

Article

Estimation of Coastal Wetland Vegetation Aboveground Biomass by Integrating UAV and Satellite Remote Sensing Data

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Abstract: Aboveground biomass (AGB) serves as a crucial indicator of the carbon sequestration capacity of coastal wetland ecosystems. Conducting extensive field surveys in coastal wetlands is both time-consuming and labor-intensive. Unmanned aerial vehicles (UAVs) and satellite remote sensing have been widely utilized to estimate regional AGB. However, the mixed pixel effects in satellite remote sensing hinder the precise estimation of AGB, while high-spatial resolution UAVs face challenges in estimating large-scale AGB. To fill this gap, this study proposed an integrated approach for estimating AGB using field sampling, a UAV, and Sentinel-2 satellite data. Firstly, based on multispectral data from the UAV, vegetation indices were computed and matched with field sampling data to develop the Field-UAV AGB estimation model, yielding AGB results at the UAV scale (1 m). Subsequently, these results were upscaled to the Sentinel-2 satellite scale (10 m). Vegetation indices from Sentinel-2 data were calculated and matched to establish the UAV-Satellite AGB model, enabling the estimation of AGB over large regional areas. Our findings revealed the AGB estimation model achieved an R^2 value of 0.58 at the UAV scale and 0.74 at the satellite scale, significantly outperforming direct modeling from field data to satellite ($R^2 = -0.04$). The AGB densities of the wetlands in Xieqian Bay, Meishan Bay, and Hangzhou Bay, Zhejiang Province, were 1440.27 g/m², 1508.65 g/m², and 1545.11 g/m², respectively. The total AGB quantities were estimated to be 30,526.08 t, 34,219.97 t, and 296,382.91 t, respectively. This study underscores the potential of integrating UAV and satellite remote sensing for accurately assessing AGB in large coastal wetland regions, providing valuable support for the conservation and management of coastal wetland ecosystems.

Keywords: aboveground biomass; Sentinel-2; random forest; multiple linear regression; carbon sink; satellite imagery



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1. Introduction

Coastal wetlands, although covering only about 3–5% of the Earth's land surface, store about 30% of the total carbon in terrestrial ecosystems [1–3], making them crucial sites for long-term storage of organic carbon. Coastal wetlands are located in the transition zone between terrestrial and marine environments, and their unique vegetation types, such as mangroves, salt marshes, and seagrass beds, together with sediment deposition, facilitate rapid carbon sequestration [4,5]. This efficient trapping of atmospheric carbon dioxide helps to mitigate global warming [6]. Among these ecosystems, salt marshes, which feature vegetation such as *reeds*, *Spartina alterniflora*, *Suaeda salsa*, and *Tamarix chinensis*, play a crucial role in China's coastal wetlands [7,8]. Coastal salt marsh vegetation exhibits extremely strong carbon sequestration capabilities, with organic carbon accounting for approximately 40–50% of the dry biomass [9]. Therefore, the aboveground biomass (AGB) of coastal wetland vegetation serves

not only as an indication of plant community growth but also as a key factor in assessing the carbon stock of salt marsh ecosystems. Conducting large-scale and precise estimations of AGB is crucial in evaluating the carbon sequestration function of coastal wetland ecosystems [10].

Traditional field surveys are renowned for their accuracy in estimating AGB. However, they are costly in terms of manpower and resources, and they carry the risk of causing ecological damage [11]. Additionally, the dynamic nature of coastal wetlands—affected by tides, rainfall, and terrain—presents significant challenges for large-scale AGB estimation [12].

Satellite remote sensing has become a mainstream method for estimating AGB due to its wide coverage and low operating cost [13]. Among them, MODIS (Moderate-Resolution Imaging Spectroradiometer) products, due to their extensive global coverage, have been extensively employed for monitoring of AGB and vegetation coverage [14]. Therefore, utilizing vegetation indices from MODIS moderate-resolution products, combined with deep learning models, can effectively quantify AGB in large-scale ecosystems such as highland grassland and seasonal wetlands [15,16]. However, the extensive coverage of MODIS satellites comes at the expense of lower spatial resolution, limiting their accuracy in AGB estimation [17]. The Landsat series offer higher spatial resolution and play an important role in quantifying biomass in coastal marsh wetlands [18]. Regression analysis between measured AGB and vegetation indices from Landsat imagery has proven effective in estimating AGB of mangroves in the Persian Gulf [19]. In some studies related to estimating AGB in lake wetlands in China, Landsat imagery is often used. By combining field-measured data from 1 m × 1 m plots in wetlands with Landsat 8 imagery, which has spatial resolutions ranging from 15 m to 30 m, researchers can establish relationship models to estimate multi-year AGB of wetlands [20]. Compared to Landsat, the Sentinel series satellites are equipped with multispectral sensors (MSIs) that offer higher spatial resolution (10 m) and higher temporal resolution (5 days). These features result in Sentinel satellites frequently being used for large-scale vegetation monitoring and disaster assessment. The rich spectral indices and texture metrics extracted from Sentinel-2 imagery have shown significant advantages in estimating the AGB of floodplain wetlands [21–23]. However, estimating wetland AGB directly from satellite imagery presents challenges due to the discrepancy between the size of field sample plots and the satellite's spatial resolution, leading to mixed pixel issues and increased uncertainty in estimation [24]. High-spatial-resolution satellites such as WorldView, with pixel sizes around 1 m, offer the potential for fine-scale estimation of wetland vegetation AGB using the Normalized Difference Vegetation Index (NDVI) extracted from their imagery [25]. Nevertheless, the high cost of this imagery limits its widespread application [26]. In this context, unmanned aerial vehicle (UAV) remote sensing imagery is a more suitable choice for fine-scale estimation of wetland vegetation AGB.

Compared to most satellite imagery, UAV remote sensing imagery has higher spatial resolution, enabling the capture of more detailed surface features. Therefore, it is often used in studies requiring high-precision information [27]. Additionally, UAV imagery offers greater customization and convenience, allowing researchers to set flight parameters such as altitude, coverage, and sensors to suit specific study needs [28]. UAVs are now widely used for estimating physiological parameters such as vegetation leaf area, chlorophyll content, and AGB in various ecosystems [29]. For instance, Sharma et al. [30] utilized UAV multispectral imagery with a resolution of 0.7 m, coupled with machine learning models such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) to quantify the AGB of oat fields in northern South Dakota. In the estimation of AGB in agricultural ecosystems, UAV remote sensing has also played a significant role. Based on spectral reflectance characteristics extracted from UAV hyperspectral imagery and field data, potato AGB was estimated using partial least squares regression [31]. In recent years, the application of UAV remote sensing technology in the retrieval of vegetation parameters in coastal wetland ecosystems is becoming popular. For example, scholars have successfully used UAVs to precisely estimate the carbon storage of mangroves in Indonesian wetlands [32]. Since UAV remote sensing provides higher-resolution images for wetland vegetation classification, the accuracy of AGB inversion results is significantly improved [33,34]. However, while UAV imagery can provide prediction results closer to actual measurement data, it is limited by flight altitude and cannot capture

imagery on a large spatial scale [35]. Therefore, its applicability is limited compared to satellite imagery, particularly for conducting large-scale AGB estimation.

Given the limitations of both satellites and UAVs in monitoring wetland vegetation AGB, achieving large-scale and fine-scale AGB estimation using a single data source is challenging. Some researchers have attempted to combine UAV and satellite data to establish a linear regression model for jointly estimating the AGB of reeds, but the accuracy still requires improvement ($R^2 = 0.59$) [36]. Therefore, this study integrated data from both UAV and satellite remote sensing sources, using UAV data as a bridge between field measurements and satellite data to develop an inversion model for scaling up the research. Initially, a model was established between field-observed AGB and UAV imagery, and its accuracy is validated. Subsequently, AGB maps at the UAV scale were generated and then matched with satellite imagery. A new model was thus developed to obtain AGB estimates at the satellite scale for coastal salt marsh wetlands, thereby establishing a multi-scale AGB estimation model integrating field, UAV, and satellite data.

