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Research Article

Application of multispectral UAV to estimate mangrove biomass in Vietnam: A case study in Dong Rui commune, Quang Ninh Province

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Abstract

Mangroves play an important role in coastal estuarine areas with different ecological functions, such as reducing the impact of waves and currents, accumulating biomass and sequestering carbon. However, estimation of terrestrial biomass in mangrove areas, especially in Vietnam, has not been fully studied. The application of unmanned aerial vehicles (UAV), mounted with multispectral cameras combined with field verification is an effective method for estimating terrestrial biomass for mangroves, as it reduces field survey time and allows for greater spatial range research. In this study, ground biomass was estimated for the mangrove area in the Dong Rui commune, based on multispectral image data obtained from UAV and survey results in 16 standard cells measuring actual biomass according to four regression models: Log-Log, Log-Lin, Lin-Log and Lin-Lin. The results of comparing the data from these four models show that the log-log model has the highest accuracy with a high correlation coefficient (R^2 = 0.831). Based on the results of the analysis and selection of ground-based biomass estimation models, a biomass map was established for the UAV flying area in the Dong Rui mangrove forest with biomass values ranging from 20 Mg/ha to 150 Mg/ha. In summary, we present a biomass estimation method through four basic linear regression models for mangrove areas, based on multispectral image data obtained from ultrahigh-resolution UAV. The resulting research results can serve as a basis for managers to calculate and synchronise the payment of carbon services, thus contributing to effectively promoting the livelihoods of local people.

Keywords

regression model, biomass, tree height, mapping mangrove

Introduction

Forests are an important part of the carbon cycle because they hold 80% of the biomass reserves on land. In forest science, one of the main areas of study is the biomass of forest ecosystems. Biomass is defined as all organic matter in living (remaining in trees) and dead forms above or below ground level (Brown et al. 1989). It is also the total amount of organic matter that can be taken from a certain area at one time. This is measured in dry tonnes per hectare (Ong et al. 2004). The carbon in the biomass of forest ecosystems is usually concentrated in four parts: living vegetation on the ground, fallen objects, tree roots and forest soil. The determination of the amount of carbon in forests is usually done through the determination of forest biomass (McKenzie et al. 2000). Due to the difficulty in obtaining data on biomass below ground, most studies have focused on estimating biomass above ground (AGB) (Lu 2007a).

Currently, the study of forest biomass has many different methods. In particular, the current popular method is still the method of direct measurement in the field on predetermined standard cells (Brown 1997,MacDicken 1997,Ketterings et al. 2001,Brown 2002,Houghton 2005,Henry et al. 2010,Henry et al. 2015,Raj 2021). In some areas of the world with highly homologous plant nests, biomass models have been established for most tree species (Jenkins et al. 2003, Jenkins et al. 2004). To improve the reliability of the biomass model, Temesgen et al. advocate building a comprehensive biomass model with the participation of more forestry variables, such as density, height and cover etc. according to different spatial scales (Temesgen et al. 2007Temesgen et al. 2015). In addition, the cross-appraisal method is also the basis for selecting the appropriate variables for the model (Picard and Cook 1984). However, the method of establishing standard cells to identify biomass is often time-consuming, laborious and especially difficult to implement in remote areas and areas with complex terrain conditions. In addition, this method cannot provide a spatial distribution of forest biomass over large areas.

