

Article

UAV LiDAR-Assisted Multi-Source Remote Sensing Estimation and Spatiotemporal Analysis of Forest Carbon Storage in Fuzhou City

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Abstract

Accurate estimation of regional forest carbon storage is essential for assessing forest carbon sink capacity and supporting climate change mitigation. This study developed a UAV-LiDAR-assisted multi-source remote sensing approach to estimate forest AGB and carbon storage in Fuzhou City. UAV-LiDAR data acquired close to satellite overpasses were used to generate temporally matched plot-scale AGB samples through individual-tree segmentation, tree height-DBH estimation, and allometric equations. After screening, 204 samples were retained. Four predictor combinations (Landsat, SAR, Landsat + SAR, and Landsat + SAR + other factors) were combined with SWR and CatBoost to build eight AGB models after RF-RFE feature selection. The optimal model was applied to analyze forest carbon storage changes from 2015 to 2023. CatBoost generally outperformed SWR, with lower RMSE, MAE, and rRMSE. The CatBoost model integrating Landsat, SAR, and other factors performed best (RMSE = 19.83 t·hm⁻², MAE = 17.02 t·hm⁻², rRMSE = 21.73%). Forest carbon storage increased from 32.43 × 10⁶ t in 2015 to 36.76 × 10⁶ t in 2023, alongside increases in forest area and carbon density. These findings suggest the potential of UAV-LiDAR for temporally matched AGB sampling and regional forest carbon storage estimation in subtropical areas, contributing to relevant SDGs.

Keywords: UAV-LiDAR-derived samples; multi-source remote sensing; CatBoost; forest carbon storage; subtropical forests; spatiotemporal dynamics



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1. Introduction

Forest ecosystems are the largest carbon pool in terrestrial ecosystems, storing approximately 77% of global vegetation carbon, and play an irreplaceable role in regulating the global carbon cycle and mitigating climate warming [1–4]. Enhancing forest carbon sinks is widely recognized as a low-cost and high-benefit pathway to mitigate climate change. Accordingly, countries around the world have placed forest carbon sinks in a prominent position in their efforts to address global warming [5–7]. Accurately estimating regional forest carbon storage is the basis for assessing forest carbon storage capacity and formulating relevant management. Moreover, the estimation of forest carbon storage usually requires the acquisition of forest aboveground biomass (AGB) [8,9]. Therefore, developing

efficient and accurate methods for estimating forest AGB at the regional scale has significant scientific value and practical importance.

Remote sensing technology has become a primary approach for regional forest AGB estimation because it enables the large-scale and repeated acquisition of land-surface information [10–12]. Currently, the major remote sensing data sources used for forest AGB estimation include optical remote sensing, synthetic aperture radar (SAR), and light detection and ranging (LiDAR) [13–15]. Optical remote sensing data, represented by the Landsat series, are mainly used to estimate forest AGB by establishing statistical relationships between AGB and spectral information such as band reflectance and vegetation indices [16,17]. Owing to their wide availability and long-term data records, optical datasets have been extensively applied in forest biomass studies. However, these data are highly susceptible to cloud and precipitation interference and are limited in their ability to capture information beneath the forest canopy because of their restricted wavelength range [18–20]. SAR data possess a certain degree of canopy penetration capability, which generally increases with radar wavelength [21–23]. Nevertheless, SAR imagery is often affected by speckle noise, which may result in the loss of information. In addition, the relatively short temporal coverage of many SAR datasets limits their suitability for long-term spatiotemporal analysis. LiDAR acquires high-precision three-dimensional forest structural information by actively emitting laser pulses and recording the returned signals [24–26]. However, traditional airborne LiDAR systems are costly, restricting their application over large areas. Spaceborne LiDAR systems, such as ICESat and GEDI, provide broader coverage but are limited by discontinuous sampling and relatively coarse spatial resolution [27,28].

Given the inherent limitations of individual remote sensing data sources, the integration of multi-source remote sensing data has become an important development direction in this field [29–31]. For example, using plot-scale AGB derived from LiDAR as training data and combining the long-term temporal coverage of optical remote sensing with the canopy penetration capability of SAR can leverage the strengths of each data source while effectively reducing dependence on traditional forest inventories [32]. However, the combined application of multi-source data also brings new challenges: information redundancy and multicollinearity among remote sensing factors from different sources may become more pronounced, imposing higher requirements on modeling methods [33,34]. Traditional regression models are constrained by linear assumptions and their sensitivity to multicollinearity, often resulting in poor performance when modeling the complex nonlinear relationships between remote sensing factors and forest AGB. In recent years, machine learning algorithms have been widely introduced into forest AGB estimation because they can flexibly fit complex nonlinear relationships and have strong generalization capability, generally achieving higher estimation accuracy than traditional parametric models [14,35–37]. Categorical Boosting (CatBoost) is a novel gradient boosting algorithm that replaces the conventional gradient estimation method with an ordered boosting mechanism. By using ordered boosting, CatBoost achieves unbiased gradient estimation, thereby mitigating gradient bias and prediction shift [38]. Owing to its ability to model nonlinear relationships and handle high-dimensional feature variables, CatBoost has recently been applied in biomass estimation, carbon stock assessment, and ecological and environmental modeling studies [39–42]. Nevertheless, the application of CatBoost to subtropical forest AGB estimation based on the integration of optical remote sensing, SAR data, and unmanned aerial vehicle LiDAR (UAV-LiDAR) information remains relatively limited, and its effectiveness and potential advantages require further investigation.

For remote sensing-based AGB estimation methods, acquiring modeling sample data is an important prerequisite. Plot-scale AGB is typically derived from forest inventory data [43]. This method is time-consuming, labor-intensive, and costly. Remote forest areas

are difficult to cover, resulting in insufficient spatial representativeness of the samples. Moreover, there is often a large temporal gap between forest inventory campaigns and satellite overpass times, leading to poor synchrony between training data and remote sensing imagery. The underlying cause of the above problems is the lack of an efficient, low-cost method capable of acquiring plot-scale AGB data synchronously with satellite overpasses. In recent years, the rapidly developing UAV-LiDAR technology has offered a new possibility to overcome this bottleneck [44]. UAV-LiDAR can acquire plot-scale laser point cloud data near the time of satellite overpasses. Plot-scale AGB estimates can then be derived through tree-height extraction, diameter at breast height (DBH) estimation, and allometric equations, thereby reducing survey costs while improving the temporal consistency between training samples and remote sensing imagery. The feasibility of this approach has been preliminarily validated in some studies [32,45], but its applicability in subtropical forests with complex canopy structures still requires systematic evaluation.

In summary, although considerable progress has been made in forest AGB estimation based on multi-source remote sensing data, two key challenges remain: (1) how to efficiently use UAV-LiDAR to generate plot-scale AGB estimates for model training that are temporally synchronous with satellite imagery under complex subtropical terrain conditions, and (2) how to effectively integrate multi-source remote sensing factors and select appropriate machine learning algorithms to improve estimation accuracy. To address these challenges, this study uses Fuzhou, a typical subtropical city on the southeast coast of China, as the study area. It explores a method for generating temporally synchronized plot-scale AGB estimates using UAV-LiDAR, thereby providing modeling samples as an alternative to traditional field inventories. Based on these samples and multi-source remote sensing data, a regional forest AGB estimation model is constructed using the CatBoost algorithm. The spatiotemporal evolution of forest carbon storage in the study area from 2015 to 2023 is then analyzed. This study aims to provide scientific support for sustainable forest management and contribute to the achievement of the Sustainable Development Goals.

2. Materials and Methods

2.1. Study Area

Fuzhou City is located on the southeast coast of China, in the eastern part of Fujian Province and in the lower reaches of the Minjiang River. The landform of Fuzhou is characterized by a typical estuarine basin, with mountainous areas in the north and terrain sloping from southwest to east. Most of the southern area consists of basins, and mountainous and hilly areas account for more than 70% of the total land area of Fuzhou City. The complex mountainous terrain and pronounced elevation differences contribute to substantial spatial heterogeneity in forest structure. In addition, variations in canopy height and canopy closure further increase the complexity of forest AGB estimation in this region. The climate is a subtropical monsoon climate. According to statistics, as of 2022, the forest coverage rate of Fuzhou City was 51.77%, ranking second among provincial capitals in China. The geographical location of the study area is shown in Figure 1.