2. Materials and Methods

2.1. Study Area

Ningbo is a port city located on the southeastern coast of China, situated in the coastal plain of Zhejiang Province. The terrain is relatively flat, and it belongs to a subtropical monsoon climate, characterized by hot and humid summers and cold and damp winters. The annual average precipitation is approximately 1200 mm. Ningbo boasts abundant natural resources [37]. This study selected three coastal salt marsh wetlands: Hangzhou Bay (HZB, central coordinates 30°19'N, 121°7'E), Meishan Bay (MSB, central coordinates 29°47'N, 121°59'E), and Xieqian Bay (XQB, central coordinates 29°33'N, 122°1'E). The three sampling sites are all coastal salt marsh wetlands, characterized by typical wetland dwarf vegetation such as reeds, *Spartina alterniflora*, and *Suaeda salsa* (Figure 1). The vegetation is dense, and human activities are rare, making large-scale field measurements difficult. Therefore, there is a local need to use remote sensing methods to estimate AGB.

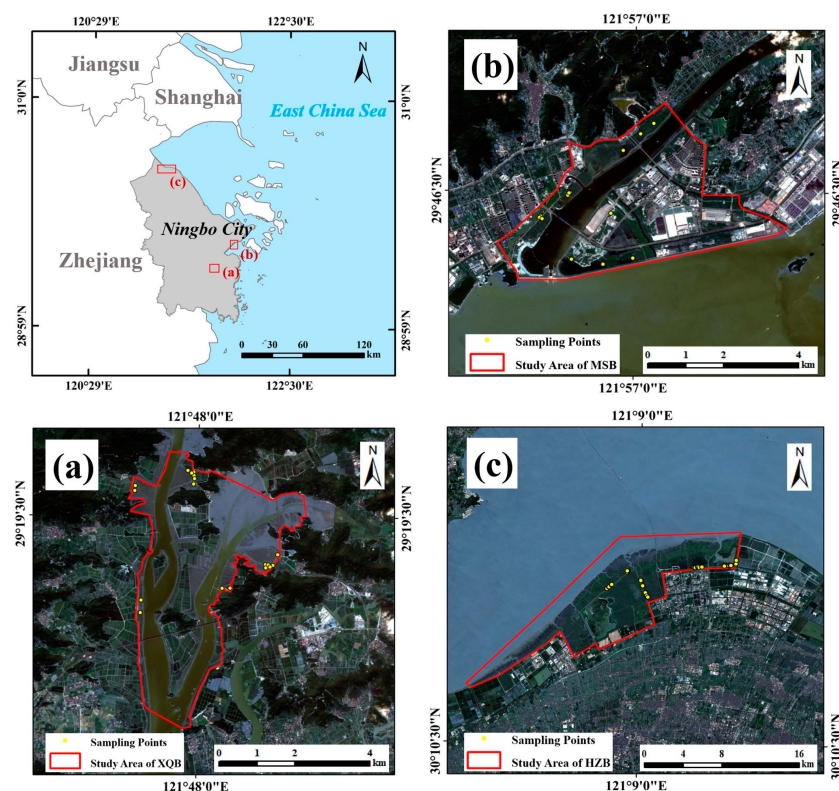


Figure 1. Study area overview. (a) Study area of Xieqian Bay (XQB). (b) Study area of Meishan Bay (MSB). (c) Study area of Hangzhou Bay (HZB).

2.2. Data Acquisition and Processing

2.2.1. Field Data Acquisition and Processing

The field data collection period spanned from 1 September 2022 to 31 October 2022, and corresponded to the maturity period of wetland vegetation. Sixty representative sampling points, each measuring $1\text{ m} \times 1\text{ m}$, were set up within the three sampling sites (Figure 2). All vegetation samples within each plot were harvested, bagged, weighed on-site, and recorded as fresh vegetation weight. The geographic coordinates of each plot were recorded using a Unistrong G970 RTK, along with data such as elevation, vegetation type, and plant height within each plot.



Figure 2. Photos showing on-site sampling. (a) Real situation of sampling site. (b) Sample setting.

After bringing the vegetation samples back to the laboratory from the field, they were placed in an oven and first heated to $105\text{ }^{\circ}\text{C}$ for 2 h. Subsequently, they were dried at $75\text{ }^{\circ}\text{C}$ for 48 h until a constant weight was achieved. The vegetation samples were then weighed to obtain the dry weight. The dry weights ranged from 392.30 g/m^2 to 2891.40 g/m^2 . A total of 56 valid vegetation AGB (dry weight) data points were selected from these samples as the measured AGB sample set.

2.2.2. UAV Data Acquisition and Processing

The UAV multispectral imagery used in this study was captured with a DJI Phantom 4 Multispectral drone. The UAV operation took place on 1 September 2022, under clear and windless weather conditions, synchronized with the on-site sampling. The DJI Phantom 4 Multispectral drone integrates one visible light camera and five multispectral cameras (blue, green, red, red edge, and near-infrared), enabling both visible light imaging and multispectral imaging. During UAV operation, the flight altitude was set to 300 m, with a horizontal flight speed of 10 m/s and a maximum vertical ascent speed of 5 m/s.

The original aerial images were preprocessed using Pix4Dmapper V4.5.6 [38] and DJI Terra V3.8.0 software [39], including steps such as radiometric calibration and orthorectification. This process produced single-band orthorectified images with a spatial resolution of 0.02 m. Subsequently, the UAV images were processed using the Layer Stacking and Seamless Mosaic functions in the ENVI 5.3 [40] software to merge the bands and create a multispectral image with five bands. The image was resampled using nearest-neighbor

resampling [41] to a spatial resolution of 1 m to match the field sample plots. Each sampling site included several UAV images, and the coverage area of these UAV images is referred to as the flight area (FA).

2.2.3. Sentinel-2 Data Acquisition and Processing

This study selected Sentinel-2 imagery as the satellite remote sensing data source. Sentinel-2 consists of two satellites, Sentinel-2A and Sentinel-2B, which are in phase with a relative orbit of 180°. Sentinel-2A was launched on 23 June 2015, and Sentinel-2B was launched on 7 March 2017. The Sentinel-2 constellation, operating with a revisit period of five days is equipped with the MultiSpectral Instrument (MSI) and operates at an altitude of 786 km, with a swath width of up to 290 km. The spectral coverage includes visible light, near-infrared (NIR), and shortwave infrared (SWIR) bands, comprising 13 spectral bands. The spatial resolution varies between 10 m, 20 m, and 60 m for different bands. It includes three red-edge bands (670–760 nm), which are particularly effective for vegetation monitoring [21,42]. Specific information is shown in Table 1.

Table 1. Description of Sentinel-2 bands.

Band	Resolution	Center Wavelength	Description
B1	60 m	443 nm	coastal aerosol
B2	10 m	490 nm	blue
B3	10 m	560 nm	green
B4	10 m	665 nm	red
B5	20 m	705 nm	red edge
B6	20 m	740 nm	red edge
B7	20 m	783 nm	red edge
B8	10 m	842 nm	NIR
B8a	20 m	865 nm	NIR
B9	60 m	940 nm	water vapor
B10	60 m	1375 nm	SWIR
B11	20 m	1610 nm	SWIR
B12	20 m	2190 nm	SWIR

Two scenes of Level-2A Sentinel-2 imagery covering the three sampling sites were downloaded from the Google Earth Engine (GEE) platform [43]. Four bands, namely B3 (green), B4 (red), B5 (near-infrared), and B8 (narrow near-infrared), which are primarily used to study vegetation, were selected and utilized. The imagery for MSB and XQB was captured on 2 October 2022, while the imagery for the HZB area was captured on 10 October 2022, coinciding with the field sampling and UAV image acquisition. The images underwent preprocessing steps including cloud masking, atmospheric correction, and radiometric calibration on the GEE platform. Subsequently, geometric correction was performed using ENVI 5.3, and the images were resampled to a resolution of 10 m.

