar data for a large geographical area is very limited (Lu, 2006; Chen, 2013; Sinha et al., 2015).

Radar satellite data

Radar data is used for estimation of forest biomass with high potential because this data is not affected much from natural conditions such as at day-night time, cloud cover, other advantages such as temporal availability, large-scale coverage, and lower saturation (Wu, 1987; Gibbs et al., 2007; Le Toan et al., 2011; Sinha et al., 2015). The long-wavelength Synthetic Aperture Radar (SAR) satellite is expected to have much promise for forest biomass map estimates (MacRoberts, 2007; Smith and Brown, 2009; Le Toan et al., 2011). The backscattering value of L-band and P-band SAR data have demonstrated sensitivity to structure, cover, volume, and biomass of the forests penetrating into the branches and stems of trees (Sun et al., 2002; Balzter, 2001; Morel

et al., 2011). A number of previous studies have shown an impressive relationship between the SAR data and biomass (Le Toan et al., 1992; Santos et al., 2010; Peregon et al., 2013).

Several researchers have reported saturation problems of the L-band SAR backscattering over highly varying levels of biomass (Imhoff, 1995; Luckman et al., 1997; Mermoz et al., 2015). However, numerous reports indicate that the L-band SAR backscattering was saturated at around 150–200 Mg/ha (Motohka et al., 2011; Avtar et al., 2013; Le Toan et al., 2013; Ni et al., 2014).

The major SAR techniques for estimates of woody volume and biomass attempted by a number of researchers so far are dual-wavelength SAR interferometry (Balzter, 2001), random volume over-ground model (Hajnsek et al., 2009), water cloud model (Cartus et al., 2012), a combination of forest structure and radiative transfer models (Brolly et al., 2012), and electromagnetic modeling (Mermoz et al., 2015). The models mentioned above are relatively complex and difficult to implement in practice. Only regression correlation models are relatively easy to apply (Le Toan et al., 1992; Englhart et al., 2011; Carreiras et al., 2013; Izuka and Tateish, 2014).

Over the last decade in Viet Nam, there have been several studies using satellite imagery for estimating biomass and forest timber, e.g. Bui et al. (2011) conducted a study on the leaf canopy biomass in Cat Tien National Park, Lam Dong province using ALOS AVNIR 2 image. Huong et al. (2011) used SPOT5 satellite image to estimate woody volume. However, these studies have used only optical image data. Due to the limited ability of optical satellite imagery in the estimation of mangrove forest biomass on the ground, the models constructed in these studies are often complex and have several intermediate steps, thus limiting the application. As an urgent and mandatory requirement from forested countries to participate in climate change adaptation and REDD programs (Saatchi et al., 2011). However, the estimation of biomass from satellite data is very challenging due to the diverse nature of forests, especially tropical forests (Sinha et al., 2015; Kumar et al., 2015).

The purpose of this study was to develop the best model for estimation of mangrove forest biomass and then to create a forest biomass map. In this study, we have used radar data from ALOS-2 PALSAR-2 (The Advanced Land Observing Satellite-2), a Japanese satellite launched in 2014, which operates in L-band radar and collects very high spatial resolution data.

Study area

Can Gio mangrove forest lie entirely in the Can Gio district of Ho Chi Minh city in South of Vietnam. The boundary ranges from Nha Be district in the north to the East Sea in the south and from Dong Nai and Ba Ria-Vung Tau provinces in the east to Long An in the west. The area measures 35 km from north to south and 30 km from east to west (*Fig. 1*).

Topographically, the Can Gio mangrove forest forms a basin with a minimum altitude range of 0 m – 1.5 m, in the northeastern sector of the forest, with downward inclines from the east, south, and west. The climate has two seasons, rainy season from May to October and dry season from November to April.