2.2. Data Sources and Preprocessing

2.2.1. Spaceborne Remote Sensing Data

Multispectral image data were obtained from the USGS Earth Explorer website (<https://earthexplorer.usgs.gov/> accessed on 29 October 2023). Landsat 8 OLI and Landsat 9 OLI-2 images of the data type L1TP, Collection 2, Tier 1 were selected. The cloud cover of each image was less than 10%. Landsat imagery acquired in 2015 and 2023 with a spatial resolution of 30 m was used in this study. The data were preprocessed through radiometric calibration, atmospheric correction, and other standard procedures. These preprocessing

procedures were performed in ENVI5.6 software. Sentinel-1 SAR data were acquired from the European Space Agency platform (<https://www.copernicus.eu/en> accessed on 29 October 2023). The Sentinel-1 data were acquired in the C-band, with two polarization modes (VV and VH). Preprocessing was conducted in the SARscape module of ENVI, including multilooking, speckle filtering, geocoding, and radiometric calibration. The SAR data were subsequently resampled to 30 m and co-registered to the Landsat imagery, with a registration error of less than 0.5 pixel. Digital elevation model (DEM) data were obtained from ASTER GDEM v3.0 released by NASA (urs.earthdata.nasa.gov accessed on 29 October 2023). These data were derived from Advanced Spaceborne Thermal Emission and Reflection Radiometer data, with a resolution of 30 m. The DEM was primarily used for remote sensing image data processing and terrain factor extraction. After preprocessing, all data were clipped to the extent of the study area.

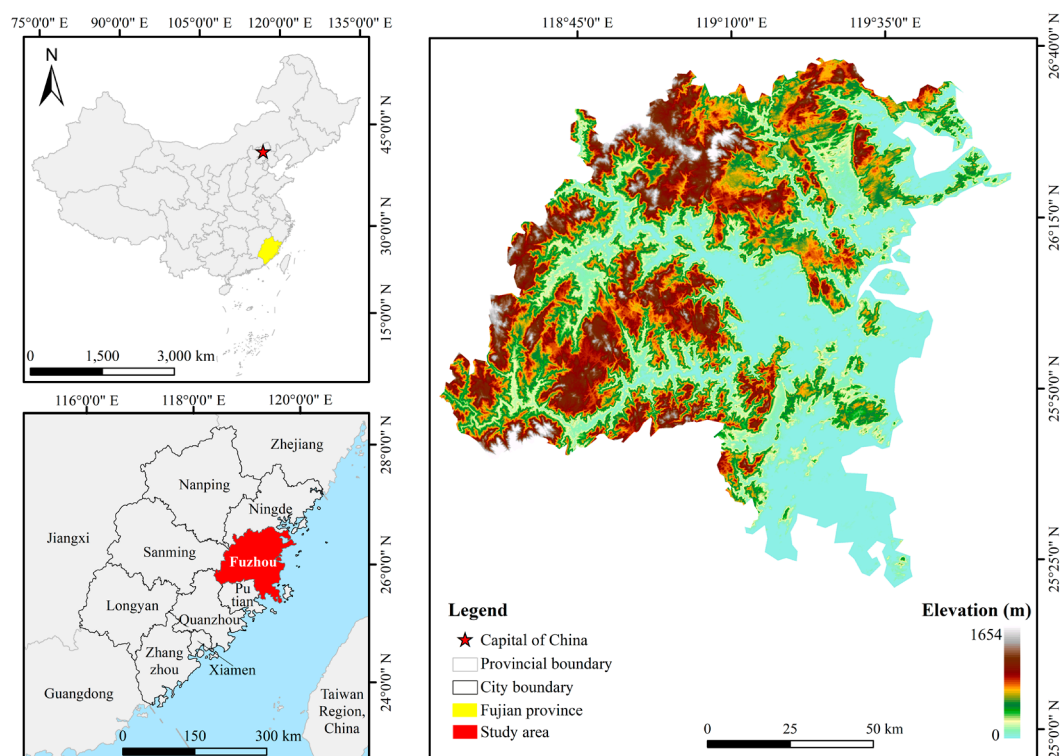


Figure 1. Geographical location of the study area. Its geographical coordinates range from 25°15' N to 26°39' N and from 118°08' E to 120°37' E.

2.2.2. UAV-LiDAR Data

The LiDAR data used in this study were acquired using the Zhihui PM-1500 airborne laser measurement system. The system has a pulse frequency of 100–2000 kHz, a ranging accuracy of 5 mm, and an angular resolution of 0.001°. It was mounted on a Yunxun-Long 120 UAV. The surveys were conducted within a few days of the satellite overpass dates to ensure temporal consistency between the UAV-LiDAR and satellite remote sensing data. The UAV-LiDAR flight areas are shown in Figure 2. The LiDAR data were first denoised using LiDAR360 (GreenValley International, Beijing, China; <https://www.lidar360.com>) software. Ground points were then classified using an improved progressive triangulated irregular network densification filtering algorithm. Finally, DEM and digital surface model (DSM) datasets with a spatial resolution of 0.5 m were generated using the inverse distance weighting interpolation method. A summary of the datasets used in this study is presented in Table 1.

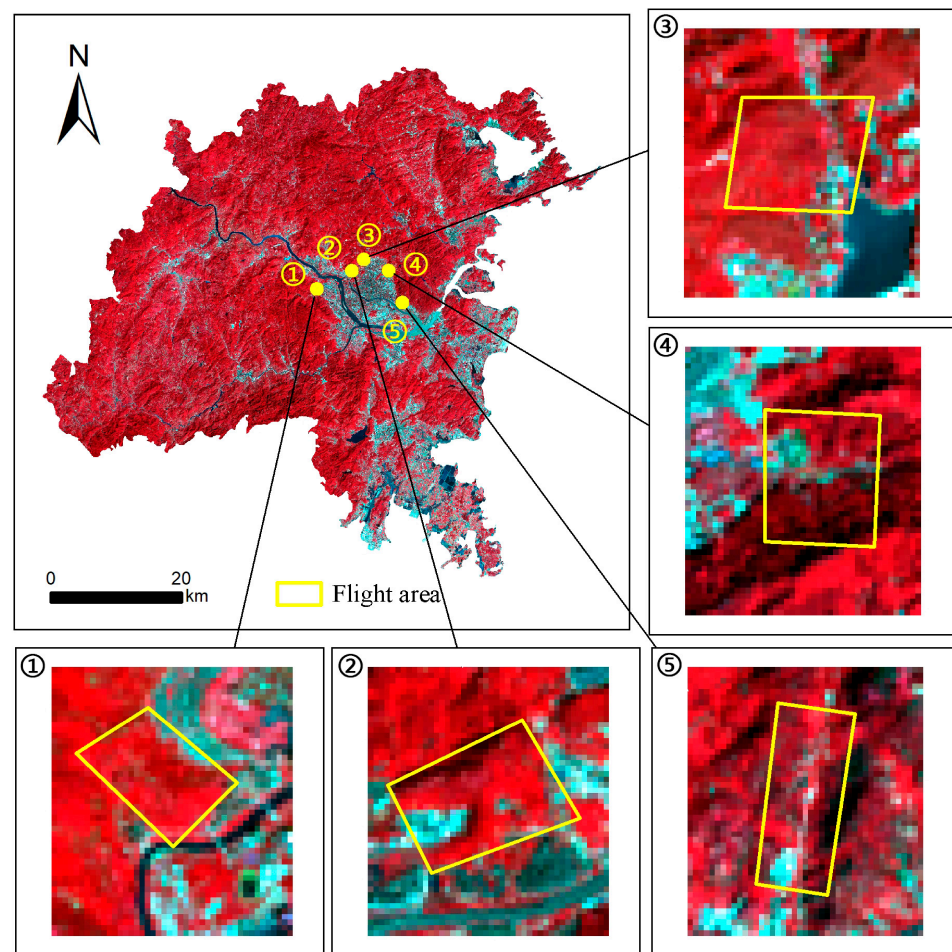


Figure 2. Survey area of UAV-LiDAR flight. A total of five survey plots were established. The numbers 1–5 represent the identification numbers of the UAV-LiDAR flight areas.

Table 1. Summary of datasets used in this study.