2.3. Steps for AGB Estimation

The overall workflow of the study mainly consists of three components (Figure 3): (1) data acquisition and preprocessing; (2) establishment of AGB estimation models based on field-observed and UAV flight area data; (3) AGB estimation based on UAV and satellite data.

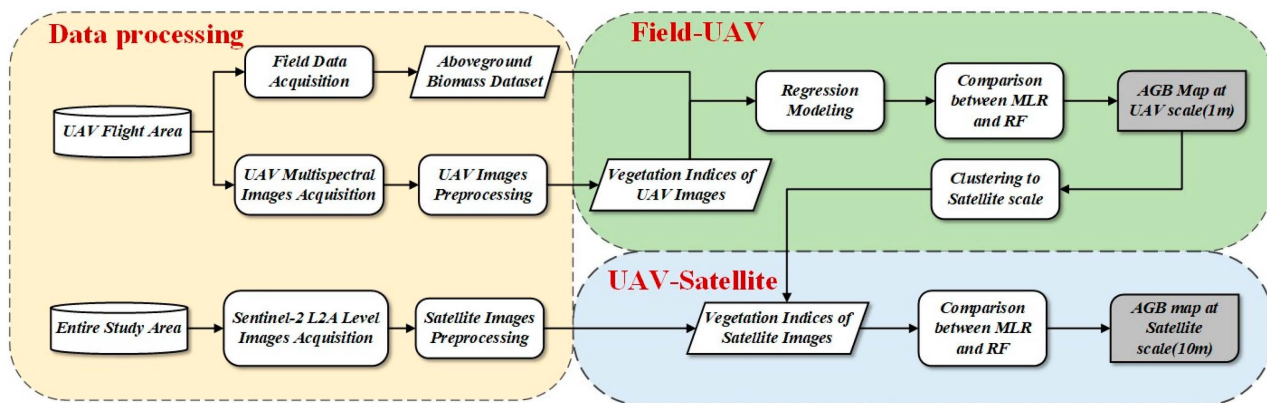


Figure 3. Overall workflow of the study (MLR: multiple linear regression; RF: Random Forest).

2.3.1. Vegetation Indexes

The vegetation index is an indicator used to assess vegetation condition and is calculated from surface reflectance or radiation data from different spectral bands [44,45]. By combining these bands from visible light and near-infrared spectra, numerical indicators that provide specific insights into vegetation conditions can be obtained.

Based on the research findings in remote sensing estimation of AGB [36,46], and taking into account the spectral bands available in multispectral UAV and Sentinel-2 imagery, this study selected nine vegetation indices, all calculated using the reflectance of vegetation in the visible, red edge, and near-infrared bands: The Normalized Difference Vegetation Index (NDVI) measures the growth status of vegetation by comparing near-infrared and red light reflectance. The Green Normalized Difference Vegetation Index (GNDVI), similar to the NDVI, uses the green band instead of red to evaluate vegetation moisture and nitrogen content. The Optimized Soil-Adjusted Vegetation Index (OSAVI) adjusts for soil background effects in the NDVI formula to assess vegetation health. The Normalized Difference Red Edge Index (NDRE) replaces the red band in the NDVI with the red edge band, making it more suitable for medium- to large-sized vegetation. The Leaf Chlorophyll Index (LCI) quantifies leaf chlorophyll and nitrogen content using near-infrared, red, and red edge bands. RVI monitors soil quality and vegetation coverage through the ratio of near-infrared to red reflectance. The Difference Vegetation Index (DVI), also using near-infrared and red bands, helps eliminate some radiation errors. The Renormalized Difference Vegetation Index (RDVI) improves upon the NDVI by being less sensitive to soil brightness and atmospheric effects, making it better for sparsely vegetated areas. Finally, the Atmospherically Resistant Vegetation Index (ARVI) corrects for atmospheric scattering, particularly aerosol influence, using the blue light band, making it suitable for monitoring vegetation under high aerosol conditions.

All of these indices are capable of effectively quantifying vegetation biomass. The vegetation indices were calculated using the Band Math tool in ENVI 5.3 and Python 3.9. The vegetation indices constructed based on the UAV and Sentinel-2 images are shown in Table 2.

The bands used by the UAV (B1, B2, B3, B4, B5) and by Sentinel-2 (B2, B3, B4, B5, B8) correspond to the green, red, red edge, and near-infrared bands, respectively.

Table 2. Vegetation indices calculated based on UAV and Sentinel-2 images.

Variables	Formulae	UAV Bands	Sentinel-2 Bands
NDVI [47]	$(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$	B3, B5	B4, B8
GNDVI [48]	$(\text{NIR} - \text{GREEN}) / (\text{NIR} + \text{GREEN})$	B2, B5	B3, B8
OSAVI [49]	$(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED} + 0.16)$	B3, B5	B4, B8
NDRE [50,51]	$(\text{NIR} - \text{RED EDGE}) / (\text{NIR} + \text{RED EDGE})$	B4, B5	B5, B8

Table 2. Cont.

Variables	Formulae	UAV Bands	Sentinel-2 Bands
LCI [52]	$(\text{NIR} - \text{RED EDGE})/(\text{NIR} + \text{RED})$	B3, B4, B5	B4, B5, B8
RVI [53]	NIR/RED	B3, B5	B4, B8
DVI [54]	$\text{NIR} - \text{RED}$	B3, B5	B4, B8
RDVI [55]	$\sqrt{(\text{NDVI} \times \text{DVI})}$	B3, B5	B4, B8
ARVI [56]	$(\text{NIR} - (2 \times \text{RED}) + \text{BLUE})/(\text{NIR} + (2 \times \text{RED}) - \text{BLUE})$	B1, B3, B5	B2, B4, B8

2.3.2. Estimation of AGB Based on UAV

The multiple linear regression (MLR) model is a statistical model used to study the relationship between a dependent variable and multiple independent variables. It extends the simple linear regression model by considering the influence of two or more independent variables on the dependent variable [57].

If the AGB of vegetation is considered as the dependent variable, denoted as Y , and $X_1, X_2, \dots, X_k$ represent the vegetation indices as independent variables, then the MLR model, assuming a linear relationship between the dependent and independent variables, can be expressed as:

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_kX_k + \varepsilon \quad (1)$$

where b_0 represents the intercept term; $b_1, b_2, \dots, b_k$ denote the regression coefficients; and ε represents the error term, which is assumed to follow a normal distribution.

This study employed backward elimination to screen the variables in the multiple regression ($p > 0.05$), determining the optimal variable combination by observing the change in the coefficient of determination R^2 . Backward elimination is a method for selecting independent variables in the MLR model. Through this method, all independent variables are initially introduced into the model, a significance threshold is set, and then variables with an impact on the dependent variable less than the significance threshold are gradually eliminated until no further elimination is possible [58]. This method makes the selection of independent variables in the model more reasonable, resulting in a more concise and effective model.

The Random Forest (RF) regression model is a typical nonlinear regression model. It is a powerful ensemble learning algorithm composed of multiple decision trees [59], which can be trained on different subsets of data using the Bootstrap Aggregating (Bagging) strategy, thereby increasing the diversity of the model [60]. RF performs well in handling high-dimensional data and complex relationships, with relatively small impact from noise and outliers, showing strong robustness. Assuming the dataset contains N samples, each with m features, for the i -th sample, its features are represented as $X_i = (X_{i1}, X_{i2}, \dots, X_{im})$, and the target variable is Y_i . The predicted output $\hat{Y}_i$ of the RF regression model can be represented as the average of predictions from all decision trees:

$$\hat{Y}_i = \frac{1}{N_{tree}} \sum_{j=1}^{N_{tree}} f_j(X_i) \quad (2)$$

In Equation (2), N_{tree} represents the number of decision trees in the RF, and $f_j(X_i)$ denotes the prediction result of the j -th decision tree for sample X_i . The prediction $f_j(X_i)$ of each decision tree is obtained by splitting features at each node, assigning samples to corresponding leaf nodes based on their feature values, and predicting using the average target variable value at the leaf nodes.