Plant diversity, about 105 plant species, belonging to 48 genera are found in Can Gio mangrove forest, including *Rhizophora apiculata* constituted the main part of the flora, together with other assemblages of *Bruguiera gymnorrhiza*, *Bruguiera parviflora*,

moment, and variance (Haralick et al., 1973; Anys et al., 1994). The formulas for the texture measurements used in this study are shown in *Equations 2–9*:

$$Contrast = \sum_{n=0}^{N_g-1} n^2 \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j) \quad (Eq.2)$$

$$Dissimilarity = \sum_{n=0}^{N_g-1} n \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j)^2 \quad (Eq.3)$$

$$Homogeneity = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p(i, j) \quad (Eq.4)$$

$$SecondMoment = \sum_i \sum_j \{p(i, j)\}^2 \quad (Eq.5)$$

$$Correlation = \frac{\sum_i \sum_j (i - \mu_x)(j - \mu_y) p(i, j)}{\sigma_x \sigma_y} \quad (Eq.6)$$

$$Entropy = \sum_i \sum_j p(i, j) \log(p(i, j)) \quad (Eq.7)$$

$$Mean = \sum_{i,j=0}^{n-1} i p_{i,j} \quad (Eq.8)$$

$$Variance = \sum_i \sum_j (i - u)^2 (p(i, j)) \quad (Eq.9)$$

where:

$p(i, j)$ is the normalized co-occurrence matrix such that $\sum (i, j = 0, n - 1, p(i, j)) = 1$
 $\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviations of p_x, p_y .

The software used in this study included ENVI versions 5.4, ArcGIS 10.2 for satellite image processing, map editing, and R for statistical analysis. The details of the ALOS-2 PALSAR-2 data used in the research are shown in *Table 1* and *Figure 2*.

Table 1. ALOS-2 PALSAR-2 data used in this research

No.	Scene ID	Observation date	Observation angle	Polarizations	Pixel resolution (m)
1	ALOS2151050200	10 March 2017	36.6°	HH, HV	6.25
2	ALOS2152303410	10 March 2017	36.6°	HH, HV	6.25

Figure 2. ALOS-2 PALSAR-2 data used in this research

Field work

Field surveys are important for collecting in situ data for accurate analysis of satellite-based estimates. We conducted a field survey during April 2017 to collect the ground truth data. In this study, the size of a sample plot is 0.05 ha (20×25 m). We measured the diameter at breast height ($D_{1.3cm}$) and tree height (H_m). We also recorded the types of tree species during the field survey by Vietnam's flora books Pham (2003).

Forty-five sample plots in total are used in this study. We used a random selection method for training (30 sample plots) and validation data (15 sample plots). The inventory data summary is provided in Table 2. The distribution of the sample plot positions is shown in Figure 3.

Table 2. Forest inventory parameters for the training data

Parameter	Training field data				Validation field data			
	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
Diameter (m)	5.83	17.60	10.16	3.25	7.11	17.60	11.62	2.93
Height (m)	6.34	17.04	12.82	2.92	7.88	17.04	14.34	2.31
Biomass ($Mg \cdot ha^{-1}$)	9.24	254.29	99.20	76.90	11.31	255.42	179.52	67.60

The survey results show that: Dense mangrove forests include dominant species as *Rhizophora apiculata*, *Bruguiera gymnorrhiza*, *Avicennia germinans*, *Sonneratia caseolaris* and *Aegyceras corniculatum*. Open mangrove forests include dominant species as *Rhizophora apiculata*, *Avicennia germinans*, *Ceriops decandra*, *Lumnitzera racemosa*, *Sonneratia caseolaris*, and *Lumnitzera racemosa*. Young forests and scrubs include dominant species as *Ceriops decandra*, *Lumnitzera racemosa*, *Avicennia germinans*, and *Rhizophora apiculata*. The components of mangrove species in study area show in Table 3.

Figure 3. Sample plot position in Can Gio Biosphere Reserve

Table 3. The components of mangrove species in the study area

No.	Forest classes	Sample plot number	Components of mangrove species in the study area by ratio 1/10
1	Dense mangrove forest	15, 17, 19, 20, 37, 39, 40, 42, 44, and 45	7.93 <i>Rhizophora apiculata</i> + 0.95 <i>Bruguiera gymnorhiza</i> + 0.86 <i>Avicennia decandra</i> + 0.25 <i>Sonneratia caseolaris</i> + 0.01 <i>Aegyceras corniculatum</i>
2	Open mangrove forests	5, 8, 9, 10, 11, 12, 13, 14, 21, 22, 28, 33, 34, 35, 36, 38, 41, and 43	2.91 <i>Rhizophora apiculata</i> + 2.91 <i>Avicennia germinans</i> + 1.58 <i>Ceriops decandra</i> + 1.44 <i>Lumnitzera racemosa</i> + 0.83 <i>Bruguiera parviflora</i> + 0.43 <i>Sonneratia caseomosa</i> + 0.07 <i>Lumnitzera racemosa</i> + 0.03 other species
3	Young forests and scrubs	1, 2, 3, 4, 6, 7, 16, 18, 23, 24, 25, 26, 27, 29, 30, 31, and 32	8.55 <i>Ceriops decandra</i> + 0.70 <i>Lumnitzera racemosa</i> + 0.70 <i>Avicennia germinans</i> + 0.03 <i>Rhizophora apiculata</i> + 0.03 other species