In the last 20 years, remote sensing techniques have been used extensively to estimate AGB (Nelson et al. 2000, Steininger 2000, Zheng et al. 2004, Lu 2007b). This is because field investigations, setting standards and direct measurements all have problems. Using remote sensing technology to determine how much biomass is in a forest has many great benefits. The time it takes to process the data is reduced, objects can be sorted quickly on a large scale and the results are less dependent on the solver's opinion. Using different methods, remote sensing data can be used to directly estimate the biomass of land. Regression analysis is the method that is most often used to make models for estimating biomass. This method usually uses the results of calculating biomass in sample cells as dependent variables. Spectral features and plant indices, such as the Enhanced Vegetation Index (EVI), are examples of independent variables (Dang et al. 2022). The models assume that biomass variables correlate linearly with the spectral response. There are also a number of studies that select non-linear investigative factor models for biomass (Li et al. 2010). In Vietnam, Landsat images were also used by the author Nguyen Hai Hoa to calculate biomass for mangroves in Quang Ninh Province (Nguyen et al. 2021) or Landsat and Sentinel-2 images were used to estimate biomass for mangroves in Thai Binh Province (Nguyen et al. 2019), with the Sentinel-2 image estimating biomass in the Kon Ha Nung Plateau area (Dang et al. 2022). However, the biomass estimates of agro-forestry ecosystems still have many errors compared to reality, with many different models estimating biomass and low satellite image resolution. With the development of sensor technology on unmanned aerial vehicles (UAV), image resolution and wave bands on accompanying sensors are increasingly improved. UAV are capable of providing ultra-high-resolution images (Bandini et al. 2017, Lorenz et al. 2017). They serve as useful for detailed studies of a specific forest ecosystem, such as the identification of vegetation indicators (Mallmann et al. 2020, Ngo et al. 2020); the establishment of tree classification maps (Hese et al. 2019); the determination of forest canopy gaps (Dang Hoi 2021); and estimates of mangrove biomass and carbon sequestration capacity (Jones et al. 2020, Navarro et al. 2020). UAV have multispectral sensors attached to red-edge and near-infrared (NIR) wave bands that allow the identification of plant indicators, such as conventional satellite images (Yaney-Keller et al. 2019, Zahra et al. 2022). In addition to providing high-resolution images, UAVs also have outstanding advantages, such as proactive flight time and limiting the effects of weather (Dezhi et al. 2018).

Webber et al. (2016) stated that mangroves are the dominant ecosystem in the tidal flats and coastal estuaries of warm, tropical and subtropical temperate areas. This ecosystem has many different kinds of life because it obtains many nutrients from river and sea sediments. Taxonomically, mangroves are very different, with mostly woody plants that can handle high levels of salt (Polidoro et al. 2010). Mangroves also provide a number of important functions, such as breeding and nesting grounds, nurseries, shelters and feeding grounds (Nagelkerken et al. 2008). They also play important non-living roles, such as preventing flooding, protecting against damage from storms and waves and improving water quality by filtering out waste from farms and factories (Boerner 1990, Morris et al. 2002). Understanding how mangroves work, how they are built and how they can store biomass and take in carbon helps develop policies and services related to carbon payment, which is one of the most important issues in the forestry sector today (Favero et al. 2022).

In this study, UAVs Phantom 4 Multispectral with cameras capable of receiving five single-spectral wave bands, including blue (Rb): 450 nm; green (Rg): 560 nm; red (Rr): 650 nm; red edge (Rre): 730 nm; and near-infrared (Rnir): 840 nm, are used to determine tree height and plant index for estimation modelling of terrestrial biomass for mangroves in Dong Rui commune, Tien Yen district, Quang Ninh Province, Vietnam. Our research demonstrates that ultra-high-resolution multispectral UAVs can be used to estimate mangrove biomass in Vietnam on larger and faster scales than using traditional and highly accurate methods. The findings provide a basis for managers to calculate and synchronise carbon service payments, effectively promoting the livelihoods of local people.

Material and methods

Study area

The mangrove research area is in the village of Dong Rui, in the District of Tien Yen, in the Province of Quang Ninh, in the northern part of Vietnam (Fig. 1). The Dong Rui commune is bordered on the east by the Ba Che River and on the west by the Voi Lon River. The terrain is relatively flat, surrounded by tidal flats gradually rising from 1 to 3 m height and mangroves. Mangroves in the Dong Rui commune and the Ramsar Xuan Thuy area are considered to be the most diverse places in northern Vietnam.

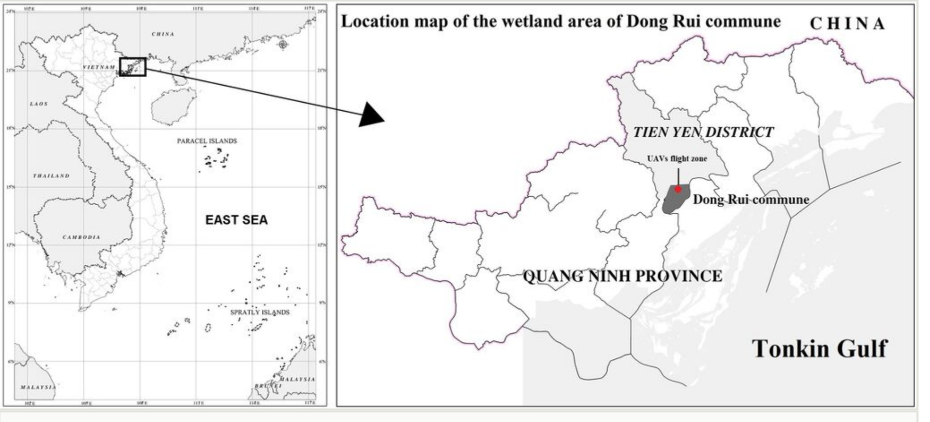

Figure 1.