RF can assess the importance of each feature in the model, aiding in identifying features that significantly impact the predicted variable. Tuning parameters is crucial to enhance the performance of the RF model. In this study, three optimized parameters were selected: (1) $n\_estimators$, which is the number of decision trees in the model. (2) max_depth or the maximum depth of the decision trees; controlling depth to avoid

overfitting. (3) max_features, which is the maximum number of features considered when splitting each node.

Two AGB estimation models, i.e., MLR and RF, were established separately based on field survey points and UAV imagery. The accuracy metrics of these models were compared, and the model with better results was chosen to reconstruct a spatial distribution map of UAV-derived AGB at a 1 m resolution.

2.3.3. Estimation of AGB Based on UAV-Satellite Model

The 1 m resolution unmanned aerial vehicle (UAV) AGB sample set, derived from field and UAV data estimation, was matched with Sentinel-2 images covering the three study sites. Each 10 m sized satellite pixel contains one hundred 1 m sized UAV AGB sample pixels, and their pixel values are cumulatively aggregated. For each study site, 2000 random sample points were selected, totaling 6000 sample points used for building the UAV-Satellite model. Using the preprocessed Sentinel-2 images' bands B2–B8, the nine indices listed in Table 1 were calculated. Combined with the extended sample points matched with satellite pixels, the MLR model and RF model were established to estimate the AGB in the study area. The accuracy metrics of both models were compared, and the one with the higher precision was selected to generate the satellite-scale AGB map in the coastal wetlands.

2.3.4. Model Assessment

Cross-validation is a statistical method used to assess the performance and generalization ability of a model. It enables a more comprehensive evaluation of the model across different subsets of data, thereby reducing reliance on a specific data partition. Common cross-validation techniques include k-fold cross-validation and leave-one-out cross-validation [61]. In this study, due to the limited number of field sample points, the data were not partitioned into training and testing sets in a certain ratio when establishing the Field-UAV model. Instead, five-fold cross-validation was applied to all variable data in both models. In the UAV-Satellite model, the variable data was randomly divided into two subsets: 70% for training, with five-fold cross-validation set up on the training set and the remaining 30% for testing to evaluate the model's generalization ability.

The model accuracy was evaluated using the R^2 (Equation (3)), root mean square error (RMSE, Equation (4)), and coefficient of variation of root mean square error (CV-RMSE, Equation (5)).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (4)$$

$$CV-RMSE = \frac{RMSE}{\bar{y}} \quad (5)$$

where y_i represents the biomass value of the i -th sample measured on the field, $\hat{y}_i$ represents the estimated biomass value of the i -th sample, $\bar{y}$ represents the mean biomass value of the measured samples, and n represents the number of samples.

3. Results

3.1. AGB Estimation Based on Field–UAV Data

3.1.1. MLR Model

The Pearson correlation coefficients (R) [62] between all vegetation index variables and the AGB of wetland vegetation, visualized in the correlation coefficient matrix (Figure 4a), indicates that, in our study, the NDVI exhibited the highest correlation with AGB ($R = 0.69$, $p < 0.01$), while the NDRE showed the lowest correlation ($R = 0.40$, $p < 0.01$). Except for

the NDRE, the R of other indices with AGB ranged from 0.6 to 0.7. It can be observed that most indices maintain a high correlation with AGB ($R > 0.6$). Ultimately, the NDVI, NDRE, LCI, and ARVI were chosen as the four variables for MLR modeling of AGB. Based on the five-fold cross-validation, the model (Figure 4b) exhibited $R^2 = 0.48$, $RMSE = 365.67 \text{ g/m}^2$, $CV\text{-}RMSE = 28.31\%$, and $p < 0.05$. Additionally, a 95% confidence interval (pink shaded area) was included in the figure, indicating that there was a 95% probability that the predicted dependent variable values fall within this interval. The MLR regression equation is presented as follows (Equation (6)):

$$Y = 14,421.9X_1 - 7426.49X_2 + 6521.07X_3 - 13,335.7X_4 - 1455.64, \quad (6)$$

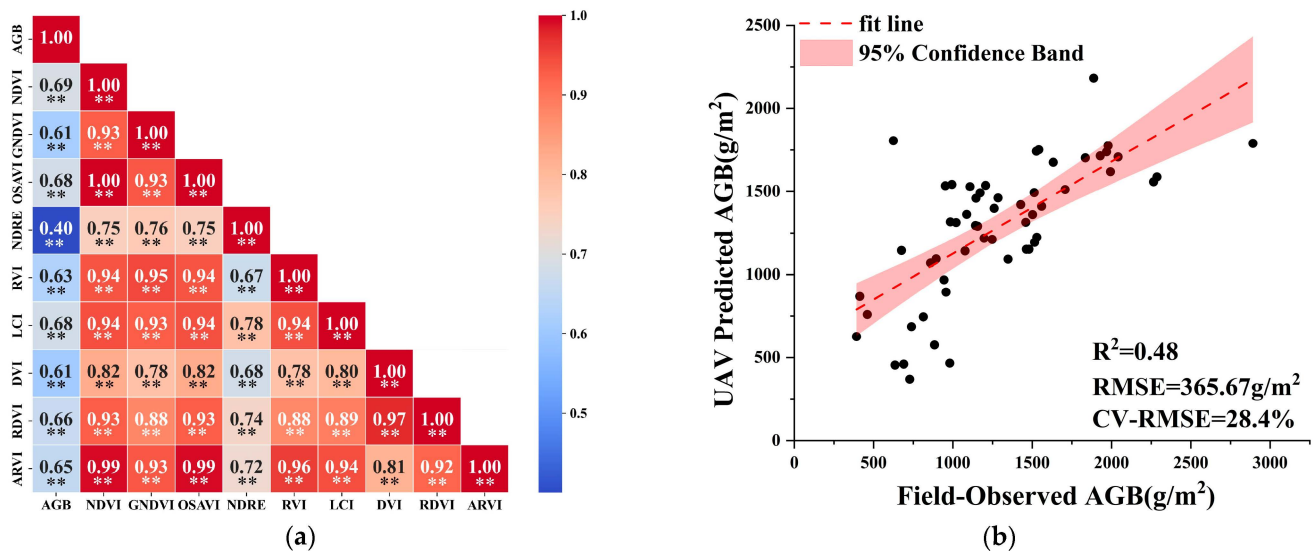


Figure 4. Multivariate linear regression model based on Field–UAV data. (a) Correlation matrix of various vegetation indices from the UAV with wetland vegetation AGB (** indicates $p < 0.01$). (b) Predicted values and measured values of multivariate linear regression based on field and UAV data.

Y represents AGB, while X_1 , X_2 , X_3 , and X_4 represent the NDVI, NDRE, LCI, and ARVI, respectively.

3.1.2. RF Regression Model

Variables were added to the RF model in descending order of importance, and the change R^2 was analyzed for different numbers of variables. The results indicate that the GNDVI and NDVI exhibited significantly higher importance in the model compared to other indices, exerting a considerable impact on the model (Figure 5a). Based on the importance of different variables, models were constructed by combining them, resulting in variations in the R^2 under different variable combinations. The model showed the best performance when the number of variables was set to three. The three feature variables in the combination were the GNDVI, NDVI, and LCI (Figure 5a,b). The predictions from the RF model built using these three variables were compared against the field-observed values (Figure 5c). The best fitting effect was achieved by setting the number of trees in the RF to 32, the depth to 3, with the estimation results being $R^2 = 0.58$, $RMSE = 330.51 \text{ g/m}^2$, and $CV\text{-}RMSE = 25.59\%$. The pink area in the figure represents the 95% confidence interval.

