

Article

Spatiotemporal Dynamics and Land Cover Drivers of Herbaceous Aboveground Biomass in the Yellow River Delta from 2001 to 2022

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Highlights

What are the main findings?

- By mining literature-derived data and incorporating LAI and LGS, the random forest model achieved high-accuracy AGB mapping ($R^2 = 0.74$) in the Yellow River Delta (2001–2022).
- Herbaceous AGB showed an overall increase, primarily driven by cropland and wetland expansion, while grassland contributed little or even negatively.

What is the implication of the main finding?

- Incorporating ecological variables significantly improves large-scale biomass estimation in herbaceous ecosystems.
- The findings support wetland conservation and sustainable land use management in delta regions.



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Abstract

Frequent channel migrations of the Yellow River, coupled with increasing human disturbances, have driven significant land cover changes in the Yellow River Delta (YRD) over time. Accurate estimation of aboveground biomass (AGB) and clarification of the impact of land cover changes on AGB are crucial for monitoring vegetation dynamics and supporting ecological management. However, field-based biomass samples are often time-consuming and labor-intensive, and the quantity and quality of such samples greatly affect the accuracy of AGB estimation. This study developed a robust AGB estimation framework for the YRD by synthesizing 4717 field-measured samples from the published scientific literature and integrating two critical ecological indicators: leaf area index (LAI) and length of growing season (LGS). A random forest (RF) model was employed to estimate AGB for the YRD from 2001 to 2022, achieving high accuracy ($R^2 = 0.74$). The results revealed a continuous spatial expansion of AGB over the past two decades, with higher biomass consistently observed in western cropland and along the Yellow River, whereas lower biomass levels were concentrated in areas south of the Yellow River. AGB followed a fluctuating upward trend, reaching a minimum of 204.07 g/m² in 2007, peaking at 230.79 g/m² in 2016, and stabilizing thereafter. Spatially, western areas showed positive trends, with an average annual increase of approximately 10 g/m², whereas central and coastal zones exhibited localized declines of around 5 g/m². Among the changes in land cover, cropland and

wetland changes were the main contributors to AGB increases, accounting for 54.2% and 52.67%, respectively. In contrast, grassland change exhibited limited or even suppressive effects, contributing -6.87% to the AGB change. Wetland showed the greatest volatility in the interaction between area change and biomass density change, which is the most uncertain factor in the dynamic change in AGB.

Keywords: aboveground biomass; herbaceous; Yellow River Delta; spatiotemporal dynamics; remote sensing mapping

1. Introduction

Herbaceous vegetation, dominant in grassland, wetland, and cropland system, contributes significantly to biodiversity, soil stabilization, and nutrient cycling [1]. These plants are vital in carbon sequestration processes, acting as short-term carbon sinks and influencing local microclimates [2]. Understanding the distribution, productivity, and ecological functions of herbaceous plants is therefore critical for sustainable land management, biodiversity conservation, and climate change mitigation. Among the various ecological attributes of herbaceous vegetation, aboveground biomass (AGB) is a key biophysical indicator representing vegetation productivity, ecosystem functioning, and carbon sequestration potential [3]. AGB refers to the total mass of living plant material above the soil surface and is essential for assessing vegetation health, land degradation, and carbon dynamics under changing climatic conditions [4]. However, traditional methods for obtaining AGB are time-consuming and labor-intensive, highlighting the need for more efficient and scalable approaches to AGB estimation.

Satellite remote sensing has emerged as the preferred approach for large-scale herbaceous AGB monitoring, offering repeated, spatially continuous, and cost-effective observations [5]. The commonly used approaches for AGB estimation involve establishing empirical models that correlate field-measured AGB with spectral reflectance information and vegetation indices (VIs) derived from remote sensing imagery [6]. While this method is straightforward, intuitive, and computationally simple, it often fails to fully exploit the rich spectral information contained in multispectral or hyperspectral data [7]. With advancements in remote sensing technologies, a variety of vegetation-related ecological indicators, such as leaf area index (LAI) and length of growing season (LGS), have become available. LAI, a key parameter for monitoring vegetation growth, is intrinsically linked to photosynthesis, respiration, and environmental processes such as the carbon cycle and precipitation interception, and serves as an effective indicator for assessing vegetation growth, estimating biomass, and predicting yield [8–10]. LGS represents the period from the onset of vegetation growth to maturity, a critical phase for carbon fixation and is closely associated with biomass accumulation. It also reflects local climatic conditions, as seasonal variations in climate factors such as precipitation can alter vegetation phenology, thereby influencing terrestrial carbon cycle [11,12]. These indicators effectively capture the growth status of vegetation and hold great potential for improving the accuracy of biomass estimation models [13–15]. However, existing studies on AGB estimation still rely primarily on spectral reflectance information and VIs at single time points, without incorporating ecological variables such as LAI and LGS that directly characterize vegetation carbon accumulation, leaving an important research gap that this study aims to address.

Compared with empirical models for AGB estimation, machine learning (ML) algorithms have demonstrated superior performance due to their strong capabilities in handling high-dimensional data, capturing complex nonlinear relationships, and automating feature

learning processes [13]. Among various ML algorithms, the random forest (RF) algorithm has become one of the most widely used and consistently effective methods in remote sensing-based AGB estimation [16–18]. RF is an ensemble learning method that constructs multiple decision trees and aggregates their predictions, which greatly enhances model stability and reduces the risk of overfitting [19]. In addition, it is capable of handling large volumes of heterogeneous data and capturing complex nonlinear interactions among variables [20]. Existing studies demonstrate that RF often outperforms other algorithms in terms of model accuracy and robustness, making it a preferred choice for vegetation biomass mapping [21].

However, the accuracy of AGB estimation based on ML algorithms is highly influenced by the availability of sufficient and reliable field-measured biomass samples [13]. In addition, Large-scale field sampling is often constrained by limited resources, high costs, and logistical challenges, especially in remote or ecologically sensitive areas [22]. Fortunately, numerous studies have focused on biomass monitoring, and many of them contain ample field sampling data reported in peer-reviewed publications [23–25]. These openly accessible studies provide a valuable source of field data, including detailed measurements, sampling dates, and geographic locations, making it feasible to compile a robust ground-truth dataset. Therefore, this study innovatively compiles and harmonizes such literature-derived biomass data to overcome the sampling limitation that hampers previous AGB estimation efforts.

The Yellow River Delta (YRD), located in eastern China, serves as an ideal case study for herbaceous AGB estimation. As one of the youngest and most dynamic coastal wetland ecosystems in the world, the YRD features vast expanses of artificial croplands, natural grasslands, and restored wetland [26]. The region plays a crucial ecological role in biodiversity conservation, shoreline stabilization, and carbon storage. However, over the past few decades, the YRD has experienced increasing ecological pressures from climate change, hydrological disruptions, and human activities, resulting in vegetation degradation and frequent land cover conversions [27]. In this context, the accurate estimation of herbaceous AGB is not only essential for monitoring vegetation productivity and restoration outcomes but also critical for assessing regional carbon stocks, evaluating grassland quality, and guiding sustainable land use practices in deltaic environments.

Therefore, this study aims to develop an efficient, scalable, and accurate framework for estimating herbaceous AGB in the YRD. Its novelty lies in addressing the critical challenge of missing field samples by utilizing data derived from literature, complemented by the introduction of two key ecological parameters—LAI and LGS—to precisely characterize vegetation growth dynamics and thereby enhance estimation accuracy. The proposed framework was subsequently applied and evaluated within the YRD region. The primary objectives are to (1) construct a robust AGB estimation model by incorporating field data from literature and integrating two critical ecological indicators: leaf area index (LAI) and length of growing season (LGS); (2) analyze the spatiotemporal dynamics of AGB over the past two decades; and (3) investigate the effects of land cover changes on biomass variability. The findings are expected to support long-term ecological monitoring, improve our understanding of vegetation dynamics, and provide scientific references for wetland conservation and regional ecosystem management.

2. Materials

2.1. Study Area

The Yellow River Delta (YRD), located in northeastern Shandong Province, China (118°07′–119°10′E, 36°55′–38°12′N), covers approximately 5934 km². With a sub-humid continental monsoon climate, the region experiences annual precipitation of 530–630 mm

(mainly from May to September) and high evapotranspiration (700–2400 mm), resulting in saline soils that constrain tree growth [27]. The terrain is low and gently undulating (1–2 m above sea level), shaped by frequent channel migrations of the Yellow River and characterized by micro-topographic features such as levees, depressions, and slopes. Due to the harsh soil and hydrological conditions, the area is dominated by salt-tolerant herbaceous vegetation [28].