We used allometric equations (Eq. 10–18) here to calculate the AGB (Above Ground Biomass) for different mangrove species as well as the main species in the study area's mangrove forest. The equations are shown in Table 4.

Table 4. Allometric equations used for mangroves species

Species	Allometric equations	References	Eq. No.
Rhizophora appiculata	$AGB = 0.235 * D^{2.42} (R^2 = 0.98)$	Ong et al. (2004)	(Eq.10)
Avicennia germinans	$AGB = 0.140 * D^{2.40} (R^2 = 0.97)$	Fromard et al. (1998)	(Eq.11)
Bruguiera gymnorrhiza	$AGB = 0.186 * D^{2.31} (R^2 = 0.99)$	Clough and Scott (1989)	(Eq.12)
Bruguiera parviflora	$AGB = 0.168 * D^{2.42} (R^2 = 0.99)$	Clough and Scott (1989)	(Eq.13)
Xylocarpus granatum	$AGB = 0.0823 * D^{2.59} (R^2 = 0.99)$	Clough and Scott (1989)	(Eq.14)
Ceriops decandra	$AGB = 0.208 * D^{2.36} (R^2 = 0.96)$	Cao (2007)	(Eq.15)
Lumnitzera racemosa	$AGB = 0.74 * D^{2.32} (R^2 = 0.99)$	Trung et al. (2009)	(Eq.16)
Sonneratia caseolaris	$AGB = 0.199 * \rho^{0.90} * D^{2.22} (R^2 = 0.99)$	Komiyama et al. (2005)	(Eq.17)
Common equation	$AGB = 0.25 * \rho * D^{2.592} (R^2 = 0.98)$	Komiyama et al. (2005)	(Eq.18)

In allometric *Equations 10–18*:

- AGB is the aboveground biomass of a tree in kilograms (kg)
- D is the diameter at breast height (1.3 m) in centimeters (cm)
- ρ is the wood density (tons dry matter/m³ fresh volume) (IPCC, 2003)

Results

Training of biomass model

Coefficient of determination (R^2) and root mean square error (RMSE) were used as metrics for evaluating relationships. The results of the relationship between each backscattering intensity (HH, HV polarizations) and biomass value on the basis of the field observation plot were analyzed using the coefficient of determination (R^2). The assessment of these relationships has been shown by regression lines: The HV polarization was highly related to the biomass, according to the linear model ($R^2 = 0.74$; RMSE = 28.16), exponential model ($R^2 = 0.69$; RMSE = 28.73), and polynomial model ($R^2 = 0.76$; RMSE = 28.03); whereas the HH polarization did not show a significant relationship with the aboveground biomass according to the linear, exponential, and polynomial models (R^2 respectively were 0.42, 0.46, and 0.42). The results are shown in *Figure 4*.

We also analyzed multiple linear regression between the parameters extracted (HH, HV, and textures) from the radar image from ALOS-2 PALSAR-2 and field biomass. As shown in *Table 5*, the adjusted coefficient of determination (R^2) between the biomass and two independent variables (HH and HV) was 0.79 and RMSE = 29.48; that of biomass and eight independent variables of textures (contrast, correlation, dissimilation, entropy, homogeneity, mean, second moment, variance) was 0.49. We used a combination of backscattering and textures variables from HH, the result obtained with $R^2 = 0.58$. However, the adjusted coefficient of determination (R^2) for the combination was 0.82 and RMSE = 27.56. The summary of the relationship between the field-measured biomass and ALOS-2 PALSAR-2 data is shown in *Table 5*.