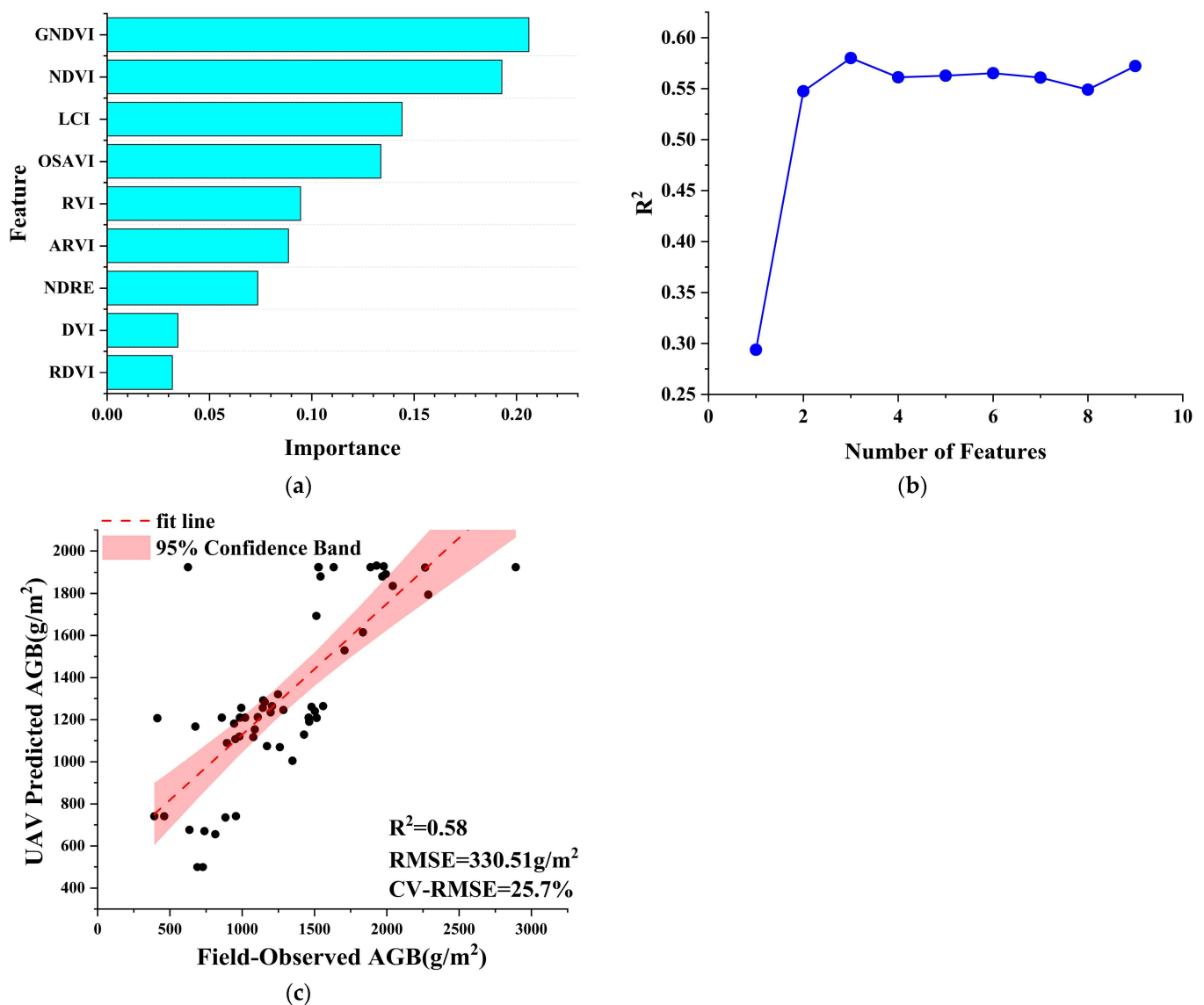


Figure 5. RF regression model based on Field–UAV data. (a) Variable importance ranking of UAV vegetation indices in the RF regression model. (b) Changes in the R^2 for models with different numbers of variables. (c) Scatter plot of predicted values and field-observed values for RF regression based on field and UAV data.

3.1.3. Comparison of Models

Both models were trained using all measured AGB samples from the three study sites. A comparison of the fitting results of the two regression models revealed that the RF regression model outperformed the MLR model in all accuracy evaluation metrics, with an increase in R^2 of 20.83%, a decrease in RMSE of 9.62%, and a decrease in CV-RMSE of 9.61% (Table 3). The reason for this outcome may be attributed to the robustness of the RF model against outliers and noisy data. The RF model is a non-linear integrated model based on multiple decision trees, which can average the predictions of each tree. In contrast, the MLR model is sensitive to outliers, which may lead to deviations in the fitting results from the actual situation.

Therefore, the RF regression model with variable selection was chosen as the model for estimating AGB based on field and UAV data, serving as the basis for constructing the UAV-based AGB estimation model.

Table 3. Fitting performance of MLR and RF models.

Models \ Metrics	R^2	RMSE/g/m ²	CV-RMSE
MLR	0.48	365.67	28.31%
RF	0.58	330.51	25.59%

3.1.4. Estimation Results of FA

Using the RF regression model after variable selection as the model for estimating AGB based on Field-UAV data, we constructed a UAV AGB sample set. The map of AGB generated using the RF regression model based on Field-UAV data is shown in Figure 6. Combining the statistical results from multiple UAV AGB maps, the maximum predicted AGB for the FA in XQB was 2394.03 g/m², for the FA in MSB was 2435.37 g/m², and for the FA in HZB was 2465.51 g/m². From the figure, it can be observed that the AGB density and maximum value of FA in XQB were both smaller than those of FA in MSB and FA in HZB. The average values were 1321.98 g/m², 1651.69 g/m², and 1674.93 g/m². The AGB density and maximum value of MSB and FA and FA in HZB were relatively close, but due to the largest area of coastal wetlands in HZB and the highest total amount of coastal saltmarsh vegetation, the total AGB in HZB was greater than that in XQB and MSB.