2.2. Field Data

This study extracted herbaceous field-measured AGB data from published scientific literature. A literature search was conducted on the Web of Science (WOS) using the topic keywords “biomass” and “grassland or shrub or cropland”. To improve efficiency and ensure data relevance, the results were sorted by relevance. A total of 7970 publications related to herbaceous biomass were initially identified, covering the period from 2010 to 2022. Each article was manually reviewed, and biomass information, along with the corresponding sampling time and geographic coordinates, was extracted from figures and tables. The AGB measurements recorded in the selected studies followed broadly consistent protocols: selecting vegetation plots of appropriate size, harvesting the aboveground parts of plants, oven-drying the samples to obtain dry biomass weight, and recording accurate geographic coordinates and sampling dates [29]. Only biomass data that explicitly described scientifically sound field sampling procedures were considered. To ensure spatiotemporal accuracy, sampling dates were required to be specified at least to the month, and spatial coordinates were required to have a precision of at least 30". Since the collected biomass data were reported in various units, all measurements were standardized to g/m². For records providing only the month and a coordinate range, the midpoint of the given range was used. Although the process of extracting data from literature represents a substantial effort, it offers greater efficiency and flexibility compared with field sampling, allowing the compilation of large datasets in a relatively short time.

In the data preprocessing stage, obvious erroneous records, such as those located outside terrestrial areas, were manually removed. Since most samples were collected within specific study sites or experimental plots, additional filtering was necessary to exclude points lacking broader representativeness. To this end, the local Moran's I was applied to assess spatial autocorrelation, with the number of neighbors set to 10 [30]. By comparing the attribute value of each point with the mean of its neighboring points, spatial outliers were identified and removed. In addition, to remove noise and improve data quality, the interquartile range (IQR) method was employed to detect and eliminate outliers. Duplicate records were also identified and removed to ensure that the dataset consisted of independent, high-quality observations suitable for regression analysis. After excluding inconsistent or unreliable, and clearly erroneous records, a total of 4717 valid sampling points for herbaceous AGB were retained. As the original biomass distribution exhibited strong left skewness, a logarithmic transformation was applied to normalize the data (Figure 1).

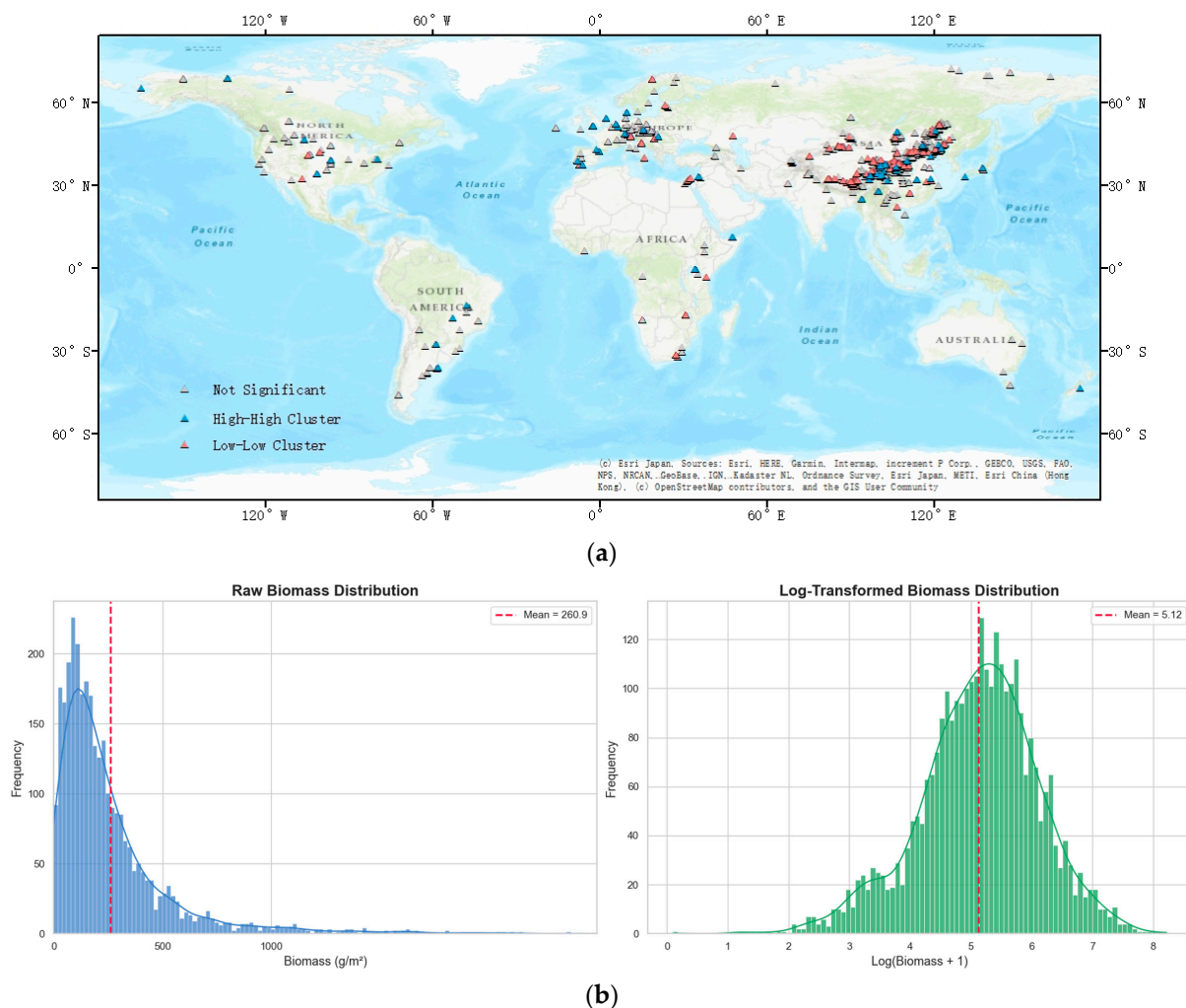


Figure 1. Spatial distribution of the sampling points and statistical distribution of the data. (a) Points identified by the local Moran's I analysis, including high-value clusters, low-value clusters, and non-significant points; outliers were excluded. (b) Distribution of AGB and its log-transformed counterpart. The log-transformed AGB values are dimensionless, as the logarithmic transformation removes the original units.

2.3. Remote Sensing Data

2.3.1. Reflectance Information and Vegetation Index

The reflectance information was derived from the Landsat satellite series and accessed via the Google Earth Engine (GEE) platform. In this study, we utilized atmospherically corrected surface reflectance data from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) spanning the period 2001–2022. The Landsat series provides a 30-m spatial resolution with a 16-day revisit cycle, offering an optimal balance between spatial detail and temporal frequency for monitoring vegetation dynamics across large areas. GEE provides Landsat surface reflectance products (Level-2), generated after radiometric calibration and atmospheric correction [31]. As for Atmospheric correction, Landsat 5 TM and 7 ETM+ use LEDAPS based on the 6S radiative transfer model [32,33], and Landsat 8 OLI applies LaSRC, which relies on MODTRAN with enhanced aerosol inversion and BRDF adjustments [34,35]. To minimize the impact of cloud contamination on Landsat observations, Landsat scenes with cloud cover >30% were excluded using the CLOUD_COVER metadata. Residual clouds and shadows were masked at the pixel level from the QA_PIXEL band (bits 3 and 4) via bitwise operations, effectively reducing cloud contamination. According to the different

advantages of each VI in reflecting vegetation growth, various VIs such as Normalized Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), Enhanced Vegetation Index (EVI), Two-band Enhanced Vegetation Index (EVI2), Difference Vegetation Index (DVI), Soil-Adjusted Vegetation Index (SAVI), Optimized Soil-Adjusted Vegetation Index (OSAVI), Modified Soil-Adjusted Vegetation Index (MSAVI), and Normalized Difference Phenology Index (NDPI) were calculated from Landsat surface reflectance products through the GEE platform (Table 1).

Table 1. AGB estimated VIs and formula.

VIs	Formula	Reference
RVI	$RVI = NIR / RED$	[36]
EVI	$EVI = 2.5 \times \frac{NIR - RED}{NIR + 6 \times RED - 7.5 \times BLUE + 0.5}$	[37]
EVI2	$EVI2 = 2.5 \times \frac{NIR - RED}{NIR + 2.5 \times RED + 1}$	[38]
DVI	$DVI = NIR - RED$	[39]
NDVI	$NDVI = \frac{NIR - RED}{NIR + RED}$	[40]
NDPI	$NDPI = \frac{NIR - (0.74 \times RED + 0.26 \times SWIR1)}{NIR + (0.74 \times RED + 0.26 \times SWIR1)}$	[41]
MSAVI	$MSAVI = \frac{(2 \times NIR + 1) - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)}}{2}$	[42]
OSAVI	$OSAVI = \frac{NIR - RED}{NIR + RED + 0.16}$	[43]

2.3.2. Land Cover Data

Frequent land use and land cover changes in the YRD, driven by both natural processes and intensive human activities, have significantly affected AGB estimation in the region. The land cover data were obtained from the Global Land Cover with Fine Classification System at 30 m (GLC_FCS30), provided by the National Center for Basic Geographic Information [44]. This dataset offers high-resolution (30 m × 30 m) global land cover classification.