Map of surveying and sampling locations in Dong Rui commune, Tien Yen District, Quang Ninh Province in northern Vietnam.

Materials and methods

Research process

The process for mapping biomass estimates is summarised in Fig. 2. Accordingly, the data required for the process include multispectral UAV images and actual biomass survey results from standard cells in the field. From multispectral UAV image data, the tree height and NDVI value were determined as a basis for building a biomass estimation model in the study area.

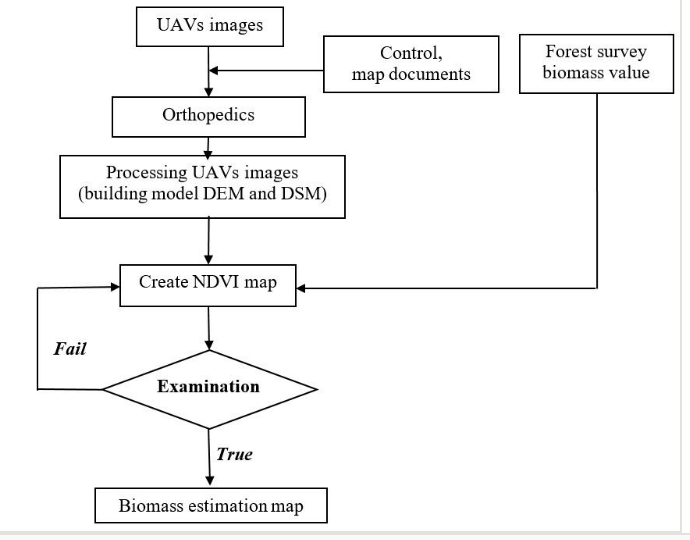

Figure 2.

UAV image processing and biomass estimated mapping.

UAV image data collection and processing

DJI GPS Pro software was used to set up UAV flight procedures in the study area with the following flight parameters: UAV flight altitude: 60 m; image coverage: 80%; flight time: 7:00 h to 8:00 h at the lowest tide; and date of capture: 15/7/2022 (Fig. 3).

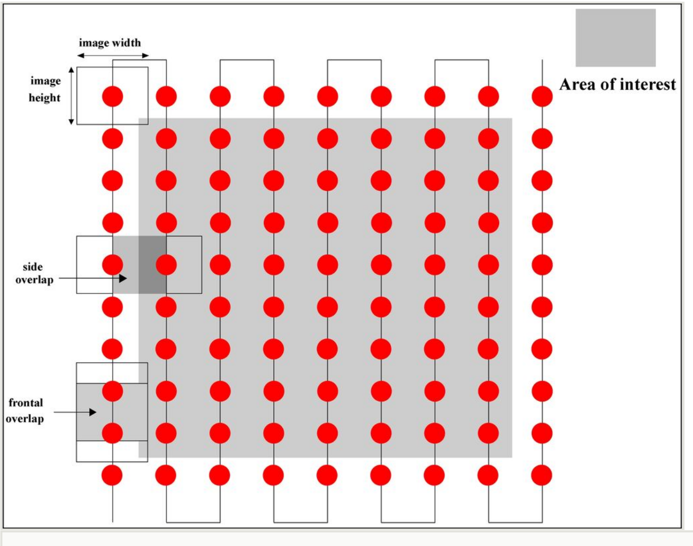

Figure 3.

UAV flight path.

The Digital Elevation Model (DEM) and Digital Surface Model (DSM) (Fig. 4) were used to determine the elevation of the mangrove biome in the study area. DEM and DSM are generated from point cloud data taken from UAV images (Al-Najjar et al. 2019). Along with GPS data from the field, this study used UAV images to look for gaps in the forest canopy to find ground points. This was done to make the DEM model more accurate. The tree height in the study area was calculated by subtracting the DSM value from the DEM value (Lisein et al. 2013).