Data Type	Acquisition Date
Landsat data	27 September 2015; 3 October 2023
SAR data	28 September 2015; 4 October 2023
DEM data	Static DEM product
LiDAR data	26 September 2023~28 September 2023

2.3. Plot-Scale AGB Estimation

A canopy height model (CHM) was generated by subtracting the DEM from the DSM. The CHM describes the spatial structure and height distribution of the forest canopy and serves as a fundamental dataset for individual tree identification and forest structural parameter extraction [46]. Based on the CHM, individual tree segmentation was performed using the watershed segmentation algorithm [26], with a tree height threshold of 2 m. In the CHM, local maxima generally correspond to tree crown tops. The algorithm first identifies local maxima in the image, which may represent the locations of individual trees. It then simulates water flow and analyzes flow paths to determine boundaries between adjacent trees, thereby completing individual tree segmentation. After segmentation, geographic coordinates, tree height, crown diameter, and other attributes of each individual tree were automatically extracted. Based on individual tree height, a tree height–DBH equation was used to estimate DBH [47], and an allometric equation was subsequently applied to calculate individual tree biomass [48]. The calculation procedures are presented in

Formulas (1) and (2), respectively. For spatial scale conversion, the flight area was first clipped from the Landsat imagery, and each 30×30 m pixel was treated as an AGB calculation unit. The raster attribute table was generated using the “Raster to Point” tool in ArcMap10.2. Based on the location coordinates obtained from the individual tree segmentation results, all trees within each pixel were identified, and their biomass values were summed and recorded in the raster attribute table. This process generated the AGB estimate for each pixel, thereby producing spatially explicit plot-scale AGB estimates.

$$DBH = \left(\frac{H - 4.716}{0.349} \right)^{1/1.047} \quad (1)$$

$$AGB = 0.0509 \times \rho \times H \times DBH^2 \quad (2)$$

where AGB is aboveground biomass, ρ is wood specific gravity (g/cm^3), with a value of 0.5274, H is tree height (m), and DBH is diameter at breast height (cm).

2.4. Feature Factor Extraction and Screening

2.4.1. Feature Factor Extraction

Based on the actual conditions of the study area, band reflectance, vegetation indices, and textural features were extracted from Landsat imagery. Backscatter coefficients and textural features were extracted from Sentinel-1 images. Texture features were derived using the gray-level co-occurrence matrix (GLCM) method implemented in ENVI, with a window size of 5×5 . In addition, elevation and fractional vegetation cover were also included. The symbols and calculation methods of all indicators are summarized in Supplementary Table S1, and the calculation methods of the texture features are provided in Supplementary Table S2. Correlation analysis and significance testing were conducted between the plot-scale AGB estimates and the remote sensing factors extracted from Landsat and Sentinel-1 imagery. Correlation was measured using the Pearson correlation coefficient, and its calculation formula is shown in Formula (3). Significance testing was conducted using the t -test. A remote sensing factor was considered to have a significant correlation with AGB when the p -value of the t -test was less than 0.05. Specifically, $p < 0.01$ indicated a highly significant correlation, and $0.01 \leq p < 0.05$ indicated a significant correlation. To avoid the influence of different units of measurement on the calculation of the Pearson correlation coefficient, AGB and each remote sensing factor were normalized to ensure consistency in data processing. Correlation analysis was performed in SPSS 27.0.

$$r = \frac{\sum_{i=1}^n (x - \bar{x})(y - \bar{y})}{\sqrt{\sum_{i=1}^n (x - \bar{x})^2} \sqrt{\sum_{i=1}^n (y - \bar{y})^2}} \quad (3)$$

where r is the Pearson correlation coefficient, x and y are variables, and $\bar{x}$ and $\bar{y}$ are the mean values of variables x and y , respectively.

2.4.2. Variable Screening Method

To investigate the effects of remote sensing factors from different data sources on AGB estimation, four combinations were established based on the source of the factors: Landsat, SAR, Landsat + SAR, and Landsat + SAR + other factors. This study adopted the recursive feature elimination (RFE) method. The principle is as follows. First, all feature variables were input into an initial model for training, and then ranked in descending order according to their feature importance. Model performance was evaluated using the root mean square error (RMSE). Next, the least important feature variable was removed, and the remaining feature variables were used to retrain and reevaluate the model. This iteration was repeated until all feature variables had been removed. During this process,

for each feature combination, the 10-fold cross-validation RMSE was recorded as the number of features gradually decreased. When the RMSE reached its minimum value, the corresponding feature subset was identified as the optimal feature subset, and the number of variables included in this subset was regarded as the optimal number of features for that feature combination. The random forest (RF) algorithm has the capability to evaluate feature importance and exhibits good regression performance. Therefore, it was used as the base model and combined with the recursive feature elimination method to form the RF-RFE algorithm [49,50].

2.5. Forest Biomass Estimation Model Construction

Stepwise regression (SWR) is a statistical modeling method that selects the optimal model by iteratively adding and removing feature variables and evaluating model fit and error after each operation. SWR has the advantages of rapid model construction, easy implementation, and the ability to present the relationship between AGB and each modeling factor in an intuitive formula with clear physical meaning. The SWR formula is shown in Formula (4):

$$AGB = \sum_{i=1}^n (\alpha_i \times x_i) + \beta \quad (4)$$

where AGB is the aboveground biomass, α_i is the regression coefficient of the independent variable x_i , n is the number of modeling factors, and β is the regression intercept.

CatBoost is a gradient boosting algorithm that uses symmetric decision trees as its base learners. Currently, applications of CatBoost to AGB estimation remain relatively limited, making it a valuable topic for exploration. The core advantage of this algorithm is its effective mitigation of gradient bias and prediction shift. All gradient boosting algorithms follow the same basic principle: they build new trees to fit the gradient of the current model. In this process, each gradient estimation uses the same set of data points used to train the current model [51]. However, this practice may cause the distribution of gradients in the feature space to deviate from the true distribution, resulting in gradient bias. To obtain an unbiased estimate of the gradient value for the k -th training sample after building the i -th tree, the training sample X_k must be excluded from model training. CatBoost uses an ordered boosting strategy, in which the gradient of each training sample is estimated using a model that has not been trained on that sample. Because X_k is not introduced during model training, this achieves unbiased gradient estimation [52]. Prediction shift is caused by gradient bias. After mitigating gradient bias using the above method, CatBoost further reduces prediction shift and improves the generalization ability of the model. Hyperparameter tuning was performed in two stages. First, single-parameter optimization was conducted to determine the approximate optimal value of each hyperparameter. Subsequently, search ranges were specified for all hyperparameters, and the optimal hyperparameter combination was identified using grid search with 10-fold cross-validation. Other parameters (e.g., early stopping parameters) were set or tuned as needed.

2.6. Model Evaluation Metrics

For models constructed based on the training set, the goodness of fit was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE). R^2 measures the goodness of fit of the model. The closer its value is to 1, the better the goodness of fit. RMSE measures the fitting error. The smaller its value, the smaller the fitting error of the model. RMSE was also used to compare with the RMSE of the test set to determine whether the model suffered from underfitting or overfitting. The calculation formulas for R^2 and RMSE are shown in Formulas (5) and (6). For model accuracy validation based on the test set, in addition to using RMSE to evaluate accuracy, the mean absolute error (MAE)

and the relative root mean square error (rRMSE) were also used. The calculation formulas for MAE and rRMSE are shown in Formulas (7) and (8).

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (6)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (7)$$

$$rRMSE = \frac{RMSE}{\bar{y}} \times 100\% \quad (8)$$

In the above formulas, y_i is the measured value of the sample. $\hat{y}_i$ is the predicted value of the sample. $\bar{y}$ is the mean of the measured values of the samples. N is the total number of samples.

2.7. Estimation of Forest Carbon Storage and Spatiotemporal Evolution Analysis in the Study Area

After selecting the optimal AGB estimation model, the AGB within Fuzhou City was estimated pixel by pixel for the years 2015 and 2023. Forest areas were extracted by masking with land cover data as a mask [53]. Due to the lack of measured forest carbon fraction, this study adopted a carbon fraction of 0.5 following international common international practice [54]. The estimated AGB was then converted to carbon density, and a multidimensional spatiotemporal evolution analysis of forest carbon storage in the study area was conducted.