2.3.3. Other Auxiliary Data

To enhance the accuracy of biomass estimation and capture environmental and vegetation-related information, two critical ecological indicators were integrated into the estimation. To ensure the consistent and reliable acquisition of ecological indicators, the relatively mature Moderate Resolution Imaging Spectroradiometer (MODIS) products were selected for this study. The MODIS MOD15A2H product version 061 was used to obtain leaf area index (LAI) data, which provides 8-day composites and effectively characterizes canopy structure and vegetation density. In addition, seasonal dynamics of vegetation growth were described using the MODIS MCD12Q2 product version 061, which offers key temporal indicators such as start-of-season (SOS), end-of-season (EOS). These phenological metrics reflect interannual variability in vegetation activity and are closely linked to biomass accumulation. The 500-m resolution MODIS products were resampled to 30 m using bilinear interpolation to align with the spatial resolution of Landsat imagery. In addition, topographic information was derived from the Shuttle Radar Topography Mission (SRTM) digital elevation model (USGS/SRTMGL1_003), which provides 30-m resolution elevation data. From this dataset, slope and aspect were calculated to represent terrain-related environmental gradients that may influence vegetation distribution and productivity across the study area.

3. Methods

3.1. Herbaceous Vegetation Extraction

Multi-year land cover data were analyzed to characterize the spatial-temporal distribution patterns of herbaceous vegetation and improve the accuracy of herbaceous biomass estimation. The original 35 land cover types from GLC_FCS30 were reclassified into three overarching categories: grassland, cropland, and wetland, to facilitate the construction of a vegetation-specific spatial mask. The land cover in 2020 is presented as an example, whereas the estimation of AGB from 2001 to 2022 employed the corresponding land cover for each respective year (Figure 2). Specifically, land cover types such as natural grassland, sparse herbaceous vegetation, and lichens and mosses were aggregated into the grassland category. Herbaceous cover cropland, rainfed cropland, and irrigated cropland were assigned to the cropland category. Wetland-related classes, including swamp, marsh, flooded flat, salt marsh, and tidal flat, were consolidated under the wetland category (Table 2). This reclassification strategy streamlined land cover information, enabling more targeted analysis of herbaceous biomass dynamics across distinct vegetation types. Furthermore, we quantified the areal changes in each land cover category from 2001 to 2022 to support the analysis of biomass variation drivers.

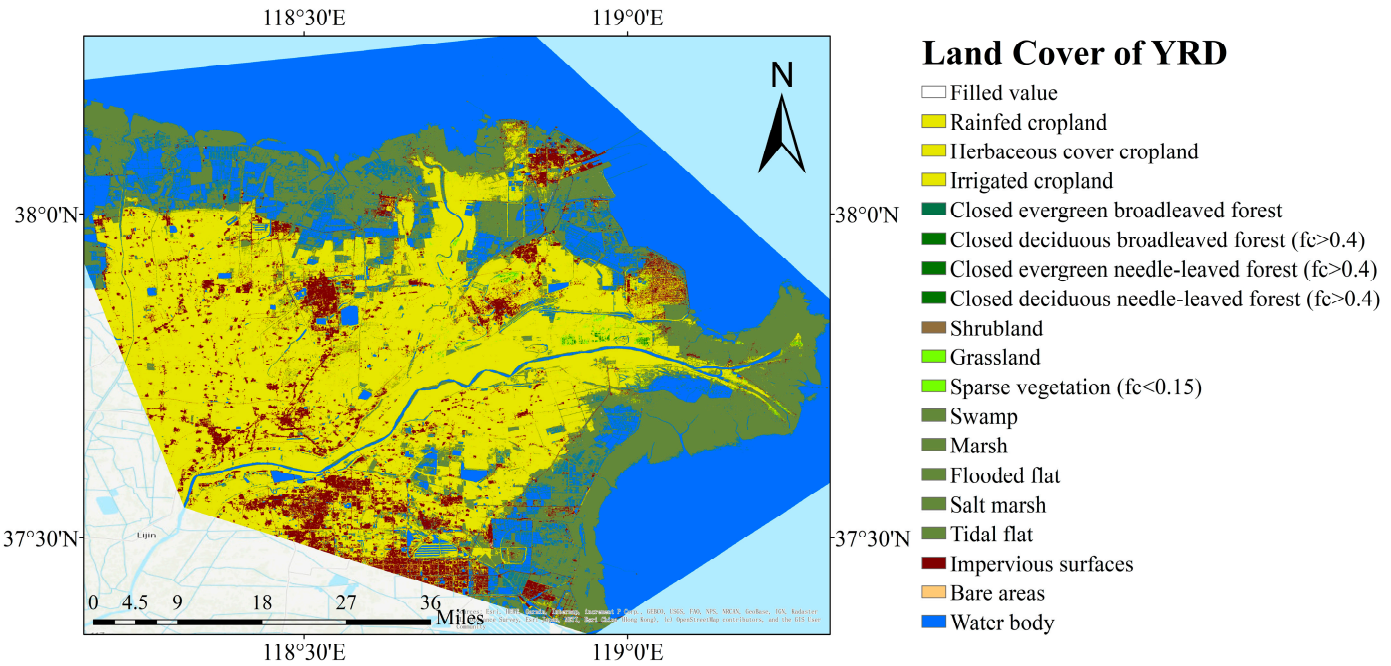


Figure 2. Land cover of YRD in 2020.

Table 2. Reclassified land cover.

Reclassified Land Cover	GLC-FCS30
Cropland	Herbaceous cover cropland, Rainfed cropland, Irrigated cropland;
Grassland	Grassland, Lichens and mosses, Sparse herbaceous ($fc < 0.15$);
Wetland	Swamp, Marsh, Flooded flat, Salt marsh, Tidal flat;

3.2. Herbaceous AGB Estimation

The RF model from machine learning was employed to construct the AGB estimation model for herbaceous vegetation. This model is selected for its ability to be insensitive to the collinearity between model input variables. To enhance the estimation accuracy of herbaceous AGB, we prioritized the incorporation of LAI and LGS, which were calculated by SOS and EOS. LAI is a widely recognized biophysical parameter that directly correlates with canopy photosynthetic potential, transpiration, and carbon assimilation. LGS reflects the duration of active vegetative growth during a given year and is strongly associated with biomass accumulation over time. A longer growing season typically allows for greater carbon fixation and biomass formation, particularly in herbaceous ecosystems where growth is highly seasonal. Therefore, a total of 18 predictor variables were used as model inputs, grouped into four categories: spectral variables, VI variables, topographic variables, and ecological variables (Table 3).

Table 3. Feature categories and variables.

Feature Categories	Variables
spectral variables	BLUE, GREEN, RED, NIR, SWIR1, SWIR2;
vegetation indices	NDVI, EVI, EVI2, RVI, DVI, OSAVI, MSAVI;
topographic variables	Elevation, Slope, Aspect;
ecological variables	LAI, LGS;

Spatiotemporal matching was performed between field-measured AGB data and satellite images to construct the training dataset for model development. For each sample, spatial matching was performed by minimizing the Euclidean distance between the geographic coordinates of the pixel center and those of the sample location. To ensure temporal consistency, satellite parameters such as spectral reflectance information, VIs, and LAI were matched using the average values derived from a 15-day window centered around the actual field measurement time of each sample. As for LGS, only annual values were available. Based on the constructed AGB estimation model, we estimated AGB in the YRD from 2001 to 2022. For each year, pixels with biomass values exceeding the 95th percentile were identified as representing the annual biomass, from which a dataset of annual AGB for 2001–2022 was generated.

To assess the modeling performance and evaluate the advantages of the RF algorithm in AGB estimation, we conducted comparative experiments using Support Vector Machine (SVM) and Artificial Neural Network (ANN) models, which have also been reported to perform well in biomass estimation [45,46]. The dataset was separated into training and testing subsets at an 8:2 ratio. To ensure optimal performance across different models, variable selection was incorporated, and the models were evaluated with and without this procedure to assess its impact on their performance. Variable selection was performed using the Least Absolute Shrinkage and Selection Operator (LASSO) algorithm, which applies a penalty function to shrink the coefficients of nonessential predictors to zero, thereby retaining only those variables with significant effects on the dependent variable [47].