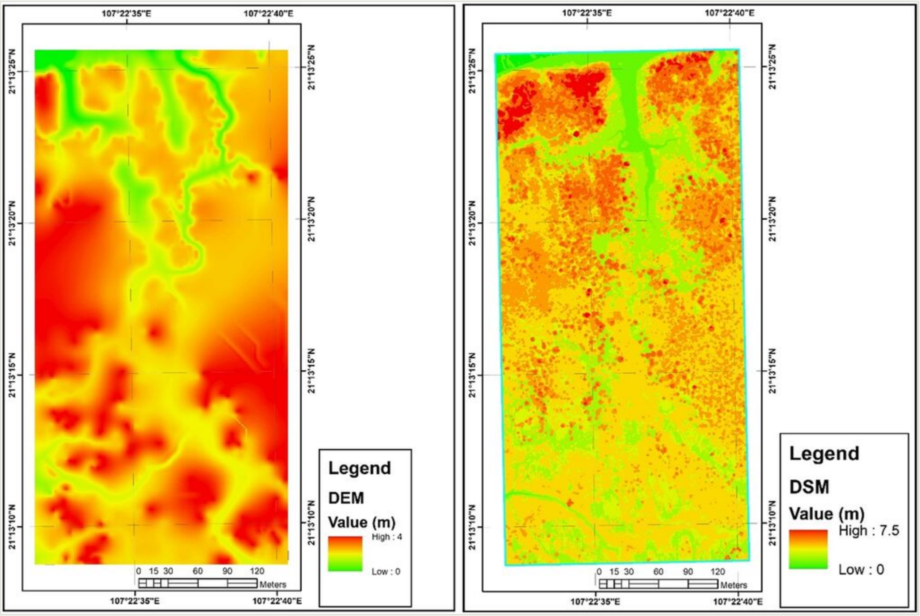

Figure 4.

DEM and DSM at UAV capture flight areas.

NDVI determination, based on remote sensing imagery

With the technical properties of multispectral UAV images, data from a Phantom 4 multispectral UAV image are used to put together and extract five monochromatic spectral channels. Blue (Rb): 450 nm ± 16 nm, Green (Rg): 560 nm ± 16 nm, Red (Rr): 650 nm ± 16 nm, Red edge (Rre): 730 nm ±16 nm and Near-infrared (Rnir): 840 nm ± 26 nm.

The Normalised Difference Vegetation Index (NDVI) is one of the most important ways to study ecology, plant growth, development and changes in plant cover. The NDVI is used in many studies (Basso et al. 2019, Pandey et al. 2019) to determine how much biomass is in an ecosystem. The NDVI index is calculated by the formula (Tucker 1979):

$$NDVI = (R_{nir} - R_g)/((R_{nir} + R_g) \quad (1)$$

Based on the information from the UAV image, the following formula was used to make the NDVI value map for the flight area in Dong Rui commune (Fig. 5).

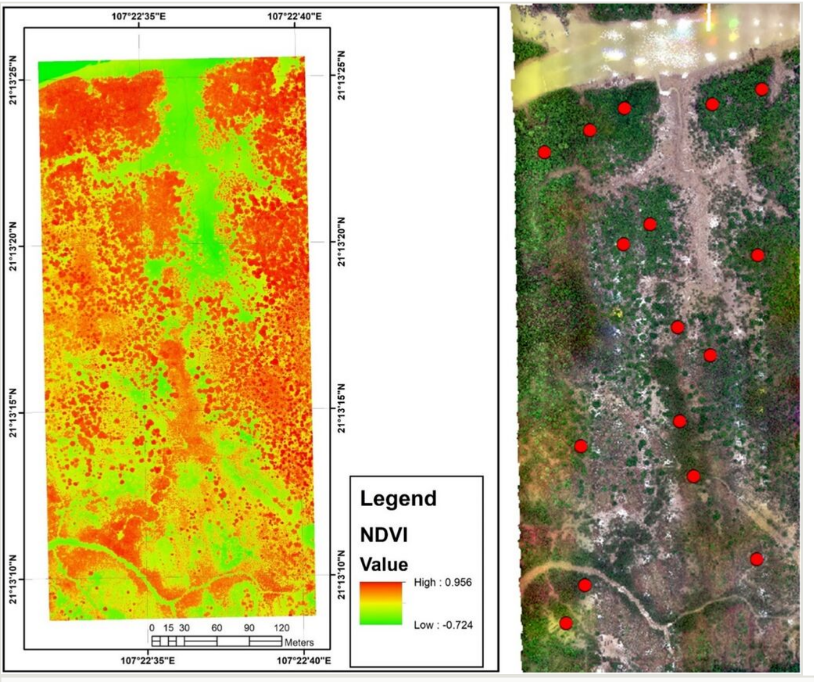

Figure 5.

NDVI value map of the UAV capture area and 16 survey standard cells.