3. Results

3.1. Plot-Scale AGB Extraction Results

The characteristics of the UAV-LiDAR and CHM data are summarized in Table 2. The five UAV-LiDAR flight areas covered a total area of approximately 475 hm² with point densities ranging from 51.25 to 85.55 pts m⁻². The surveyed areas spanned elevations from 4.28 to 347.58 m and exhibited substantial variation in canopy structure. Mean canopy heights ranged from 5.80 to 14.95 m, while the 95th percentile canopy height ranged from 11.91 to 24.57 m, indicating that the selected sites captured diverse forest structural conditions within the study area. The extracted AGB estimates are expressed as biomass density (t·hm⁻²). To reduce the influence of outliers on model construction, AGB samples were screened using the criterion of mean $\pm$ 2 standard deviations. In addition, obvious outliers were manually removed based on the ground point classification results and the extracted remote sensing factors. After screening, a total of 204 AGB samples were retained for model development and validation. To ensure similar data distribution characteristics between the training and testing datasets, stratified sampling was employed to divide the samples into training and testing sets at a ratio of 7:3. The distributions of the full sample set, training set ($n = 143$), and testing set ($n = 61$) are shown in Figure 3.

Table 2. Characteristics of UAV-LiDAR flight areas.

Flight Area	Area (hm ²)	Density (pts m ⁻²)	Point Spacing (m)	Elevation Range (m)	Mean CHM (m)	P95 CHM (m)
①	142.22	51.25	0.140	4~214	9.36	18.93
②	83.44	85.55	0.108	37~227	10.26	18.39
③	84.68	56.01	0.134	53~348	14.95	24.57
④	77.34	81.09	0.111	84~322	10.29	19.90
⑤	87.21	59.35	0.130	33~329	5.80	11.91

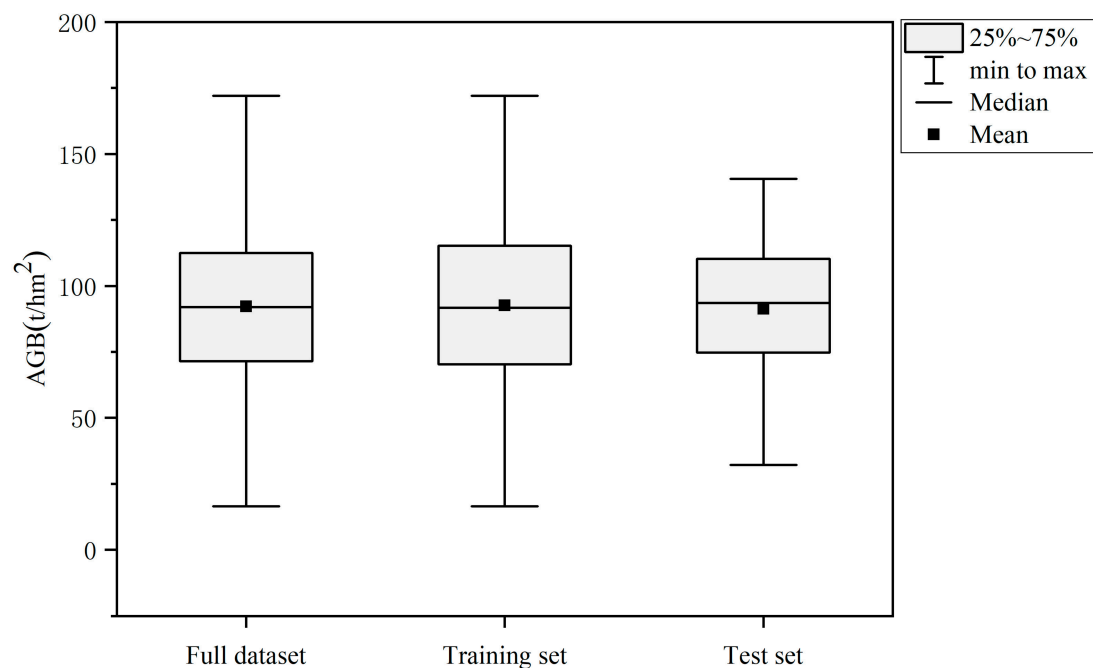


Figure 3. Box plot of the full sample set, training set, and test set. In each box, the central horizontal line and the small square denote the median and the mean, respectively. The box boundaries indicate the first (Q1) and third (Q3) quartiles, and the whiskers extend to the minimum and maximum values. No outliers were identified.

3.2. Feature Variable Screening Results

The Pearson correlation coefficients between each remote sensing factor and AGB are shown in Table 3. Feature variables with non-significant correlations were removed based on Pearson correlation analysis. A total of 50 remote sensing factors remained. These included 4 band reflectance factors from Landsat, 4 vegetation index factors, and 30 band texture features. From Sentinel-1, there were 2 backscatter coefficient factors and 8 texture features. Two additional factors came from other sources. After screening using RF-RFE, the remaining feature variables for each combination are shown in Table 4. Although the number and specific selection of modeling factors varied across combinations, several patterns emerged. When Landsat data were included, band reflectance, vegetation indices, and band texture features were always present. When SAR data were included, backscatter coefficients and texture features were always present. In addition, the topographic factor elevation was also selected as a modeling factor. This indicates that AGB estimation is influenced by multiple types of remote sensing factors.

Table 3. Correlation between each factor and AGB.

Remote Sensing Factor	r	Remote Sensing Factor	r	Remote Sensing Factor	r	Remote Sensing Factor	r
B2	−0.442 **	B3_EN	−0.561 **	B5_HO	0.422 **	VV	−0.167 *
B2_ME	−0.347 **	B3_SM	0.569 **	B5_CO	−0.440 **	VV_ME	−0.193 **
B2_VA	−0.238 **	B3_CC	0.323 **	B5_DI	−0.466 **	VV_VA	−0.01
B2_HO	0.435 **	B4	−0.395 **	B5_EN	−0.397 **	VV_HO	0.063
B2_CO	−0.353 **	B4_ME	−0.380 **	B5_SM	0.358 **	VV_CO	−0.144 *
B2_DI	−0.414 **	B4_VA	−0.247 **	B5_CC	−0.098	VV_DI	−0.122
B2_EN	−0.453 **	B4_HO	0.237 **	VH	−0.182 **	VV_EN	0.083
B2_SM	0.465 **	B4_CO	−0.337 **	VH_ME	−0.240 **	VV_SM	−0.069
B2_CC	0.224 **	B4_DI	−0.297 **	VH_VA	0.107	VV_CC	0.145 *
B3	−0.470 **	B4_EN	−0.291 **	VH_HO	−0.019	RVI	0.311 **
B3_ME	−0.516 **	B4_SM	0.223 **	VH_CO	−0.048	NDVI	0.294 **
B3_VA	−0.341 **	B4_CC	0.027	VH_DI	−0.022	GNDVI	0.410 **
B3_HO	0.532 **	B5	−0.349 **	VH_EN	0.161 *	ARVI	0.292 **
B3_CO	−0.396 **	B5_ME	−0.274 **	VH_SM	−0.164 *	H	0.423 **
B3_DI	−0.501 **	B5_VA	−0.358 **	VH_CC	0.127	FVC	0.288 **

Note: ** indicates $p < 0.01$ from the t -test, and * indicates $0.01 \leq p < 0.05$. ME represents the mean, VA represents the variance, HO represents the homogeneity, CO represents the contrast, DI represents the dissimilarity, EN represents the entropy, SM represents the second moment, and CC represents the correlation.

Table 4. Screening results of feature variables for each combination.

Modeling Combination	Number	Modeling Factors
Landsat	12	B2, B3, GNDVI, ARVI, B3_CO, B3_EN, B3_SM, B5_ME, B5_VA, B5_HO, B5_CO, B5_EN
SAR	7	VV, VH, VV_ME, VV_CO, VV_CC, VH_ME, VH_EN
Landsat + SAR	17	B2, B3, GNDVI, ARVI, B3_CO, B3_EN, B3_SM, B5_ME, B5_VA, B5_HO, B5_CO, VV, VH, VH_CO, VV_CC, VH_ME, VH_EN
Landsat + SAR + other factors	15	B2, B3, GNDVI, ARVI, B3_CO, B3_EN, B3_SM, B5_VA, B5_HO, B5_CO, VV, VH, VV_CO, VH_EN, H

3.3. Comparison of Model Fitting Results

The fitting performance and accuracy validation results of the estimation models based on SWR and the CatBoost algorithm are summarized in Tables 5 and 6. The optimal hyperparameter combinations of the CatBoost models are provided in Supplementary Table S3. From Table 5, the highest R^2 of the SWR model was only 0.466, whereas the R^2 values of the CatBoost models all exceeded 0.8, with a maximum of 0.962. This indicates that the CatBoost algorithm is substantially superior to SWR in fitting capability. From Table 6, the accuracy ranking for each modeling combination was Landsat + SAR + other factors > Landsat + SAR > Landsat > SAR, demonstrating a clear advantage of multi-source data. Considering both model fitting performance and test accuracy, the CatBoost model constructed using the Landsat + SAR + other factors combination achieved the best overall performance ($R^2 = 0.962$, RMSE = 19.83 t·hm^{−2}). Therefore, this model was selected for subsequent AGB estimation.