Variable selection was performed using the LASSO algorithm with ten-fold cross-validation. The optimal regularization parameter ($\lambda = 0.39$) was automatically determined to control the penalty strength, resulting in 12 retained predictor variables (Table 4). Subsequently, estimation models were constructed using both the full feature set and the reduced feature set, and their predictive performance was compared. Both datasets were partitioned into training and testing subsets at an 8:2 ratio. Models were trained using the training sets and evaluated on the testing sets.

Table 4. Features before and after variable selection using LASSO.

Feature Selection	Features
Selected by LASSO	NIR, SWIR1, Slope, Aspect, LGS, BULE, LAI, Elevation, SWIR2, GREEN, RED, DVI;
Not Selected	EVI, EVI2, OSAVI, MSAVI, NDVI, RVI;

For AGB regression prediction, three types of models were constructed: RF, SVM, and ANN. In the RF model, 78 decision trees were employed, with a maximum depth of 10 and a minimum of 3 samples per leaf. Random sampling and out-of-bag estimation were introduced to enhance generalization and reduce overfitting. The SVM model utilized a radial basis function (RBF) kernel to capture the nonlinear relationship between input features and biomass, with the penalty parameter and tolerance (C and ϵ) adjusted to control model fitting. The ANN model adopted a fully connected multilayer architecture comprising four hidden layers with 256, 128, 64, and 32 neurons, respectively, using ReLU activation. Dropout layers were incorporated to prevent overfitting, and the model was trained using the Adam optimizer with early stopping based on the validation loss to ensure optimal generalization. To accommodate the characteristics of different algorithms, the input features for the SVM and ANN models were standardized to ensure that all features had the same scale and unit.

The Model performance was evaluated using standard regression metrics, including the coefficient of determination (R^2 ; Equation (1)), root mean square error (RMSE; Equation (2)) and mean relative estimate error (REE; Equation (3)) and precision (Equation (4)). They are defined as:

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - x_i)^2}{n}} \quad (2)$$

$$REE = \sqrt{\frac{\sum_{i=1}^n ((y_i - x_i)/y_i)^2}{n}} \quad (3)$$

$$\text{precision} = (1 - REE) \times 100\% \quad (4)$$

where x_i and y_i are the predicted AGB and measured AGB of the i^{th} plot, respectively; $\bar{y}$ is the average of the measured AGB, and n is the total number of plots.

3.3. Trend Analysis

The Sen's Slope estimator was used to evaluate the temporal trends of AGB with the Mann–Kendall (MK) test to assess its statistical significance. Sen's Slope provides a robust estimate of trend direction and magnitude, while the MK test, as a non-parametric method, determines whether the trend is statistically significant without assuming a specific data distribution [48,49]. A positive slope indicates an increasing trend in AGB, and a significant MK test result confirms the reliability of the observed trend.

3.4. Driving Forces Detection

The Structural Decomposition Analysis (SDA) framework was employed to quantify the relative contribution of different land cover drivers to AGB changes. SDA is a decomposition method used to assess the effect of certain driving forces on indicator changes [50]. Using this method, we decomposed the AGB changes in cropland, grassland, and wetland into three components: area effect, density effect, and interaction effect.

The area effect ($\text{Effect}_{\text{area}}$; Equation (5)) reflects AGB changes resulting from shifts in land cover area while holding biomass density constant; increases in area lead to higher total biomass, whereas decreases reduce it. The density effect ($\text{Effect}_{\text{density}}$; Equation (6)) captures changes attributable to variations in AGB density within stable land covers, with increases in productivity or structural growth producing positive effects and declines yielding negative effects. The interaction effect ($\text{Effect}_{\text{interaction}}$; Equation (7)) quantifies the synergistic influence of simultaneous changes in area and density; concurrent increases in both area and density amplify total biomass more than either effect alone. The total effect ($\text{Effect}_{\text{total}}$; Equation (8)) of a given land cover type in a specific year is calculated as the sum of its three individual effects (area, density, and interaction). The annual contribution rate of that land cover type is then obtained by dividing its total effect by the sum of the total effects of all three land cover types (cropland, grassland, and wetland) in the same year (Equation (9)).

$$\text{Effect}_{\text{area}_i} = B_{T_i} \times (A_{T_i} - A_{T_{i-1}}) \quad (5)$$

$$\text{Effect}_{\text{density}_i} = (B_{T_i} - B_{T_{i-1}}) \times A_{T_i} \quad (6)$$

$$\text{Effect}_{\text{interaction}_i} = (B_{T_i} - B_{T_{i-1}}) \times (A_{T_i} - A_{T_{i-1}}) \quad (7)$$

$$\text{Effect}_{\text{total}} = \text{Effect}_{\text{area}} + \text{Effect}_{\text{density}} + \text{Effect}_{\text{interaction}} \quad (8)$$

$$\text{Contribution}_{\text{landcover}} = \frac{\text{Effect}_{\text{total\_landcover}}}{\text{Effect}_{\text{total\_all}}} \quad (9)$$

where B_{T_i} is baseline biomass density at times T_i , and A_{T_i} is land cover areas at times T_i .

By applying this method, we can attribute biomass changes in each land cover type to specific driving factors, offering important data support for subsequent ecological and environmental management strategies.

4. Results

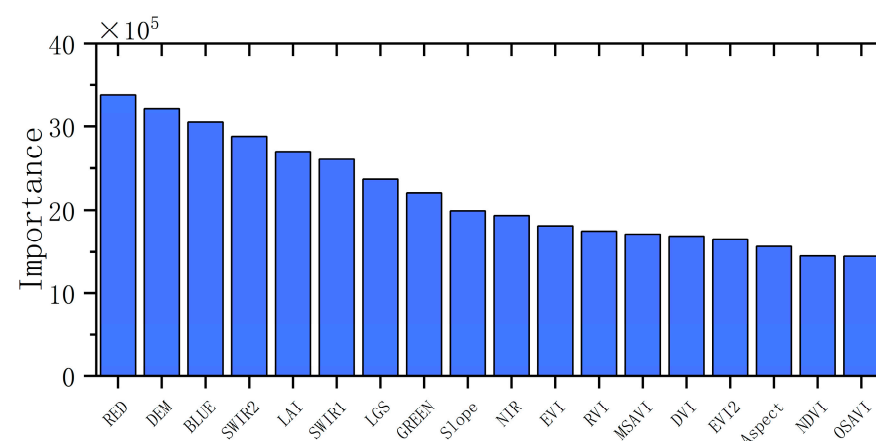
4.1. Accuracy Assessment of AGB Modeling

The accuracy evaluation results of the six AGB estimation models are presented in Table 5. Among them, the RF model achieved the best performance, with a precision of 88.07%, RMSE of 77.13 g/m², and R² of 0.74. After variable selection, the RF model's performance slightly declined, with R² decreasing to 0.71 and RMSE increasing to 98.79 g/m². In contrast, the SVM model showed an improvement after variable selection, with R² increasing from 0.67 to 0.69 and RMSE decreasing from 137.33 g/m² to 121.76 g/m², indicating that variable selection positively affected SVM performance. The ANN model exhibited a precision of 85.96%, RMSE of 224.75 g/m², and R² of 0.55; after variable selection, its performance further declined (R² = 0.51), representing the lowest accuracy among the models. These results clearly indicate that the RF model outperformed the SVM and ANN models across all evaluation metrics. Overall, these results clearly indicate that the RF model outperformed the SVM and ANN models across all evaluation metrics, and the RF model using all predictor variables achieved the highest accuracy. Therefore, the RF model was selected as the optimal regression approach for estimating herbaceous AGB in this study.

Table 5. Accuracy assessment of three models.

Model	R ² (Testing Sets)	RMSE (g/m ²)	Precision (%)
RF	0.74	77.13	88.07%
LASSO-RF	0.71	98.79	88.19%
SVM	0.67	137.33	80.63%
LASSO-SVM	0.69	121.76	80.30%
ANN	0.55	224.75	85.96%
LASSO-ANN	0.51	260.01	86.49%

Further analysis of predictor importance revealed that LAI and LGS ranked among the top 5 and top 7 most influential variables, respectively (Figure 3). Notably, both ecological variables outperformed all VIs in terms of importance scores. This underscores the significant contribution of incorporating LAI and LGS to improving the accuracy and robustness of the AGB estimation model. In addition, the RED and BLUE bands are strongly absorbed by chlorophyll, reflecting photosynthetic activity and vegetation physiological status. SWIR2 is sensitive to leaf water content and structure, capturing variations in leaf moisture and biomass [51]. DEM represents terrain heterogeneity, indirectly affecting vegetation growth and improving biomass prediction accuracy.