Determination of biomass regression model

To compare the accuracy of mangrove biomass estimation regression models, the following four basic regression models were used (Gujarati 2014):

1. Log - Log Paradigm: Log10(AGB)= a*log10(NDVI value) + b*TreeH + c (2)

2. Log – Lin Paradigm: Log10(AGB)= a*(NDVI value) + b* TreeH + c (3)

3. Lin – Log Paradigm: AGB= a*log10(NDVI value) + b* TreeH - c (4)

4. Lin – Lin Paradigm: AGB= a*(NDVI value) + b* TreeH - c (5),

where AGB is the Above Ground Biomass (unit: Mg/tonne) and TreeH is the tree height (unit: m).

The right way to choose a model is to choose weighted functions that show a strong, objective relationship between the biomass value variable and the UAV spectroscopy reflection. An effective tool for determining that correlation is based on regression function theory. The results of this step are checked and evaluated by taking measurements on biomass value images to compare with standard monitoring data for biomass investigation in the field taken at the same time as the data.

Verify the accuracy of the model

Based on the tree height map that has been established from UAV imagery along with biomass data from 16 standard cells (10 m x 10 m) taken right at the time of flight, the accuracy of the model was checked. At each standard cell, the tree diameter was measured and the tree height for biomass estimates was determined. The equation for AGB can be represented as follows (Komiyama et al. 2005):

AGB = 0.251*ρ x D*$^{2.46}$ *(6)*

where AGB: Above Ground Biomass (kg); *ρ*: wood density (g/cm^3); D = diameter at 0.3 m with Rhizophoraceae species; and D = diameter at breast height for other species (cm). To be uniform in terms of biomass units, all will be converted to Mg/ha.

Using correlation analysis and linear regression, maps of tree height, NDVI values based on UAV images and biomass data from 16 fact-checking standard cells are used to find correlations between the variables. This is the first step in mapping biomass reserves, where the NDVI value and the tree height data are independent variables and AGB is the dependent variable. From there, we determined the initial linear equation: $y = a \cdot x + b$.

The Pearson correlation coefficient for two variables x and y from a sample of size n is calculated by the formula:

(7)

where Y_i and $\overline{Y_i}$ are the estimated variables and their average values, respectively.

x_i and $\overline{X_i}$ are measurement variables and their average values.

n is the the sample size of the dataset.

The two variables x and y are completely independent and unrelated if R = 0. If $0.1 \le R^2 < 0.3$: low correlation; if $0.3 \le R^2 < 0.5$: average correlation; $0.5 \le R^2 < 1$: high correlation; if $R^2 = 1$: any value of x, we can determine the value of y (Wackerly et al. 2008). The standard error (SE) is used as a measure of accuracy in calculating the quality and quantity of biomass reserves (i.e. AGB obtained from linear regression analysis) by comparing them to the biomass reserves of standard plots that have been established in the field.

Results

Build a tree height map

Tree height maps (Fig. 6) were made in the study area using the DSM and DEM models that were made using UAV flight data and field terrain measurements.

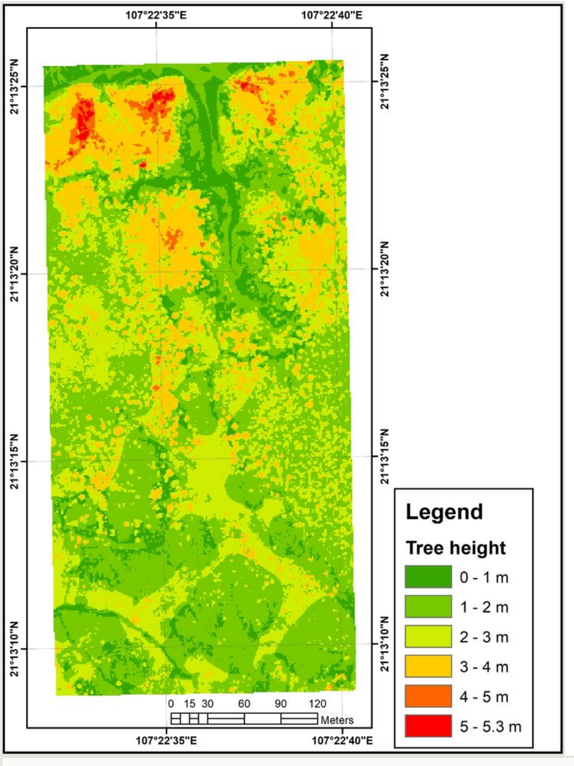

Figure 6.