Table 5. Summary of estimation model results on the training set.

Modeling Combination	Evaluation Metric	SWR	CatBoost
Landsat	R^2	0.466	0.829
	RMSE (t·hm ^{−2})	24.63	15.20
SAR	R^2	0.078	0.807
	RMSE (t·hm ^{−2})	32.14	17.68

Table 5. *Cont.*

Modeling Combination	Evaluation Metric	SWR	CatBoost
Landsat + SAR	R ²	0.448	0.886
	RMSE (t·hm ^{−2})	24.94	12.13
Landsat + SAR + other factors	R ²	0.440	0.962
	RMSE (t·hm ^{−2})	25.23	7.60

Table 6. Comparison of validation accuracy of estimation models.

Modeling Combination	Evaluation Metric	SWR	CatBoost
Landsat	R ²	0.331	0.372
	RMSE (t·hm ^{−2})	22.73	22.28
	MAE (t·hm ^{−2})	19.10	19.10
	rRMSE (%)	24.85	24.35
SAR	R ²	0.067	0.264
	RMSE (t·hm ^{−2})	25.95	23.67
	MAE (t·hm ^{−2})	21.76	19.60
	rRMSE (%)	28.36	25.87
Landsat + SAR	R ²	0.356	0.534
	RMSE (t·hm ^{−2})	21.84	20.71
	MAE (t·hm ^{−2})	18.18	16.97
	rRMSE (%)	23.93	22.69
Landsat + SAR + other factors	R ²	0.366	0.568
	RMSE (t·hm ^{−2})	21.50	19.83
	MAE (t·hm ^{−2})	18.15	17.02
	rRMSE (%)	23.55	21.73

3.4. Spatiotemporal Distribution of Forest Carbon Storage

3.4.1. Overall Characteristics of Forest Carbon Storage in the Two Periods

The spatial distribution of forest carbon density in the two periods is shown in Figure 4. The statistical results of forest area, carbon density, and carbon storage are presented in Table 7. As shown in Figure 4, the spatial pattern of forest carbon density in Fuzhou City exhibits a distribution of “high in the west and low in the east, high in the north and low in the south.” High-value areas are concentrated in the western mountainous region, and carbon density decreases toward the southeastern coastal area. Carbon density in plain areas is generally low, showing an overall pattern of “high in mountainous areas and low in plains.” Quantitatively, forest carbon storage in the western region is relatively high and generally decreases from northwest to southeast. Table 7 shows that forest carbon storage, forest carbon density, and forest area in Fuzhou City all exhibited increasing trends. In 2023, forest carbon storage in Fuzhou City reached 36.76×10^6 t, an increase of 13.35% compared with 2015, with an average annual growth rate of 1.67%. The forest carbon storage data for Fuzhou in 2015 and 2023, generated in this study, are openly available in Zenodo [55].

Table 7. Forest carbon storage statistics of Fuzhou City in 2015 and 2023.

Year	Forest Area ($\times 10^4$ hm ²)	Forest Carbon Density (t·hm ^{−2})	Forest Carbon Storage ($\times 10^6$ t)
2015	74.60	43.47	32.43
2023	81.29	45.22	36.76
Increment	+6.69	+1.75	+4.33
Change rate	8.97%	4.03%	13.35%
Average annual change rate	1.12%	0.50%	1.67%

Note: Forest area was derived from the 30 m resolution China land cover data provided by the team of Liu Liangyun at the Aerospace Information Research Institute, Chinese Academy of Sciences [53].

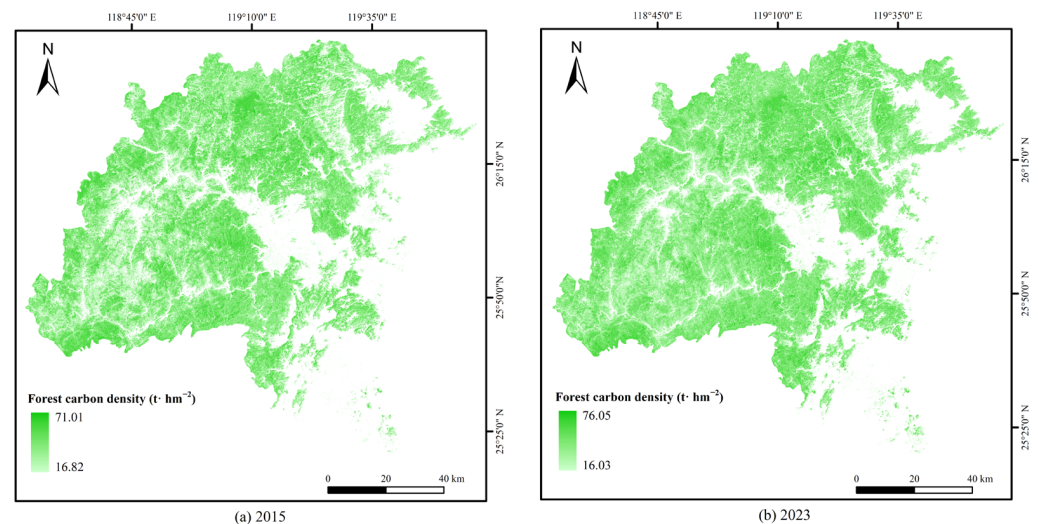


Figure 4. Estimation of forest carbon storage in the study area for the two time phases. (a) Forest carbon density in 2015; (b) Forest carbon density in 2023. Carbon density values were derived from the optimal CatBoost model and a carbon fraction coefficient of 0.5. The spatial resolution is 30 m.

3.4.2. Spatial Pattern of Forest Carbon Density Change

Based on the difference in carbon density between 2015 and 2023, five change levels were defined: basically stable, slightly increased, significantly increased, slightly decreased, and significantly decreased. The area and proportion of each change level are shown in Table 8, and the spatial distribution is shown in Figure 5. As shown in Figure 5, the areas with significant changes in forest carbon density are mostly located along forest edges. The areas with significant increases are mainly concentrated in the southwestern part of Fuzhou City. Table 8 also shows that from 2015 to 2023, forest carbon density in Fuzhou City exhibited a stable and increasing trend. The area that remained basically stable accounted for 53.60% of the total. The area with an increase exceeding $5 \text{ t} \cdot \text{hm}^{-2}$ accounted for 36.54%, while the area with a decrease exceeding $5 \text{ t} \cdot \text{hm}^{-2}$ was relatively small. These results indicate that forest carbon density in Fuzhou City showed an overall positive trend over the eight-year period.

Table 8. Area statistics of forest carbon density change in Fuzhou from 2015 to 2023.

Change Levels	Significantly Decreased	Slightly Decreased	Basically Stable	Slightly Increased	Significantly Increased
Area ($\times 10^4 \text{ hm}^2$)	3.28	5.03	45.21	19.59	11.23
Proportion	3.89%	5.96%	53.60%	23.22%	13.32%

3.4.3. Evolution of Carbon Storage Class Structure

To further understand the changes in forest carbon storage and its area across different classes in Fuzhou City over time, the estimated carbon density was classified into five classes according to the distribution characteristics of carbon density in the study area. These five classes were defined from low to high as Classes 1–5. The spatial distribution of forest carbon storage classes in Fuzhou City in 2015 and 2023 is shown in Figure 6. To visually display the direction and magnitude of transitions among carbon storage classes, a Sankey diagram was generated based on spatial overlay analysis of the two carbon density classification maps (Figure 7). As shown in Figure 7, the transition flows were predominantly upward. Over the eight-year period, the carbon storage classes exhibited an overall upward shift in class structure. Specifically, the area proportion of Class 1 increased

slightly from 0.01% to 0.06%, and that of Class 5 increased from 0.31% to 1.64%, while the area proportions of Classes 2 and 3 decreased by 5.91% and 5.04%, respectively. Notably, the area proportion of Class 4 increased significantly by 9.57%. These changes indicate that a considerable area of Class 3 forests shifted to Class 4 through continued carbon accumulation, and some Class 2 forests shifted to Class 3, showing an overall upward trend between classes and confirming the continuous optimization of the forest carbon storage class structure in Fuzhou City.