**Figure 3.** Variables importance of RF model.

4.2. Spatial Distribution of AGB in the YRD

Considering the frequent land cover conversions in the YRD and to illustrate the spatial variability of AGB over multiple years, the spatial distribution of AGB in selected benchmark years were showed: 2001 (Figure 4a), 2005 (Figure 4b), 2010 (Figure 4c), 2015 (Figure 4d), and 2020 (Figure 4e), along with the multi-year average AGB (Figure 4f) (Figure 4). The results reveal a continuous expansion in the spatial extent of AGB from 2001 to 2020. Apparently, cropland showed higher AGB values, and a general upward trend in biomass levels was observed over time. In particular, the western agricultural zones of the delta reached the highest biomass levels by 2020. While the southern coastal zones near the sea showed relatively lower AGB, likely due to soil salinization and vegetation degradation.

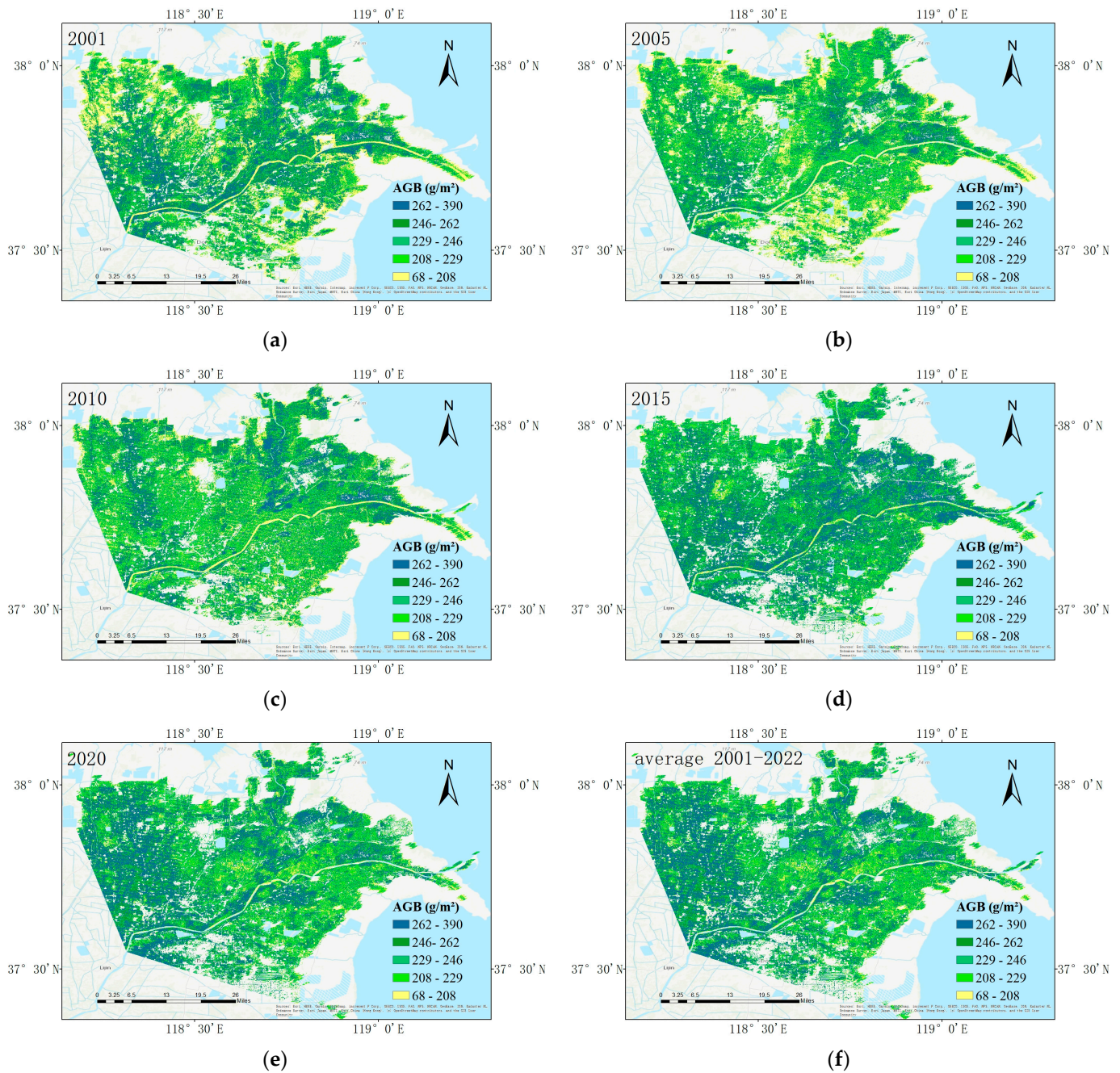


Figure 4. Spatial distribution of herbaceous AGB in YRD from 2001 to 2020. (a) AGB in 2001. (b) AGB in 2005. (c) AGB in 2010. (d) AGB in 2015. (e) AGB in 2020. (f) Multi-year average AGB.

4.3. Interannual Variation in AGB

Figure 5 shows the annual average AGB from 2001 to 2022. Overall, AGB exhibited a fluctuating upward trend. From 2001 to 2007, AGB remained at a relatively low level and slightly declined, reaching its lowest point 204.07 g/m^2 in 2007. Subsequently, from 2008 to 2012, biomass increased steadily, peaking in 2012 at 221.97 g/m^2 . After a temporary decline in 2013–2015, a notable surge occurred in 2016, reaching a maximum of 230.79 g/m^2 . From 2016 onward, AGB remained stable, fluctuating between $215\text{--}225 \text{ g/m}^2$, indicating a sustained high productivity in the region.

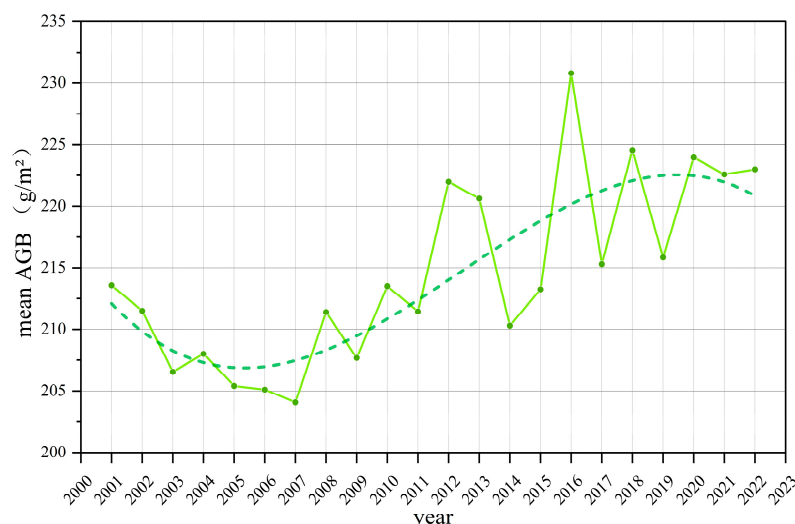


Figure 5. Annual average AGB in the YRD from 2001 to 2022.

Figure 6 illustrates the Sen's Slope of herbaceous AGB over the study period. AGB in most areas showed a trend of steady change, especially in the western cropland, which exhibited continuous AGB improvements, with an average of about 10 g/m^2 per year. In contrast, the northeast coastal and central regions showed negative growth, indicating partial degradation of AGB. In addition, strong AGB reductions occurred in the southern coastal areas, suggesting that the area may be anthropogenically developed or destroyed.

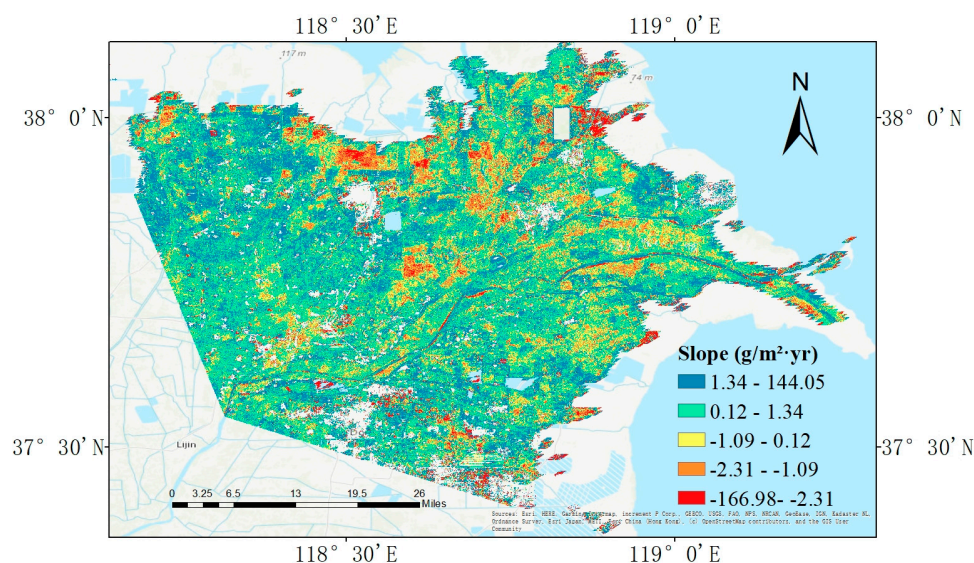


Figure 6. The spatial distribution of the annual maximum AGB change trend in YRD (2001–2022).