Map of tree height flight area captured by UAV.

According to Fig. 6, the height of mangrove trees in the bay area ranges from 1.0 to 5.3 m, with the *Kandelia obovata* population, with an average height of 1.5 to 2.5 m, forming a narrow band and prevailing in the low-tide area along the Ba Che River. In the middle of the north, it borders the Ba Che River with the highest average tree height, with the tallest trees reaching 5.3 m. In addition to the northern area where the species is concentrated and dominated by *Bruguiera gymnorhiza*, this species is scattered in the middle tide area with an average height of 4 to 5 m. The further from the Ba Che River, to the south of the study area, the greater the mangrove tree tends to decrease in height. The average height of *Rhizophora stylosa* at UAV is lower than that of *Bruguiera gymnorhiza*, averaging between 2 and 3 metres, with *Aegiceras corniculatum* averaging between 1 and 1.5 metres in height.

Development of mangrove biomass estimation maps

Selection of a biomass estimation model

From 16 standard cells of field biomass measurements, the results of the image analysis from UAVs and the basic regression functions (formulas (2), (3), (4) and (5)), basic regression models were made for the Dong Rui mangrove biomass estimate at the UAV capture flight area (Fig. 7 and Table 1).

Table 1.

Results of building regression models.

Models	*Formula*	R^2	*RMSE*
Log-Log	Log10(AGB)= - 1.082*log10(NDVI) + 0.841*log10(TreeH) – 2.670	0.831	0.040
Log-Lin	Log10(AGB)= - 0.664*NDVI + 0.098*TreeH – 1.926	0.788	0.045
Lin-Log	AGB= - 0.023*log10(NDVI) + 0.015*log10(TreeH) – 0.002	0.817	0.001
Lin-Lin	AGB= - 0.014*NDVI + 0.002*TreeH + 0.013	0.822	0.001

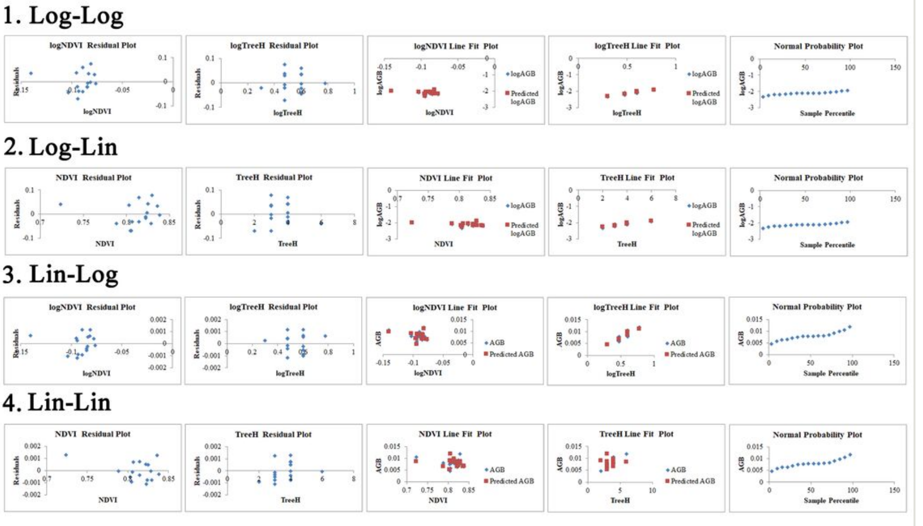

Figure 7.

Regression model development for mangrove biomass estimation.

Table 2 shows that the Log-Log regression model was chosen to estimate the biomass of mangroves in the UAV capture flight area when the highest R^2 value, 0.831 and the lowest RMSE, 0.040, were reached. To evaluate the above-mentioned built model, we identified the root mean square error (RMSE) and mean absolute error (MAE) and calculated the correlation coefficient between the field data and the data extracted from the model and the modelling efficiency (ME) index (Nash and Sutcliffe 1970). The assessment results are shown in Table 2.

According to Table 2, the results of the comparison of the component model and the results of the field survey at 16 standard cell points showed that the average dM value reached -0.001. There are four standard cell points with component model values equivalent to the field survey results, six standard cell points with a deviation component model value equal to the field survey results of 0.001 and the remaining six standard cell points with a deviation model value from the field survey value ranging from 0.002 to 0.006.

Table 2.

Biomass regression model construction accuracy (units: ‰).