No.	Model	Relationship	Coefficient of determination (R^2)
		<i>Single-variable model</i>	
1	Model 1	$AGB = 33.121HH + 555.81$	0.42
2	Model 2	$AGB = 44.318HV + 945.99$	0.74
3	Model 3	$AGB = 40278e^{0.4689 \times HH}$	0.46
4	Model 4	$AGB = 5E + 06e^{0.5883 \times HV}$	0.72
5	Model 5	$AGB = -2.4301HH^2 - 31.429HH + 13$	0.42
6	Model 6	$AGB = 1.9415HV^2 + 118.03HV + 1641.2$	0.76
		<i>Multil-variable model</i>	
7	Model 7	$AGB = 957.79 + 11.58HH + 36.79HV$	0.79
8	Model 8	$AGB = -16817.86 - 1733.35Contrast + 49.90Correlation + 10249.89Dissimilarity - 254.70Entropy + 16974.67Homogeneity + 23.41Mean - 1084.849SecondMoment + 40.53Variance$	0.49
9	Model 9	$AGB = 3084.31 + 168.53Contrast + 36.17Correlation - 1090.15Dissimilarity - 89.71Entropy - 1729.60Homogeneity - 17.23Mean - 427.95SecondMoment + 16.09Variance + 39.53HH$	0.58
10	Model 10	$AGB = -65714.04 - 6726.42Contrast + 2.46Correlation + 40273.92Dissimilarity - 115.77Entropy + 67144.71Homogeneity - 6.04Mean - 432.67SecondMoment + 28.39Variance + 46.61HV$	0.81

We have selected training models with $R^2 > 0.7$ (high correlated) as validation models. Models 2 ($R^2 = 0.74$; RMSE = 28.16), 4 ($R^2 = 0.72$; RMSE = 33.64) 6 ($R^2 = 0.75$; RMSE = 28.73), 7 ($R^2 = 0.78$; RMSE = 29.87), and 10 ($R^2 = 0.81$; RMSE = 27.76). The results of the validation model are shown in *Figure 5*.

Figure 5. The validation results: (a) Model 2, (b) Model 4, (c) Model 6, (d) Model 7, and (e) Model 10. The 1:1 cross plots between the predicted and ground data are shown

We have found Model 10 to be the best, including training model ($R^2 = 0.81$; RMSE = 27.76) and validation model ($R^2 = 0.82$; RMSE = 27.56), and have selected the Model 10 for map mangrove biomass for Can Gio Biosphere Reserve, Ho Chi Minh, city in South of Vietnam.

Mapping

The model derived by the best combination of the HV backscattering intensity and eight textures from ALOS-2 PALSAR-2 (Model 10) is shown below:

$$\text{Biomass (Mg.ha}^{-1}\text{)} = -65714.04 - 6726.42\text{Contrast} + 2.46\text{Correlation} + 40273.92\text{Dissimilarity} - 115.77\text{Entropy} + 67144.71\text{Homogeneity} - 6.04\text{Mean} - 432.67\text{SecondMoment} + 28.39\text{Variance} + 46.61\text{HV}$$

This model was used to produce the aboveground biomass map in Can Gio Biosphere Reserve, Ho Chi Minh city in South of Vietnam. The results show that very rich mangrove forest is 13843.66 ha (18.45%), rich mangrove forest area is 20188.03 ha (26.90%), medium mangrove forest area is 7517.89 ha (10.02%), poor mangrove forest area is 4648.30 ha (6.19%), bare soil area is 730.30 ha (0.97%), and the water body area is 28120.15 ha (37.47%). More details are shown in *Table 6* and the biomass map is shown in *Figure 6*.

Figure 6. Aboveground biomass map of Can Gio Biosphere Reserve

Table 6. Aboveground biomass distribution of Can Gio Biosphere Reserve

No.	Classes	Biomass level (ton.ha ⁻¹)	Area	
			(ha)	(%)
1	Vey rich forest	>300	13843.66	18.45
2	Rich forest	200-300	20188.03	26.90
3	Medium forest	100-300	7517.89	10.02
4	Poor forest	0-100	4648.73	6.19
5	Bare soil	-	730.30	0.97
6	Water body	-	28120.15	37.47
	Total		75048.76	100.00