The Mann–Kendall trend significance (Figure 7) shows that a significant increase in AGB was observed along the main branches of the Yellow River and in intensive cropland areas in the west, while significant declines were primarily concentrated in the central and coastal regions, possibly due to soil salinization, wetland degradation, or anthropogenic disturbances.

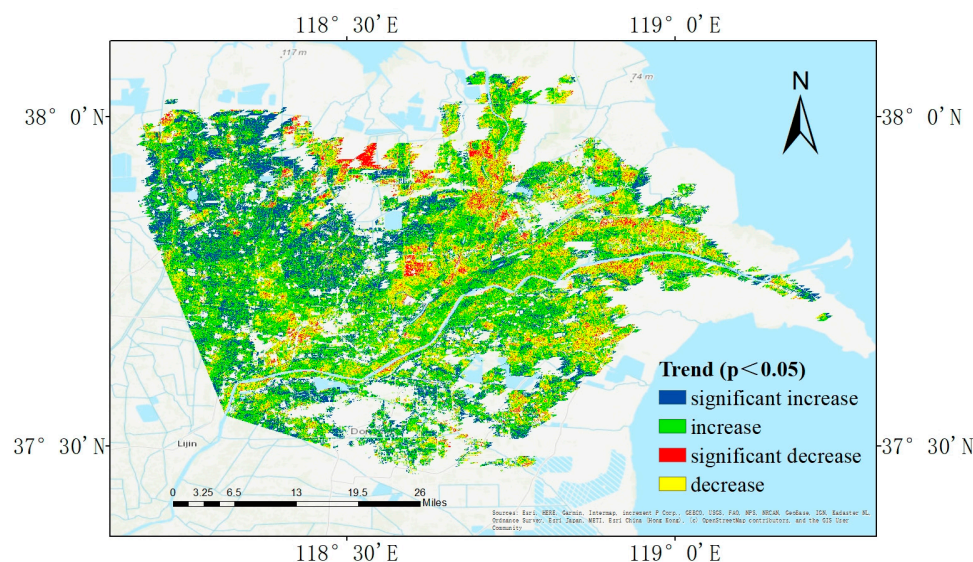


Figure 7. The trend significance of AGB changes in YRD (2001–2022).

Overall, herbaceous AGB in the YRD exhibited a fluctuating but generally increasing trend from 2001 to 2022, with distinct temporal phases. Biomass remained relatively low and slightly declined until 2007, followed by a steady rise peaking in 2012, a brief decrease in 2013–2015, and then a marked increase in 2016, after which AGB stabilized at a high level. Spatially, the expansion of high-biomass areas was most evident in the western cropland zones, which showed sustained and significant growth, whereas parts of the central and coastal regions experienced persistent declines, likely due to soil salinization, wetland degradation, or anthropogenic disturbances. These results indicate a gradual improvement of herbaceous AGB across much of the region over the past two decades, but also reveal localized degradation hotspots that require targeted ecological restoration and adaptive land management strategies.

4.4. Effects of Land Cover Changes on AGB

The contributions of different land cover types to AGB changes from 2001 to 2022 are shown in Figure 8. Over the 22 years, cropland and wetland were the main positive contributors to biomass increase, with cropland contributing 54.2% and wetland contributing 52.67%, while grassland, contributing −6.87%, had limited and often negative impacts on AGB dynamics. Wetland exhibited consistently positive and significant contributions throughout the study period, highlighting their dominant role in enhancing biomass. However, the magnitude of their contribution has gradually declined in recent years. Cropland contributions showed pronounced interannual variability, remaining relatively low during the early 2000s, followed by a marked increase after 2010, with prominent peaks during 2011–2012 and 2015–2016. The contribution from cropland has since stabilized with a gradual upward trend. In contrast, grassland had a greater influence between 2001 and 2005, including both positive and negative effects. However, their overall impact diminished over time, and in later years, they exhibited a slight negative contribution to biomass change. Overall, wetland and cropland served as the major positive drivers of AGB accumulation, while grasslands played a relatively minor and occasionally suppressive role.

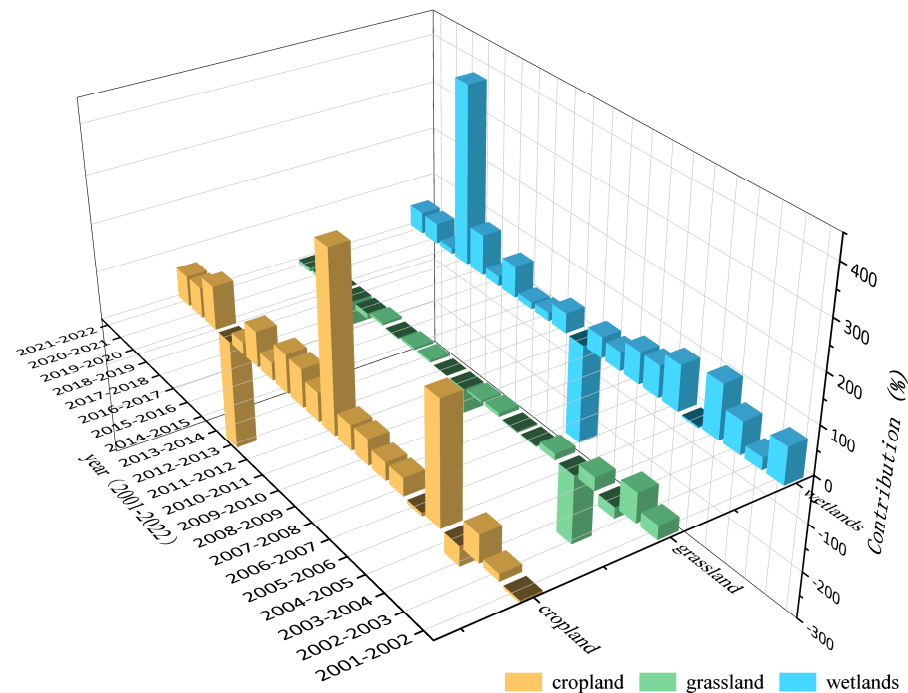


Figure 8. Contributions of land cover to AGB changes in YRD (2001–2022). Higher values indicate higher contributions to AGB changes, positive values represent contributions to AGB increases, and negative values represent contributions to AGB reduction.

Figure 9 illustrates the influence of different land cover types on AGB changes from 2001 to 2022, including area effects, density effects, and interaction effects. During 2001–2005, cropland contributed positively to AGB mainly through area expansion, but declines in productivity led to negative density effects. Additionally, the interaction effect was negative, suggesting that the expansion of low-quality land failed to enhance ecological performance and instead hindered biomass accumulation. In 2016–2017 and 2021–2022, both area and density effects for cropland were negative, while the interaction effect turned positive, which may be attributed to the abandonment of low-productivity lands or the contraction of degraded regions. These results highlight the importance of improving ecological quality, rather than relying solely on spatial expansion to boost biomass. Grassland exhibited relatively minor fluctuations across all three effects, with a marked decrease in area during 2001–2008, after which their contribution to biomass change became negligible. In contrast, wetland showed pronounced interannual variability in area, density, and interaction effects, highlighting their high ecological sensitivity. Over the two decades, both the area and density effects exerted substantial influence, whereas the interaction effect was predominantly positive from 2001 to 2012 but shifted to a primarily negative relationship between 2012 and 2022.

Overall, cropland exerted a relatively stable influence on AGB dynamics, grassland variations remained within a controllable range, while wetland, due to their complex ecological characteristics, played an unstable and uncertain role in biomass regulation, representing a major source of instability in AGB change.