Forest survey cell number	Field data (M_F)	Component model (M_M)	Model difference (dM) dM = $M_F - M_M$
1	0.010578	0.00803	**0.003**
2	0.005795	0.01214	**-0.006**
3	0.007847	0.00929	**-0.001**
4	0.004632	0.00927	**-0.005**
5	0.009857	0.00904	**0.001**
6	0.008375	0.00893	**-0.001**
7	0.011783	0.00871	**0.003**
8	0.008006	0.00845	**0**
9	0.007441	0.00683	**0.001**
10	0.006419	0.0063	**0**
11	0.007003	0.00737	**0**
12	0.007799	0.00867	**-0.001**
13	0.007908	0.00834	**0**
14	0.006363	0.01153	**-0.005**
15	0.008068	0.00982	**-0.002**
16	0.009123	0.00801	**0.001**
Average	***0.0079***	***0.009***	***-0.001***
	MAE		0.002
	MAE(%)		**28**%
	ME	0.91	
	R^2	0.831	
	RMSE	0.04	

In general, for the Log-Log regression model for mangrove biomass estimates, the mean error value reaches 0.002 and the average absolute error value reaches 0.002 (28%). The evaluation result of the model effectiveness index reached 0.91.

Build biomass estimation maps

A mangrove biomass estimate map (Fig. 8) was made, based on the results of the Log-Log model selection for biomass estimation in the UAV flight area.

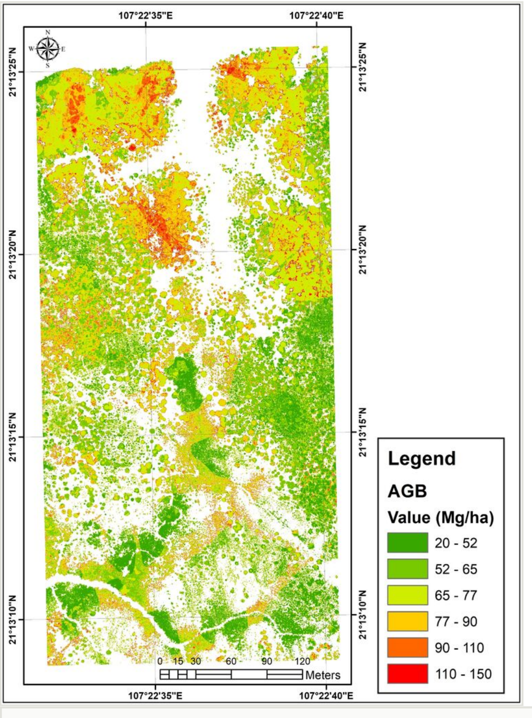

Figure 8.

Mangrove biomass estimation map of the UAV capture flight area.

According to Fig. 8, mangrove biomass values at the UAV flight site ranged from 20 Mg/ha to 150 Mg/ha, with biomass values ranging from 52 Mg/ha to 90 Mg/ha predominant. Furthermore, the highest biomass values are concentrated in the northern part of the study area, where *Rhizophora stylosa* and *Bruguiera gymnorhiza* species predominate, with average heights reaching between 3 and 5 m. The points with high biomass values scattered throughout the UAV flight area are those where *Bruguiera gymnorhiza* species are present, with an average height of 4 to 5 m. Areas with low biomass values are concentrated to the south and southeast of the UAV capture flight area with *Aegiceras corniculatum* predominant, with tree heights reaching only 1 to 1.5 m.

Discussion

Mangroves are becoming increasingly important and projects to reduce damage and adapt to global climate change are especially interesting. Large-scale quantitative research on forest biomass (Favero et al. 2022, Page-Dumroese et al. 2022) helps to confirm the role of forest plants in the global carbon cycle. It also helps to develop policies and services related to carbon. Moreover, mangroves are forest ecosystems that are especially important for coastal areas; they are not only carbon sinks, but also valuable in preventing various types of natural disasters, such as coastal erosion, minimising wave and flow impacts and providing coastal ecosystem services (Chung et al. 2022). Combining UAV flight data and survey results, field surveys are a useful approach for identifying certain structural features and estimating biomass in mangrove ecosystems.