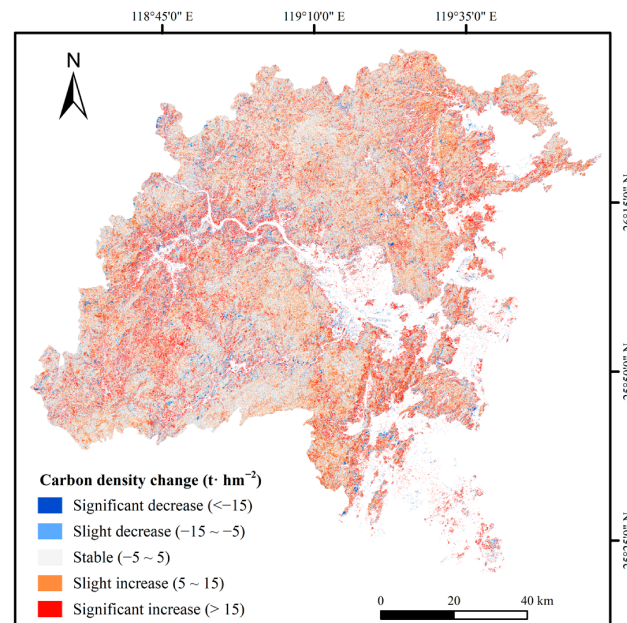


Figure 5. Difference in carbon storage between 2015 and 2023. Carbon density difference was calculated as the value in 2023 minus that in 2015 and classified into five levels: significant decrease ($<-15 \text{ t}\cdot\text{hm}^{-2}$), slight decrease (-15 to $-5 \text{ t}\cdot\text{hm}^{-2}$), stable (-5 to $5 \text{ t}\cdot\text{hm}^{-2}$), slight increase (5 to $15 \text{ t}\cdot\text{hm}^{-2}$), and significant increase ($>15 \text{ t}\cdot\text{hm}^{-2}$).

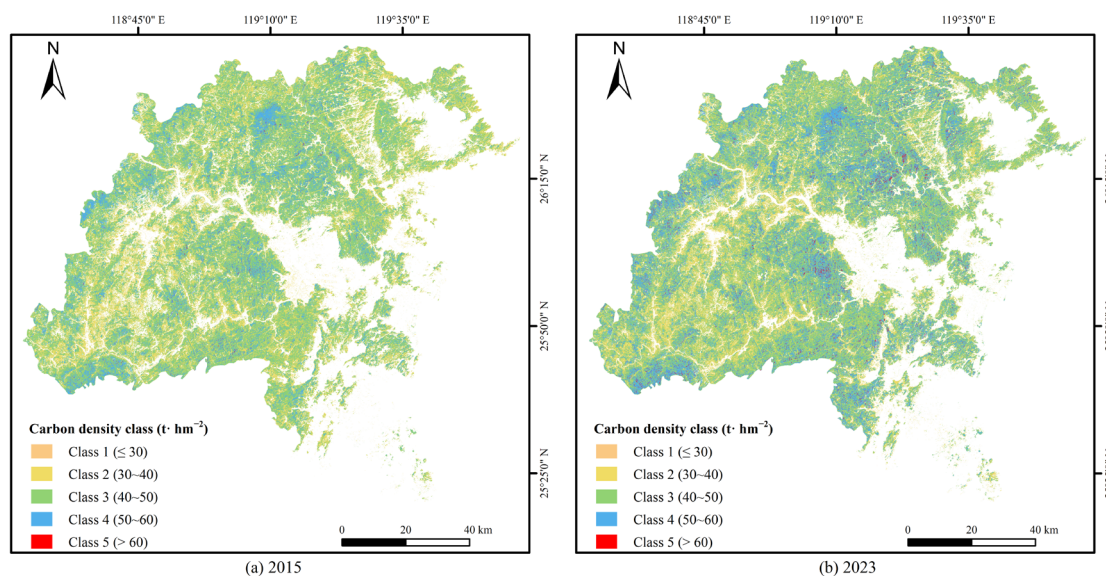


Figure 6. Distribution of forest carbon storage grades between the two time phases. Spatial distribution of forest carbon density classes in the study area. (a) 2015; (b) 2023. Five classes were defined: Class 1 ($\leq 30 \text{ t}\cdot\text{hm}^{-2}$), Class 2 ($30\text{--}40 \text{ t}\cdot\text{hm}^{-2}$), Class 3 ($40\text{--}50 \text{ t}\cdot\text{hm}^{-2}$), Class 4 ($50\text{--}60 \text{ t}\cdot\text{hm}^{-2}$), and Class 5 ($>60 \text{ t}\cdot\text{hm}^{-2}$).

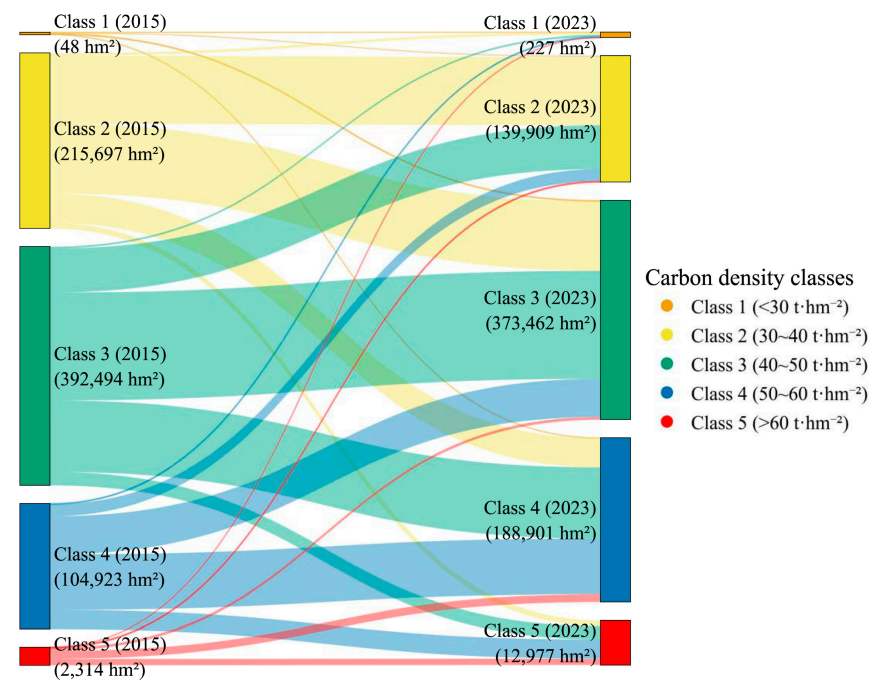


Figure 7. Sankey diagram of forest carbon storage in the study area. Sankey diagram of forest carbon storage class transitions between 2015 and 2023. Five classes were defined: Class 1 ($\leq 30 \text{ t} \cdot \text{hm}^{-2}$), Class 2 ($30\text{--}40 \text{ t} \cdot \text{hm}^{-2}$), Class 3 ($40\text{--}50 \text{ t} \cdot \text{hm}^{-2}$), Class 4 ($50\text{--}60 \text{ t} \cdot \text{hm}^{-2}$), and Class 5 ($>60 \text{ t} \cdot \text{hm}^{-2}$). The width of each flow represents the area transferred between classes.

3.4.4. Differentiation of Carbon Storage Across Elevation Zones

To explore the relationship between topographic factors and the spatial differentiation of forest carbon storage, four elevation zones were delineated based on the elevation range of Fuzhou City (0–1654 m, mean 348 m, standard deviation 294 m), using approximately one standard deviation combined with area distribution. The four zones were 0–50 m, 50–350 m, 350–650 m, and ≥ 650 m. The statistical results of forest area, carbon storage, and carbon density for each elevation zone in the two periods are shown in Table 9. As shown in Table 9, in terms of spatial distribution, forest carbon density increased with elevation, and the pattern was consistent across the two periods. The 50–650 m elevation range was the main distribution area of forest carbon storage, accounting for more than 70% of both total area and total carbon storage. Regarding spatial changes, the 50–350 m zone had the largest increments in both area and carbon storage ($+3.14 \times 10^4 \text{ hm}^2$ and $+1.79 \times 10^6 \text{ t}$). The 0–50 m zone had the highest growth rates (area +60.31%, carbon storage +66.67%), and the magnitude of change in both area and carbon storage decreased with increasing elevation. Regarding carbon density change, both the increment and growth rate were higher in high-elevation zones than in low-elevation zones.