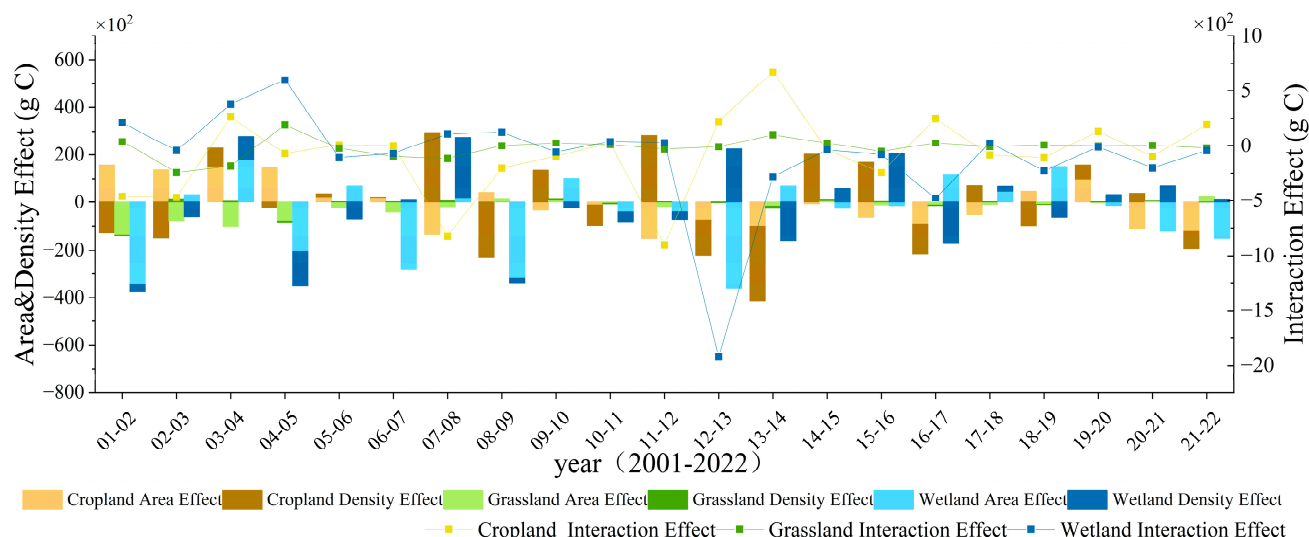


Figure 9. Area, density, and interaction effect of land cover types on AGB changes in YRD (2001–2022). Area effect refers to the influence of changes in land cover area on AGB changes; density effect refers to the influence of changes in AGB density on AGB changes; and interaction effect refers to the combined impact of area and density changes acting together on AGB changes.

5. Discussion

5.1. Uncertainty Analysis of Literature-Derived Data

In this study, we developed an AGB estimation model using 4717 samples derived from published literature, achieving an R^2 of 0.74, which demonstrates a strong ability to estimate AGB. We also compared the performance of the RF model with other machine learning algorithms, and the results demonstrated its distinct advantage in AGB estimation, which is consistent with findings from previous studies [5,52]. Despite rigorous data screening and processing to ensure sampling consistency and accuracy, variations in sampling methods, temporal resolution, and spatial precision still limit the applicability of literature-derived datasets for high-resolution analyses. Furthermore, many studies lack truly random sampling and often collect data in experimental plots or grazing areas [53,54]. To further assess the effects of sampling uncertainty and evaluate the model's robustness, we estimated the average AGB for July 2024 using the developed model and compared it with field measurements collected during the same period (Figure 10). The results showed a good correlation between predicted and observed values ($R^2 = 0.728$), although a slight underestimation was observed, likely due to the overrepresentation of low-biomass samples in the dataset.

Nevertheless, the literature-derived data provide access to a large number of field measurements collected across diverse regions and time periods, significantly increasing the number of samples. With the rapid development of data-driven approaches and computational power, efficiently obtaining large and reliable datasets has become increasingly important. This study demonstrates a practical strategy for assembling large-scale biomass datasets from published literature. Future research efforts could focus on employing advanced data processing, integrating region-specific modeling strategies, and prioritizing locally acquired field data to improve model calibration and overall robustness.

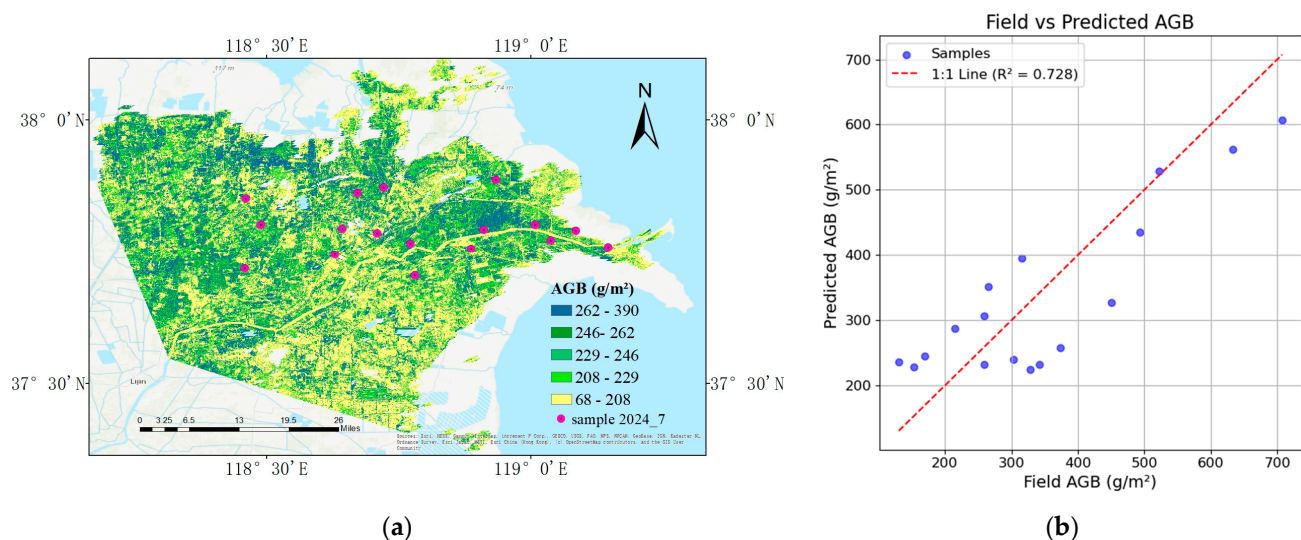


Figure 10. Evaluation of herbaceous AGB in July 2024. (a) Estimated AGB and field sampling location. (b) Comparison of Predicted and Measured AGB.

5.2. Effectiveness of LAI and LGS in AGB Estimation

Variable importance analysis in the RF model indicated that both LGS and LAI play an important role in enhancing model performance. To further investigate their effectiveness to AGB estimation, we re-developed the models by sequentially removing these two variables (Figure 11). For a more pronounced comparison, 78 representative sampling sites within the study area were selected for this analysis. By taking the results from model without LAI and LGS as baseline, the incorporation of LAI and LGS individually led to improvements in model accuracy of 5.7% and 12.9%, respectively. The inclusion of LAI effectively mitigated the overestimation observed in high-biomass regions, resulting in a more stable and reliable model. This finding confirms that both variables contribute to improving AGB estimation, which is consistent with previous studies [55–57]. Notably, LGS exerted a stronger influence than LAI, which aligns with ecological theory, as the length of the growing season directly relates to the amount of carbon fixed by vegetation. Previous studies have reported that the influence of LGS on biomass is significant in warm regions [12]. The YRD, being a temperate semi-humid area, confirms that phenology has a notable impact on the accuracy of AGB estimation. The current estimation did not include climatic factors such as drought, which has been identified as critical drivers of biomass variability through their influence on water and heat availability [58]. Future studies should investigate the interactions between multiple environments variables and biomass accumulation, with particular attention to plant carbon fixation processes, to further improve the accuracy of AGB estimation.

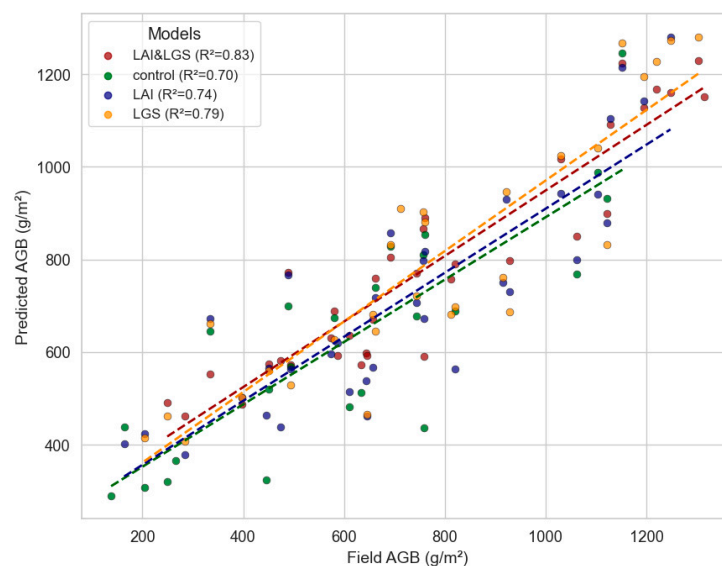


Figure 11. Model performance under different scenarios of LAI and LGS inclusion.