Discussion

The sensitivity of the radar signal to the biomass depends on the frequency, polarization, and incidence angle (Le Toan et al., 1992; Dobson et al., 1992; Van Truong et al., 2017). The forest structure is a complex matter; and the radar signal is sensitive to forest's characteristics as well as the horizontal and vertical structure of the forest. The L-band ALOS-2 PALSAR-2 data can penetrate into the forested canopy, and the backscattering is sensitive to the size of branches and tree trunks, which are main component of the forest biomass. The backscattering intensity received by a SAR sensor is characterized by the polarized (horizontal or vertical) combinations of the transmitted and received signals (Anys et al., 1994; Izuka et al., 2015; Kumar et al., 2015). The HH polarization receives the signal reflected straight from an object. Therefore, it is more sensitive to changes in moisture, and thus the HH backscattering intensity varies highly between dry or wet objects. Conversely, the HV polarization receives a signal reflected at a 90 degree angle from an object. In other words, the HV polarization receives a very different signal reflected at a different angle away from the received direction. Forest structures are complex in nature, resulting in volumetric rather than surface scattering. Therefore, HV data is more sensitive to the biomass than HH data. The structural information obtained from the SAR data provides additional information about the forest canopy structure (combination of horizontal and vertical forest structures). Thus, the combination of backscattering and textural parameters from SAR data has improved the model of biomass estimation in this study.

Some literature overviews of satellite data application for biomass estimation have been reviewed by Sinha et al. (2015), Tsitsi et al. (2016), and Kumar and Mutanga (2017). They have concluded that radar satellite data are more potential for biomass estimates especially in the tropical forest region, where forest structures are complex and often covered by clouds. Recent studies have also shown promising results for the estimation of forest biomass using satellite radar data. For example, Basuki et al. (2013) reported R^2 from 0.70 to 0.75 for biomass estimates; Minh et al. (2018) have obtained high correlation ($R^2=0.71$) between the radar signal and in situ biomass, Ghosh and Behera (2018) have estimated aboveground biomass with high accuracy ($R^2 = 0.71$), and Berninger et al. (2018) have also shown high model performance ($R^2 = 0.70-0.76$). Other studies have also obtained high correlation between the mangrove forest biomass and radar data. For example, Pham et al. (2018) got $R^2 = 0.59$ between biomass and radar data, Argamosa et al. (2018) obtained high correlation (R^2 of 0.79) between forest

biomass and radar data. In general, major concerns of the researches are to improve the accuracy of the biomass estimates using satellite data, and our research is not an exception. Nevertheless, major limitation of the SAR system for estimating biomass is that the backscattering intensity becomes saturated when the biomass exceeds a certain critical value, even with the HV backscattering intensity. In this research, the best-validated model showed saturation point around 200–250 Mg.ha⁻¹. Therefore, the model presented in the research is sensitive to the biomass until that biomass value is reached.

Conclusions

In this study, we have developed a methodology for biomass estimation and mapping of mangrove forests. A case study in Can Gio Biosphere Reserve, Vietnam was conducted based on ALOS-2 PALSAR-2 data and field plot data. From the results of this study, we have obtained the following conclusions:

- HV polarization has a better relationship with mangrove forest biomass when compared to HH polarization in the single-variable model.
- Combined HV and HH polarization by multi-variable models have improved relationship to the biomass compared to single-variable models.
- We obtained $R^2 = 0.58$ by the combination of backscattering variables and textures variables (contrast, correlation, dissimilation, entropy, homogeneity, mean, second moment, and variance) using HH polarization. However, by replacing the backscattering and textures variables from HV polarization, the model significantly improved ($R^2 = 0.82$; RMSE = 27.56) the biomass estimates. This best model was used to produce an up-to-date biomass map of Can Gio Biosphere Reserve.
- The saturation in this study was found to be around 200–250 Mg.ha⁻¹. This result was improved compared to previous studies.
- The results showed that very rich mangrove forest is 13843.66 ha (18.45%), rich mangrove forest area is 20188.03 ha (26.90%), medium mangrove forest area is 7517.89 ha (10.02%), and poor mangrove forest area is 4648.30 ha (6.19%).

The estimation of mangrove forest biomass using the satellite data is important for monitoring mangrove biomass changes over time. We recommend monitoring of mangrove biomass changes every two years or at least every five years (according to the forest inventory period of Vietnam), using radar satellite data. Our hope is that the satellite based monitoring of mangrove forests can contribute significantly to the sustainable management of mangrove forests and to the participation on REDD+ programs.

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