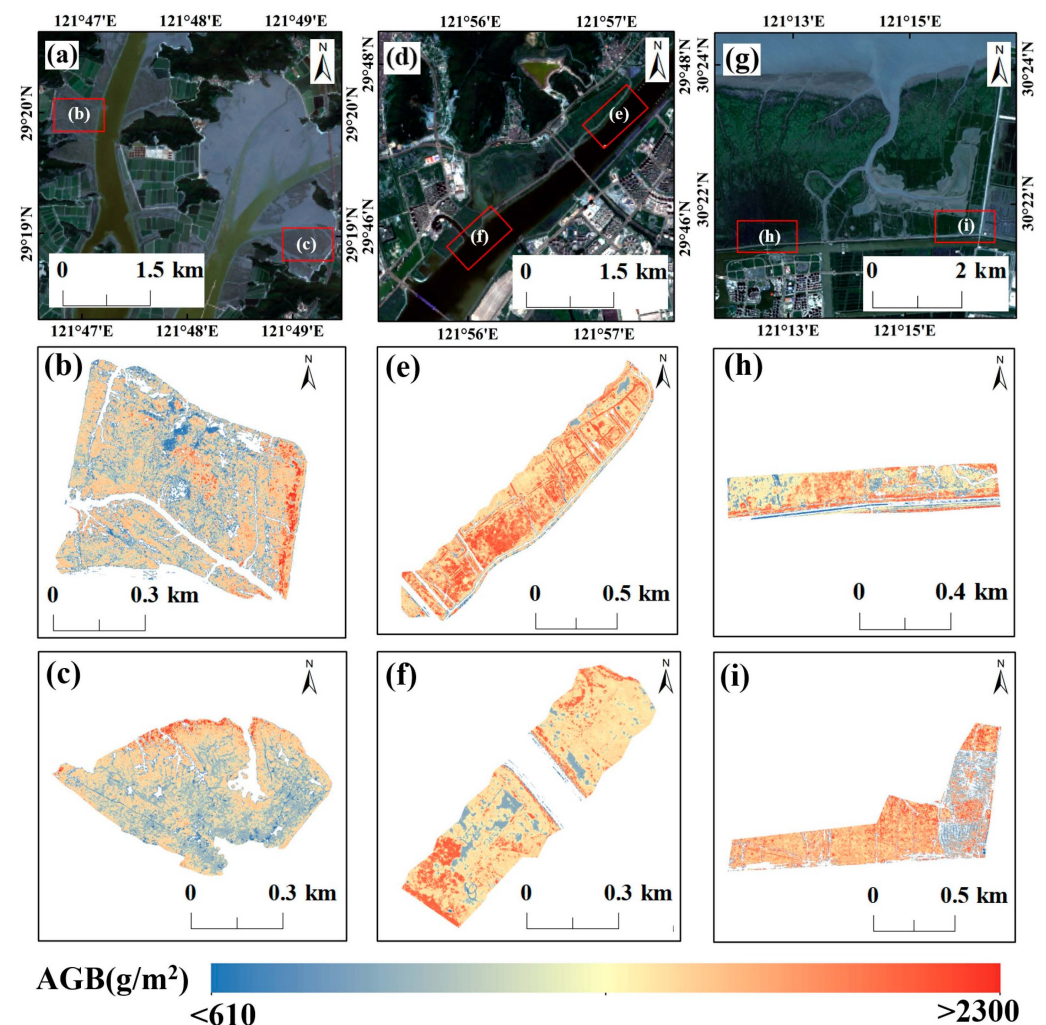


Figure 6. AGB results estimated by the RF regression model based on Field-UAV data. (a–c) Satellite image and UAV AGB map of FA in XQB, (d–f) satellite image and UAV AGB map of FA in MSB, (g–i) satellite image and UAV AGB map of FA in HZB. (FA: flight area; XQB: Xieqian Bay; MSB: Meishan Bay; HZB: Hangzhou Bay).

3.2. AGB Estimation Based on Satellite Data

3.2.1. MLR Model

From the UAV-scale AGB sample set, sample points were randomly selected, and nine vegetation indices were computed based on Sentinel-2 images corresponding to these points; 2000 sample points were selected for each site, totaling 6000 sample points across the three sites. By calculating the Pearson correlation coefficients between wetland vegetation AGB and all satellite vegetation index variables, a correlation matrix heatmap was obtained (Figure 7a). The variable with the highest correlation coefficient was OSAVI ($R = 0.55$, $p < 0.01$), while the lowest was RVI ($R = 0.24$, $p < 0.01$). Most variables had correlation coefficients between 0.4 and 0.5, generally lower than those in the UAV–Satellite MLR model. Based on the backward elimination method, nine vegetation indices were selected for modeling, all of which had significance levels below 0.01, meeting the backward elimination method's preset significance threshold of 0.05. The fitting results on the test set are shown in Figure 7b, with $R^2 = 0.61$, $RMSE = 231.68 \text{ g/m}^2$, $CV\text{-}RMSE = 15.0\%$, $p < 0.01$. The MLR equation is shown in Equation (7):

$$Y = 1,076,041.58X_1 + 373,652.77X_2 + 146,781.55X_3 + 80,029.16X_4 + 102,831.79X_5 - 956,802.06X_6 - 190,698.41X_7 + 107,416.53X_8 - 583,173.01X_9 + 24,477.81 \quad (7)$$

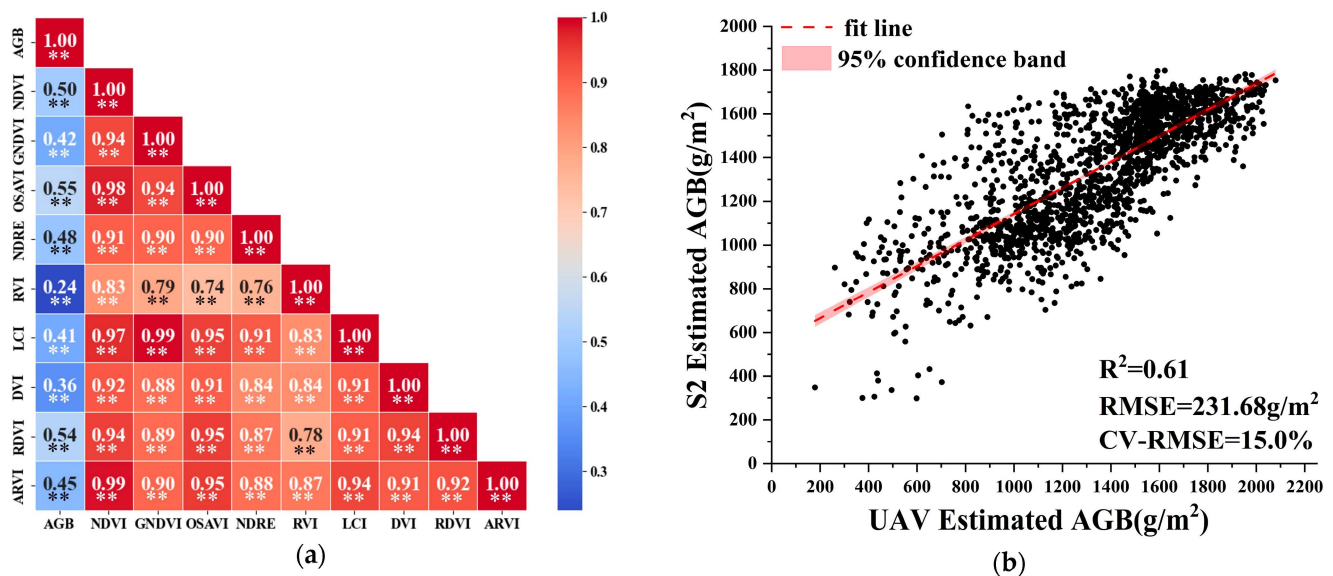


Figure 7. Multivariate linear regression model based on UAV–Satellite data. (a) Correlation matrix of various vegetation indices from the satellite with wetland vegetation AGB (** indicates $p < 0.01$). (b) Predicted values and measured values of multivariate linear regression based on UAV and satellite data.

In the equation, Y represents AGB, while X_1 to X_9 correspond to the NDVI, GNDVI, OSAVI, NDRE, LCI, RVI, DVI, RDVI, and ARVI, respectively.

3.2.2. RF Regression Model

Based on the same 6000 sample points as in Section 3.2.1, the RF model for AGB estimation was then established to predict AGB in the study area. Upon sorting the variables' importance in the model, it was observed that the importance of each vegetation index in the model varied. The OSAVI ranked first in importance, and was notably more significant than the other variables, as evident from the graph. The RVI and DVI ranked second and third in importance, respectively (Figure 8a).