Table 9. Forest carbon storage across elevation zones in Fuzhou, 2015–2023.

Year	Item	Elevation (m)			
		0~50	50~350	350~650	≥ 650
2015	Area ($\times 10^4 \text{ hm}^2$)	1.94	25.72	28.18	18.75
	carbon storage ($\times 10^6 \text{ t}$)	0.75	10.83	12.34	8.50
	Carbon density ($\text{t} \cdot \text{hm}^{-2}$)	38.56	42.11	43.79	45.36
2023	Area ($\times 10^4 \text{ hm}^2$)	3.11	28.86	29.77	19.54
	carbon storage ($\times 10^6 \text{ t}$)	1.25	12.62	13.63	9.25
	Carbon density ($\text{t} \cdot \text{hm}^{-2}$)	40.05	43.74	45.79	47.36

Table 9. Cont.

Year	Item	Elevation (m)			
		0~50	50~350	350~650	≥650
Change	Area ($\times 10^4$ hm ²)	+1.17	+3.14	+1.59	+0.79
	Change rate	60.31%	12.21%	5.64%	4.21%
	carbon storage ($\times 10^6$ t)	+0.50	+1.79	+1.29	+0.75
	Change rate	66.67%	16.53%	10.45%	8.82%
	Carbon density (t·hm ⁻²)	+1.49	+1.63	+2.00	+2.00
	Change rate	3.86%	3.87%	4.57%	4.41%

4. Discussion

4.1. Analysis of Plot-Scale AGB Acquisition

The number of plot-scale AGB samples was lower than expected. The main reason is the high forest coverage in the survey area, where dense overlapping branches and tree canopies significantly block the laser pulses emitted by the UAV-LiDAR. The penetration process of laser pulses can be compared to sunlight. If sunlight is visible beneath the canopy, laser pulses have a relatively high chance of reaching the ground. Conversely, if sunlight is completely blocked, laser pulses are also less likely to penetrate the dense canopy layers and are reflected back upon encountering tree crowns or branches, resulting in a small number of effective ground return points [56]. In this situation, DEM generation relies on interpolation algorithms that estimate elevations based on limited surrounding ground points, leading to reduced DEM accuracy in some areas. Since the CHM is the difference between the DSM and the DEM, if an area has insufficient ground points and the interpolated DEM is too low, the CHM value becomes abnormally high. Conversely, if the DEM interpolation is too high, the CHM becomes abnormally low. This leads to overestimation or underestimation of extracted tree height in such areas. Nevertheless, estimating plot-scale AGB using UAV-LiDAR remains feasible, and the number of samples obtained is sufficient to support subsequent analysis. It should be noted that in extremely dense forest areas, the information acquisition capability of UAV-LiDAR still has certain limitations, resulting in a slightly lower actual number of samples than expected. However, with just five flight areas, more than 200 plot-scale AGB samples can be obtained within two days. This approach offers significant advantages such as short acquisition time, ease of operation, and low labor and equipment costs. In addition, the timing of data acquisition is highly consistent with the overpass times of Landsat and Sentinel-1 satellites, ensuring the temporal consistency of the multi-source data. These advantages are difficult to achieve with traditional forest field surveys. Even for natural forests with relatively complex structures, although DEM accuracy in some areas may be insufficient for biomass estimation, appropriately increasing the number of flight areas can effectively expand the sample size.

4.2. Analysis of Modeling Factor Selection

Due to the spectral response characteristics of vegetation, the remote sensing factors from Landsat generally showed stronger correlations. However, some Landsat factors had relatively high correlation coefficients with each other, suggesting possible multicollinearity. In contrast, the correlations among Sentinel-1 remote sensing factors were relatively low, with more factors showing non-significant correlations. Theoretically, AGB is positively correlated with SAR backscatter coefficients [57]. However, existing studies have shown that backscatter coefficients exhibit a saturation effect in AGB estimation. The saturation value increases with longer wavelengths. Sentinel-1 is a C-band SAR sensor with a saturation value of 30–50 t·hm⁻² [58,59]. The mean biomass in the study area exceeded 90 t·hm⁻²,

which reduced the sensitivity of SAR. In addition, the polarization mode of SAR also affects the correlation. The correlations of VH and its textural features were higher than those of VV. This is consistent with the findings of Chen [60] and Wu [61]. The reason is that VH backscatter is primarily dominated by volume scattering from woody material, whereas VV is also influenced by ground scattering. Regarding topographic factors, elevation affects forest growth by influencing temperature conditions. However, the highest elevation in the study area is 1654 m with a mean of 356 m, so the temperature variation is limited. High-elevation areas experience less human disturbance and may instead accumulate more biomass.

The common characteristics of the feature variables selected across different factor combinations indicate that biomass is influenced by a combination of multiple factors. Table 4 shows that the most frequently eliminated factors were Landsat-derived factors. This is consistent with the observation that Landsat factors had strong intercorrelations. When vegetation cover is extremely high, the amount of red light absorbed by vegetation reaches saturation [62]. This may explain why the red band and its textural features were frequently excluded. The vegetation indices RVI and NDVI, which are closely related to the red band, also exhibited saturation. More textural features were retained because they can describe complex canopy structures and reduce the effect of canopy shadows. This makes them perform better in forests with high canopy closure and complex structure [63]. From the perspective of data sources, when Landsat and Sentinel-1 data were used together, more SAR remote sensing factors were eliminated. This is consistent with the result in Table 3 that SAR remote sensing factors had relatively low correlations.

4.3. Model Comparison Analysis

4.3.1. Performance Comparison Between SWR and CatBoost Models

The low goodness of fit of the SWR model can be attributed to the following factors. In terms of variable selection, SWR uses a stepwise forward-selection and backward-elimination strategy and retains only variables that pass the t-test ($p < 0.05$). When strong collinearity exists among independent variables, some factors that have explanatory power for AGB may be discarded due to statistical non-significance, resulting in the loss of a large amount of feature information. In terms of model structure, there are complex nonlinear relationships between AGB and remote sensing factors. As a linear model, SWR cannot capture such nonlinear relationships, leading to underfitting. In contrast, CatBoost, as a non-parametric machine learning algorithm, can flexibly adjust model complexity according to data characteristics and achieve better fitting performance. In the test set accuracy validation, the Landsat + SAR + other factors combination performed best within both modeling methods, indicating that multi-source remote sensing offers greater advantages for biomass estimation in the study area compared with single-source data. Two reasons may explain this. First, the inclusion of SAR factors improved the estimation performance in low-biomass areas. Second, multi-source remote sensing factors can simultaneously reflect horizontal canopy structure and vertical forest structural information, enriching the explanatory variables of the model. In addition, the test accuracy of the CatBoost models was consistently slightly higher than that of SWR, but the improvement was limited. This may be related to the relatively small sample size, which prevented CatBoost from fully exploiting its advantage in handling large datasets, whereas SWR maintained a certain level of accuracy under small-sample conditions.

4.3.2. Analysis of Overfitting in the CatBoost Model

Although the CatBoost model achieved high fitting accuracy on the training dataset, its performance on the testing dataset was lower, indicating a certain degree of overfitting.

Overfitting is a common issue in machine learning models trained with limited samples, as random noise may also be learned during the training process, thereby reducing model generalization ability [64]. In this study, overfitting may have arisen from two main factors. On the one hand, the study area exhibits strong spatial heterogeneity in forest conditions and considerable topographic variation. On the other hand, the relatively limited sample size may have constrained the model's generalization capability. Despite the presence of some overfitting, the RMSE, MAE, and rRMSE values of the testing dataset remained within a reasonable range, indicating that the model still possessed good predictive performance. From a methodological perspective, RF-RFE feature selection, hyperparameter optimization, and an early-stopping strategy were employed to reduce model complexity and partially alleviate overfitting. In addition, the samples were divided into training and testing datasets using stratified random sampling, ensuring similar data distributions between the two datasets and improving the reliability of model evaluation results.