This study discussed a way to determine how much biomass is on the surface of a coastal mangrove forest in northern Vietnam using data from UAV and the results of identifying biomass directly at verification points. This method can be combined with medium-resolution satellite images such as Sentinel or WorldView-2 for biomass estimates for mangrove ecosystems on a larger scale (Navarro et al. 2019, Qiu et al. 2019). The Log-Log model in this study had the highest accuracy in mangrove AGB estimates (R^2 = 0.831), equivalent to the XGBoost regression model applied in the mangrove biomass study in the Beibu Gulf, China (R^2 = 0.8319, RMSE = 22.7638 Mg/ha) (Tian et al. 2021), but this accuracy is higher when compared to the Catboost regression model applied to the AGB estimate of invasive mangroves in typical subtropical estuaries in China (R^2 = 0.7644, RMSE = 11.1725 Mg/ha) (Tian et al. 2022). Applying AGB estimation models that differ from satellite imagery data is also mentioned in many studies in different regions, but has lower accuracy than using UAV data when compared to this study. For example, in mangroves in the Red River Delta Biosphere Reserve, Vietnam, a biomass model was built using the XGBR-GA model, based on Sentinel-2, Sentinel-1 and ALOS-2 PALSAR-2 data (R^2 = 0.683, RMSE = 25.08 Mg/ha) (Pham et al. 2020); in Iran, the support vector regression model, based on Sentinel-2A and ALOS-2 PALSAR-2 satellite imagery data estimated AGB for the Hyrcanian forest area with results of R^2 = 0.73, RMSE = 38.68 Mg/ha (Vafaei et al. 2018).

According to the results of biomass estimates in the Dong Rui mangrove forest, the average biomass at the UAV flight area ranges from 20 Mg/ha to 150 Mg/ha. In general, the average biomass of mangroves in the Dong Rui commune is lower when compared to some studies in mangrove areas of the world, for example, in the Sundarbans mangrove forest in Bangladesh, where the average AGB of mangroves here varies from 111.36 Mg/ha to 299.48 Mg/ha for standard cells (Rahman et al. 2021), but higher than that in the Magallanes area in Agusan del Norte, Philippines, where the average mangrove biomass is relatively low, ranging from 1.66 Mg/ha to 39.52 Mg/ha. When comparing the Dong Rui mangrove forest area with some other areas in Vietnam, the biomass value here is quite similar to the mangrove area of Thai Binh Province (ranging from 22.57 Mg/ha to 37.74 Mg/ha) (Nguyen et al. 2019) or in Hai Phong City (mangrove biomass values range from 39 Mg/ha to 100 Mg/ha for each tree species), while the mangrove biomass in southern areas of Vietnam, such as Ca Mau Province, has a higher value (average is 191.1 Mg/ha with a range of 49.6 to 357.4 Mg/ha) (Tran et al. 2022).

In this study, however, LiDAR data have not yet been used with a UAV to process data for estimating mangrove biomass. Using the UAV-LiDAR combination method is considered one of the most effective combination tools for determining tree height and establishing

AGB maps for mangrove forests (Dezhi et al. 2019). LiDAR data have certain advantages in investigating the vertical, three-dimensional structure of mangroves (Tian et al. 2022). Meanwhile, ultra-high-resolution UAVs can also use taxonomy for individual tree species or mangrove plant preferences, serving to estimate biomass by species or by specific plant preferences, ensuring greater accuracy. In addition, biomass estimates from UAVs can serve as "key points," combined with medium-resolution satellite images, to identify biomass for forest ecosystems on a larger scale.

Conclusions

In this study, we developed a method and a biomass estimation model for mangroves in the Dong Rui commune, Vietnam. The method was based on four linear regression models that combined UAV data and biomass estimation results from the field. We propose that UAV image data can identify mangrove biomass with high accuracy, which could replace the traditional standard method of field-based data collection.

However, this study still has certain limitations. UAV data combined with LiDAR data can more accurately determine mangrove structure, such as height and canopy area, for building biomass estimation models. In addition, UAVs have limitations in range and wind resistance and depend on battery life.

Our results can be used as a starting point to develop more accurate ways to estimate biomass in mangrove areas. In the future, UAV sites could be used instead of traditional field surveys at standard plots to estimate biomass. These sites could be used with medium-resolution satellite imagery, which is very useful for making biomass maps for larger areas

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Author contributions

To complete the article, the authors participated in the article's stages with the following contents: “Dung T.N. and Hoi D.N. writing and designing articles; Dung T.N., Hoi D.N. and Khanh Q.N. wrote the manuscript; Hieu H.V.N., Cuong D.H., Thanh V.P. and Ngoc T.D. analysed satellite image data; Dung T.N. and Hoi D.N. completed the article”.

Conflicts of interest

The authors declare that they have no conflicts of interest.

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