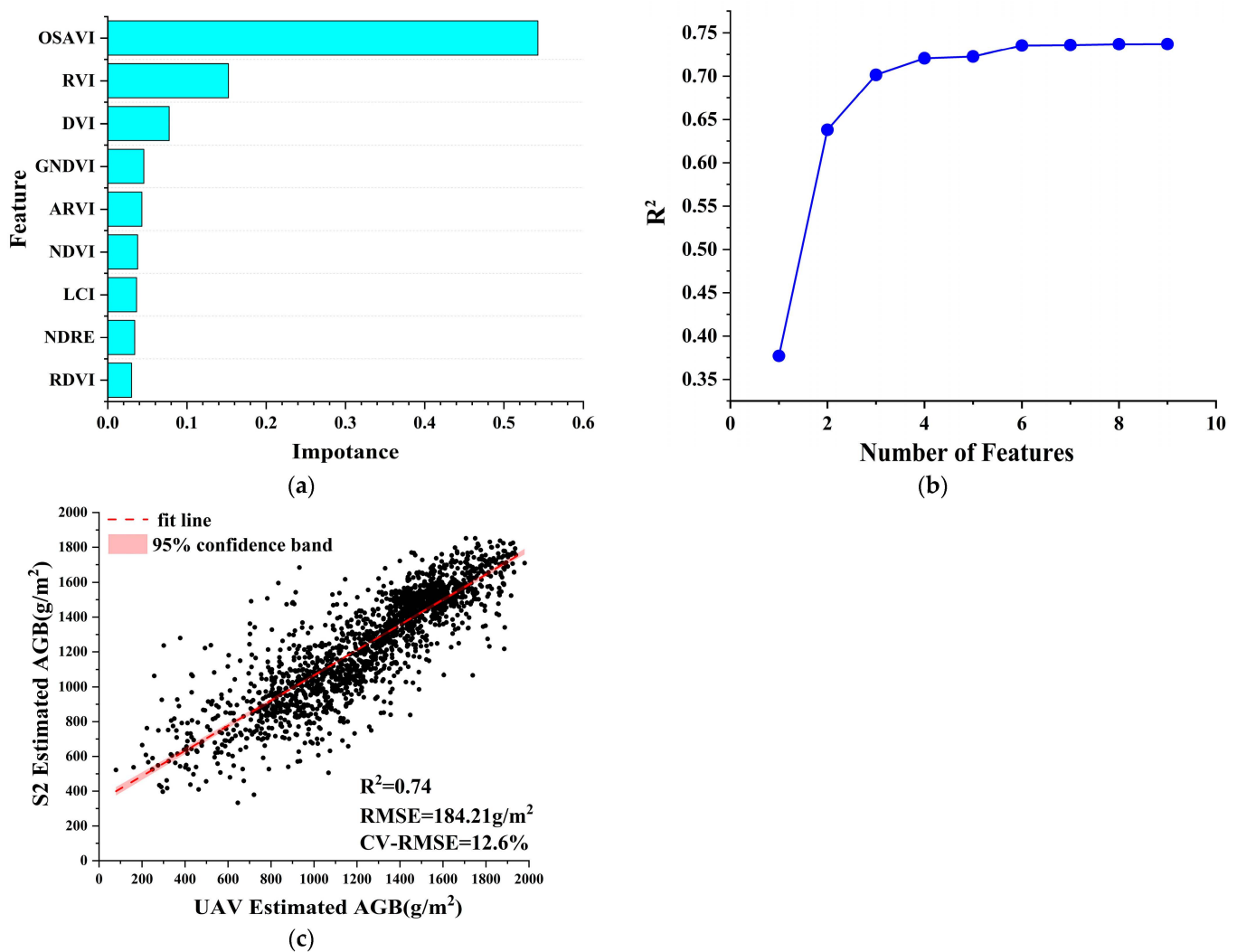


Figure 8. RF regression model based on UAV–Satellite data. (a) Variable importance ranking. (b) Variation in the number of variables. (c) Fitting results.

According to the importance of different variables, they were combined to construct the RF regression model, and the change in R^2 of the model under different combination of variables was analyzed. It can be observed that when using all variables, i.e., when the number of variables was nine, R^2 reached its maximum value, indicating a good fit of the model (Figure 8b). The RF regression model constructed based on this variable combination was used to estimate the AGB for the three study sites. The best fitting effect was achieved by setting the number of trees in the RF to 166, the depth to 12, and the maximum number of features to 7, with $R^2 = 0.74$, RMSE = 184.21 g/m², and CV-RMSE = 11.90% (as shown in Figure 8c).

From the UAV-scale AGB sample set, sample points were randomly selected, and nine vegetation indices were computed based on Sentinel-2 images corresponding to these points, and 2000 sample points were selected for each site, totaling 6000 sample points across the three sites.

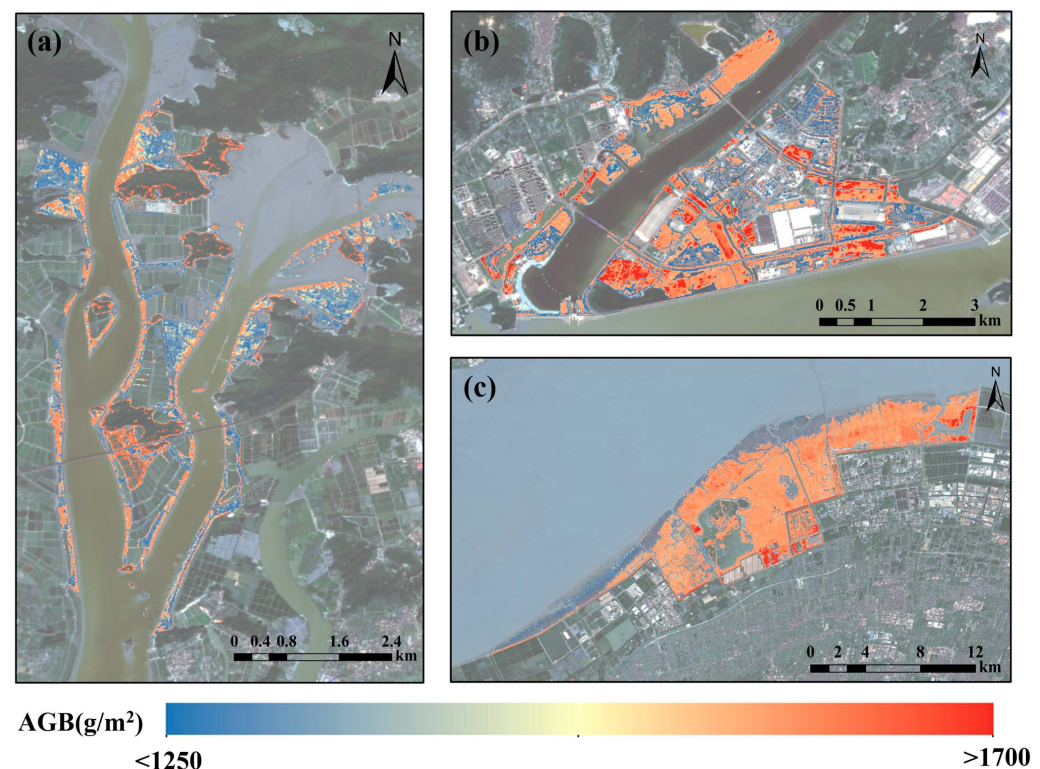
3.2.3. Estimation Results of Whole Study Area

Comparing the fitting results of the two regression models, it is evident that, similar to the Field–UAV model, the RF regression model still outperforms the MLR model in all metrics. Specifically, R^2 increased by 21.31%, RMSE decreased by 20.49%, and CV-RMSE decreased by 20.67% (Table 4).

Table 4. Fitting performance of MLR and RF models.

Models	Metrics	R ²	RMSE/g/m ²	CV-RMSE
	MLR	0.61	231.68	15.0%
	RF	0.74	184.21	11.91%

The spatially continuous distribution maps of AGB for the three study sites, obtained through satellite data and RF regression modeling, are shown in Figure 9. Among the three research sites, HZB exhibits the highest AGB density, with the highest number of pixels concentrated in the range of 1600–1700 g/m² in its AGB map, while the AGB maps of XQB and MSB were concentrated in the range of 1550–1630 g/m², with the highest number of pixels. The maximum average AGB value was found in HZB, at 1545.11 g/m², followed by MSB and XQB, with average AGB values of 1508.65 g/m² and 1440.27 g/m², respectively. The southern coast of HZB is the largest coastal salt marsh wetland area in Ningbo City. Due to continuous conservation efforts, the vegetation growth environment is favorable, resulting in higher AGB. Conversely, the salt marsh wetlands in MSB and XQB are located near ports and urban development areas, which are significantly impacted by human activities, leading to less favorable vegetation growth and lower AGB compared to HZB, consistent with the predictions presented in this paper.