Therefore, although the CatBoost model exhibited a certain degree of overfitting, its predictive accuracy on the testing dataset remained sufficient for regional-scale forest AGB estimation. Future studies could further improve model generalization and stability by expanding UAV-LiDAR sample coverage, increasing sample size, and incorporating additional ecologically meaningful explanatory variables.

4.4. Spatiotemporal Evolution Analysis of Forest Carbon Storage

From 2015 to 2023, forest carbon storage, carbon density, and forest area in Fuzhou exhibited a synergistic growth pattern. This trend is closely associated with regional forest conservation policies, the designation of ecological protection redlines, and continuous afforestation programs implemented during the study period. These measures not only reduced the loss of existing forest resources but also continuously expanded forest area through afforestation, thereby serving as important drivers of the increase in total forest carbon storage. In terms of carbon storage class structure, forests gradually shifted from low- and medium-level carbon storage classes toward higher-level classes, indicating a continuous optimization of the regional forest carbon pool structure. Subtropical forests generally require approximately 10–20 years to transition from young stands to middle-aged stands characterized by rapid increases in carbon density [48]. Therefore, the monitoring period considered in this study is still insufficient for newly established forests to fully realize their carbon sequestration potential. As these newly established forests gradually mature, their carbon sink capacity is expected to increase further, providing continued support for future growth in regional forest carbon storage.

The elevational differentiation analysis revealed distinct spatial patterns of carbon storage change. High-elevation areas exhibited a clear density-driven growth pattern, which is consistent with the vertical gradient of human disturbance intensity. Because human activities are relatively limited at higher elevations, mature forests can persist for longer periods and continuously maintain their carbon sequestration functions. In contrast, low-elevation areas were characterized primarily by an area-driven growth pattern. These areas are the main targets of afforestation activities, where newly established forests mainly consist of young stands with relatively low carbon density. The rapid expansion of forest area also diluted the average carbon density at the regional scale. As these young forests progressively mature, the rate of carbon density increase in low-elevation areas is expected to accelerate. Consequently, the forest carbon storage growth pattern in Fuzhou may gradually shift from an area-driven mode to a combined area- and density-driven mode. Meanwhile, forest conservation policies are expected to ensure the long-term preservation of natural forests in high-elevation areas, allowing them to continue functioning as stable carbon sinks.

From a sustainable development perspective, the spatiotemporal patterns of forest carbon storage revealed in this study provide important insights for regional ecological management and the achievement of carbon neutrality goals. The continuous increase in forest carbon storage between 2015 and 2023 indicates an enhancement of the carbon sequestration capacity of regional forest ecosystems and provides quantitative evidence for evaluating the effectiveness of regional carbon neutrality strategies. In this regard, the findings contribute to the achievement of SDG 13 (Climate Action) by supporting climate change mitigation through enhanced forest carbon sequestration. Furthermore, the observed spatial differentiation in forest carbon storage dynamics across elevation gradients highlights distinct management priorities for different regions. High-elevation areas primarily maintain high carbon density through the conservation of mature forests, whereas low-elevation areas increase carbon storage mainly through afforestation expansion. These findings provide a scientific basis for natural forest conservation, ecological restoration, and afforestation planning, thereby promoting the sustainable management of forest resources and supporting the implementation of SDG 15.2 (Sustainable Forest Management). In the future, the integration of long-term monitoring and high-precision carbon storage assessment could further support decision-making for regional ecological civilization development and forest carbon sink management.

4.5. Uncertainty Analysis

Although the proposed approach enabled efficient estimation of regional forest carbon storage, the results may still be affected by uncertainties associated with data sources, parameter settings, and model construction procedures. First, the AGB data used for model development were not derived from conventional forest inventories but were estimated from UAV-LiDAR data. Consequently, errors introduced at different processing stages may have accumulated and ultimately affected the AGB estimation results. In particular, in areas with complex canopy structures and severe crown overlap, the CHM-based watershed segmentation algorithm may produce over-segmentation or under-segmentation, thereby affecting the accuracy of individual-tree parameter extraction. Owing to the lack of independent field measurements at the individual-tree level, no quantitative validation of the segmentation results was conducted in this study. Therefore, segmentation errors and their propagation through subsequent tree height, DBH, and biomass estimation processes have not been fully quantified. In addition, individual-tree DBH was estimated using a tree height–DBH equation. However, the relationship between tree height and DBH is influenced by multiple factors, including species composition, stand age, site conditions, and tree competition. The use of a single empirical equation may therefore introduce errors that are subsequently propagated to biomass estimation results. Likewise, biomass allometric equations are empirical relationships and inherently involve uncertainty. Furthermore, although the five UAV-LiDAR flight areas selected in this study covered different elevation gradients and forest structural conditions, and 204 AGB samples were obtained after quality screening, these samples may not fully represent the spatial heterogeneity of forest ecosystems across Fuzhou. Finally, a fixed carbon conversion coefficient (0.5) was used to convert forest biomass into carbon storage. Because actual carbon content varies among tree species and forest types, the use of a uniform conversion coefficient may introduce additional uncertainty into carbon storage estimates. Therefore, the accuracy metrics reported in this study should be interpreted in relation to the UAV-LiDAR-derived AGB estimates used for model development and validation. The estimated forest carbon storage values provide useful regional-scale information, while their reliability could be further improved by incorporating field survey data, species-specific information, regionalized parameter systems, and quantitative uncertainty assessment in future studies.

In addition to the uncertainties discussed above, several limitations related to data sources and study design should be acknowledged. Sentinel-1 is a C-band SAR sensor and is subject to signal saturation in high-biomass areas; therefore, future studies could incorporate L-band SAR data (e.g., ALOS-2/PALSAR-2) to further improve estimation accuracy. Moreover, UAV-LiDAR may fail to acquire sufficient ground returns in densely forested areas, resulting in reduced DEM accuracy in some locations. This limitation could be addressed by integrating high-precision DEM products or conducting supplementary ground surveys for calibration. Finally, the temporal span of the spatiotemporal analysis was limited to eight years because of SAR data availability. Future studies could extend the analysis period by addressing consistency and compatibility issues among different SAR sensors, thereby providing a more comprehensive understanding of long-term changes in regional forest carbon storage.

5. Conclusions

This study integrated Landsat, Sentinel-1 SAR, and UAV-LiDAR data to develop an AGB estimation model for Fuzhou City and analyze the spatiotemporal dynamics of forest carbon storage from 2015 to 2023. The proposed framework provides a new approach for remote sensing-based estimation of forest carbon storage at the regional scale in subtropical areas. The main conclusions are as follows:

- (1) The method of deriving AGB estimates from UAV-LiDAR point cloud data demonstrated considerable application potential. It can provide training samples that are temporally synchronized with satellite overpasses, thereby partially overcoming the high cost and limited timeliness associated with traditional forest inventory surveys.
- (2) Following correlation analysis and RF-RFE feature selection, Landsat-derived texture features exhibited strong explanatory power for AGB estimation. The CatBoost algorithm outperformed the stepwise regression model, and the integration of multi-source remote sensing data achieved higher accuracy than any single data source. Among all tested models, the CatBoost model combining Landsat, SAR, and other factors achieved the highest estimation accuracy. These results indicate that the synergistic use of optical, SAR, and auxiliary information can effectively improve forest AGB estimation in subtropical regions with complex terrain.
- (3) During the study period, forest carbon storage, carbon density, and forest area in Fuzhou all exhibited increasing trends, accompanied by a continuous optimization of the carbon storage class structure. Spatially, carbon density increased with elevation. Low-elevation areas were characterized by an area-driven growth pattern, and the maturation of newly established forests is expected to promote a gradual transition from an area-driven mode to a combined area- and density-driven growth mode.

In summary, the framework integrating UAV-LiDAR, multi-source remote sensing data, and the CatBoost algorithm provides a promising approach for forest carbon storage estimation in subtropical regions. The proposed method has considerable potential for regional forest carbon sink monitoring and assessment and may provide useful references for forest resource management, sustainable development, and climate change mitigation studies.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18189340/s1>. Table S1: Summary of remote sensing variables used for forest AGB estimation. Table S2: GLCM-based texture features and calculation formulas. Table S3: Hyperparameter search ranges and optimal values of the CatBoost model.

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