5.3. Drivers of AGB Variation in the YRD

The YRD is predominantly covered by herbaceous vegetation and has experienced frequent land cover changes over the past decades. In this study, we focused on the dynamics of cropland, grassland, and wetland to evaluate their contributions to biomass changes and assess the ecological status of the region. Over the past twenty years, cropland, accounting for 58% of the area, has remained relatively stable, whereas grassland, accounting for only 1% and wetland, which cover 41% of the region, have fluctuated considerably and exhibited an overall declining trend (Figure 12a). For cropland, although its area has remained relatively stable, its total AGB has consistently stayed around or even exceeded 600,000 g C over the years. Moreover, the mean AGB has shown an overall increasing trend over the past two decades, with a slight decline in the most recent five years. This indicates that cropland biomass density has played a dominant role in driving cropland overall AGB variation (Figure 12b). Specifically, during 2018–2019, the significant decline (-2.31 g/m^2), in average biomass—indicating reduced productivity—combined with a notable decrease (-86.79 km^2), in cropland area, led cropland to exert its largest negative contribution to overall biomass. For grassland, both its area and total AGB exhibited a similar declining trend. Although the AGB per unit area has increased, the limited overall area restricts its potential to rapidly restore carbon sequestration capacity through quality improvements alone. Therefore, maintaining grassland area from further encroachment should be a key priority (Figure 12c). For wetland, the total AGB has generally declined over the past two decades in line with the reduction in wetland area. Correspondingly, for wetland, where biomass is primarily driven by area changes, a slight expansion in wetland area during 2018–2019 resulted in a markedly increased relative contribution of wetland to overall biomass that year. However, in the past five years, the continuous increase in AGB per unit area has led to a stabilization or even a slight increase in total AGB. Although wetland have historically been the primary driver of biomass fluctuations in the region, recent environmental protection policies have shown positive effects, resulting in a gradual stabilization of AGB variability associated with wetland (Figure 12d). These findings suggest that ecological conservation efforts should not only aim to maintain wetland area but also focus on improving wetland quality. The observed area fluctuations and AGB changes also reflect substantial governmental efforts to protect the YRD environment. Previous studies have shown that since 2005, the implementation of twelve water diversion and sediment regulation policies has gradually enhanced freshwater resources in the delta, reducing

landscape fragmentation [27]. To achieve a sustainable balance between human development and ecological conservation, future policies should not only prioritize land cover restoration but also implement comprehensive measures to enhance vegetation quality.

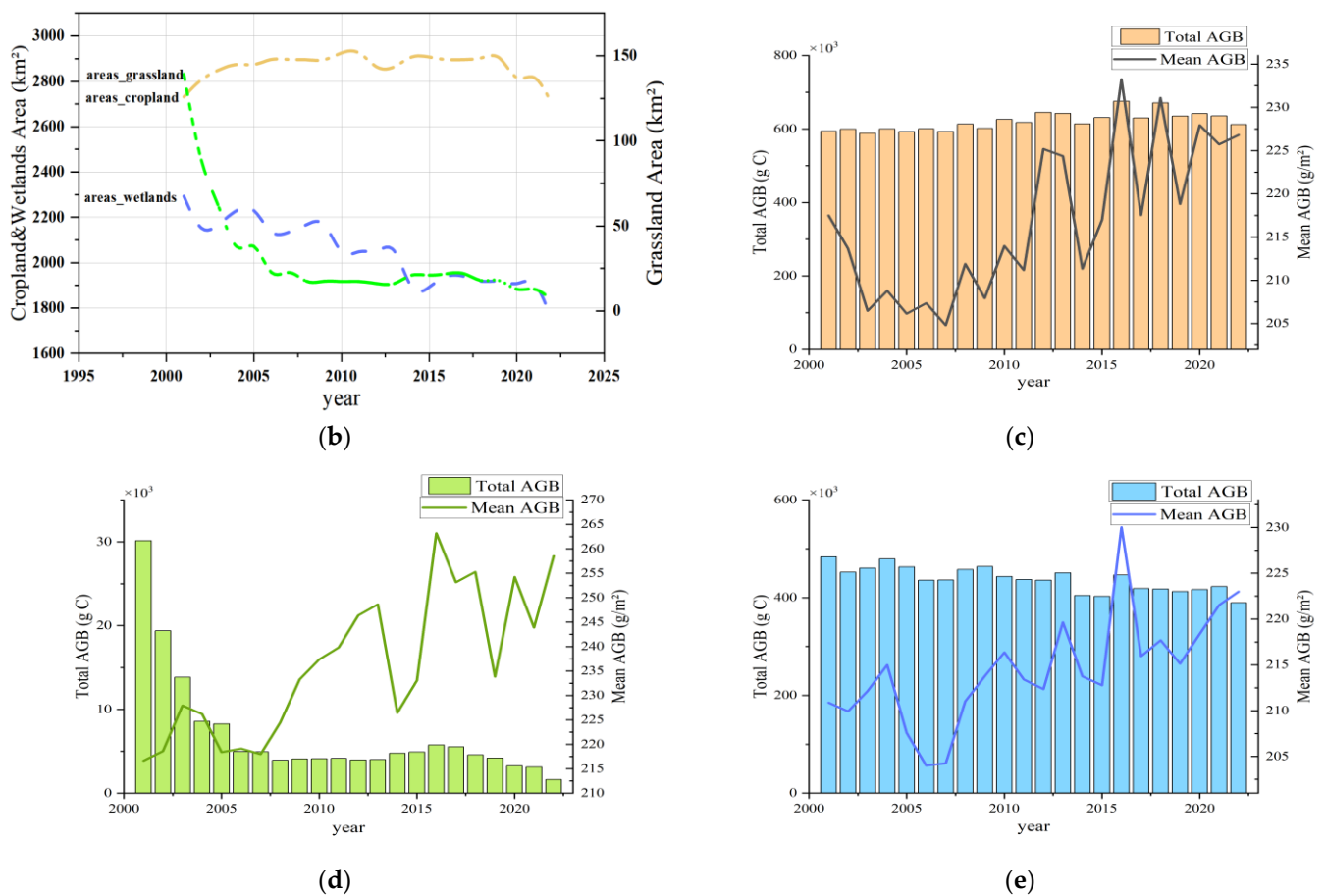


Figure 12. Land cover area and AGB changes in the YRD from 2001 to 2022. (a). Land cover area changes. (b). Cropland AGB changes. (c). Grassland AGB changes. (d). Wetland AGB changes.

6. Conclusions

In this study, we collected 4717 herbaceous AGB samples through literature-based data synthesis. By incorporating LAI and LGS, along with reflectance information, VIs and topographic variables, we developed a robust AGB estimation model using the RF algorithm. This model was applied to estimate AGB across the YRD from 2001 to 2022. Subsequently, we analyzed the spatiotemporal dynamics of AGB over the past 22 years and assessed the influence of different land cover types on biomass changes.

The main findings are as follows: (1) The RF model incorporating LAI and LGS outperformed other machine learning algorithms, achieving high estimation accuracy with an R^2 of 0.74. (2) During 2001 to 2022, the higher biomass was consistently observed in croplands, particularly in the western region, while lower values were concentrated in areas south of the Yellow River, especially in coastal zones. (3) AGB exhibited a fluctuating upward trend from 204.07 g/m² to 230.79 g/m² during 2007–2015. Since 2016, AGB has remained relatively stable, fluctuating between 215 g/m² and 225 g/m², indicating sustained productivity across the region. (4) AGB increased markedly along the main branches of the Yellow River and in intensively cultivated croplands, while coastal zones showed significant declines. (5) Cropland and wetland were the primary positive drivers of AGB accumulation, with croplands showing stable contributions while wetland introduced

high variability; grasslands had modest and occasionally suppressed effects, collectively shaping the spatial heterogeneity of AGB dynamics.

Overall, this study highlights the importance of integrating ecological variables, which substantially enhance the effectiveness and reliability of AGB estimation in herbaceous-dominated landscapes. The observed spatial expansion and increasing trend of AGB over the past two decades reflect the evolving vegetation productivity in the YRD. However, the heterogeneous responses among different land cover types, especially the instability observed in wetland areas, underscore the complex and sensitive nature of deltaic ecosystems. These findings not only provide a scientific basis for large-scale biomass monitoring and ecological assessment but also offer valuable guidance for land use management and wetland conservation in coastal regions.

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