**Figure 9.** AGB estimation results based on satellite data using RF regression model. (a) XQB, (b) MSB, (c) HZB.

4. Discussion

Traditional methods relying on field-based measurements and estimates of AGB through allometric growth equations, directly matching the satellite pixels [63], are more suitable for forest ecosystems characterized by single-tree canopy cover and larger volumes. In coastal wetland salt marsh ecosystems dominated by low vegetation, field biomass is often primarily represented by the dry weight of vegetation harvested within sample plots. Consequently, ground-level plots are typically set to small sizes, around 1 m × 1 m [64]. Moreover, due to the harsh growing conditions within coastal wetlands, conducting field

surveys is challenging, resulting in insufficient ground-level data collection. Consequently, establishing high-precision estimation models between medium- to low-resolution satellite imagery and small, limited ground-level sampled plots becomes difficult. As a result, the estimation outcomes fail to capture the spatial heterogeneity of coastal wetlands. This capability meets the demands for fine-scale vegetation monitoring [65]. However, due to limitations imposed by flight altitude, sensors carried by UAVs cannot capture imagery on a large scale. Therefore, its applicability is far less universal compared to satellite remote sensing, lacking the capability to conduct large-scale AGB estimation in coastal wetlands.

The joint estimation model established in this study, bridging field-based, UAV, and satellite data, overcomes the mismatch between field samples and satellite pixels. This approach expands the estimation scale while avoiding the averaging issue caused by mixed pixels. Matching field data with high-resolution UAV imagery for modeling yields significantly better fitting results compared to direct Field–Satellite modeling (Figure 10). Leveraging the AGB sample set from UAV data not only compensates for the shortage of field samples but also allows for processing the UAV sample set ($1\text{ m} \times 1\text{ m}$) based on the pixel size of Sentinel-2 imagery, thus obtaining an AGB sample set compatible with satellite pixels. Consequently, this approach enables the generation of continuous AGB spatial distribution maps at the satellite scale (Figure 8), previous studies have achieved similar results by integrating field-based AGB measurements with UAV hyperspectral data, airborne LiDAR data, and satellite data ($R^2 = 0.59$) [36].

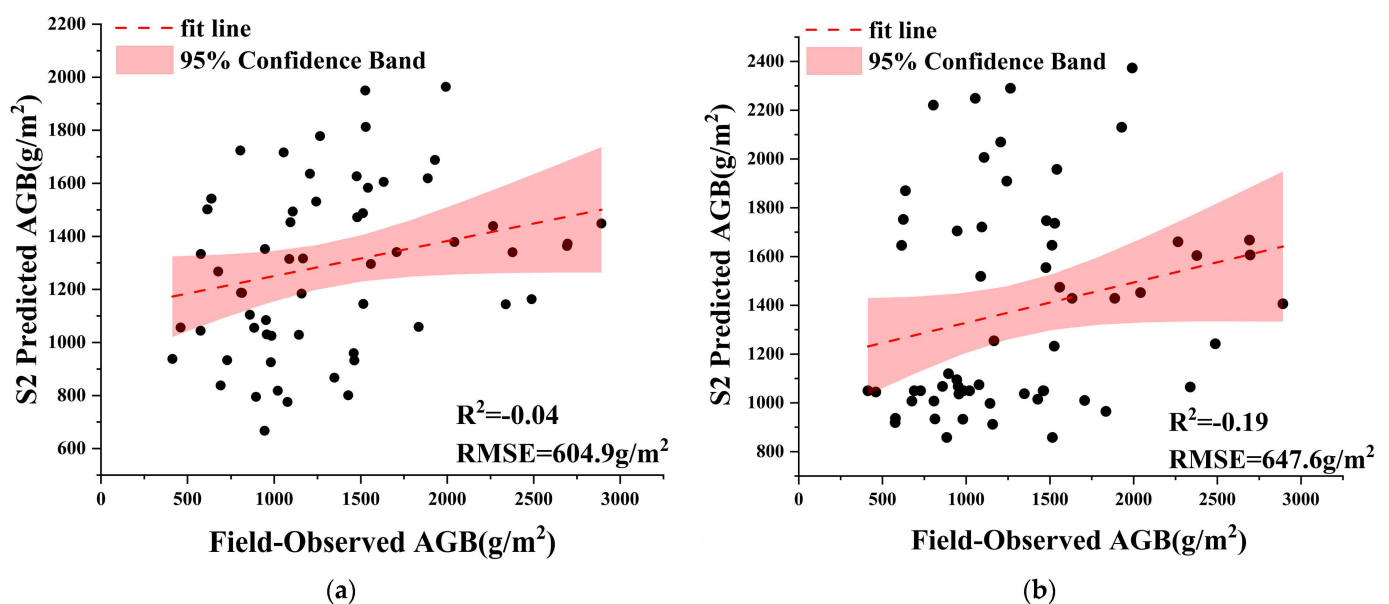


Figure 10. Fitting performance of AGB estimation models based on Field–Satellite data. (a) MLR, (b) RF regression.

While this study achieved promising results in the AGB estimation of coastal wetland salt marsh vegetation through an integrated air-land-space approach, there are still some limitations. Firstly, the study was constrained by equipment limitations. In recent years, an increasing number of scholars have considered using multi-source remote sensing data to retrieve vegetation physiological parameters [24,27,36]. The saturation of optical signals caused by dense vegetation can affect the accuracy of the retrieval results. In such cases, the introduction of LiDAR-derived vegetation canopy height structure indices can effectively address the underestimation of AGB caused by optical signal saturation [66]. Therefore, in future research, integrating optical remote sensing imagery with LiDAR point cloud data for the joint estimation of AGB in coastal wetlands will be explored to further enhance the accuracy of the experimental results. Additionally, the RF models are regarded as black-box models, making it difficult to interpret the specific influence of each feature on the prediction results. Moreover, in cases of small sample sizes, there is a

risk of overfitting with RF models, which can impact the experimental results. Therefore, designing regression models suitable for small samples will also be one of the challenges to overcome in future research.

5. Conclusions

To address the issue of low accuracy in direct Field–Satellite AGB estimation results, this study first established AGB estimation models for the FA site based on field survey data and UAV remote sensing imagery. Upon comparison of the fitting accuracy of the two models, the RF model ($R^2 = 0.58$, RMSE = 330.51 g/m², and CV-RMSE = 25.59%) outperformed the MLR model and was utilized to estimate the AGB of the FA site. The maximum predicted AGB for the FA in XQB was 2394.03 g/m², for the FA in MSB was 2435.37 g/m², and for the FA in HZB was 2465.51 g/m². The UAV–Satellite RF model achieved an R^2 of 0.74, RMSE of 184.21 g/m², and CV-RMSE of 11.90%. The wetland AGB densities for XQB, MSB, and HZB were 1440.27 g/m², 1508.65 g/m², and 1545.11 g/m², respectively. The total AGB amounts were 30,526.08 t, 34,219.97 t, and 296,382.91 t, respectively. The predicted results and satellite-scale AGB spatial distribution maps indicate that the AGB density of salt marsh vegetation in HZB was slightly higher than that in MSB and XQB. Additionally, due to the largest area of coastal wetlands in HZB, it had the highest total AGB of salt marsh vegetation compared to MSB and XQB. The integrated approach of using UAV and satellite remote sensing for estimating AGB provides valuable insights for remotely sensing vegetation physiological parameters in coastal salt marsh ecosystems.

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