

## Article

# Comparative Assessment of Planar Density and Stereoscopic Density for Estimating Grassland Aboveground Fresh Biomass Across Growing Season

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## Abstract

Grassland aboveground biomass (AGB) serves as a critical indicator of ecosystem productivity and carbon cycling, playing a pivotal role in ecosystem functioning. The advances in hyperspectral and terrestrial Light Detection and Ranging (LiDAR) data have provided new opportunities for grassland AGB monitoring, but current research remains predominantly focused on data-driven machine learning models. The black-box nature of such approaches resulted in a lack of clear interpretation regarding the coupling relationships between these two data types in grassland AGB estimation. For grassland aboveground fresh biomass, the theoretical estimation can be decomposed into either the product of planar density (PD) and plot area or the product of stereoscopic density (SD) and grassland community volume. Based on this theory, our study developed a semi-mechanistic remote sensing model for grassland AGB estimation by integrating hyperspectral-derived biomass density with extracted structural parameters from terrestrial LiDAR. Initially, we built hyperspectral estimation models for both PD and SD of grassland fresh AGB using PLSR. Subsequently, by integrating the inversion results with grassland quadrat area and community volume measurements, respectively, we achieved quadrat-scale remote sensing estimation of grassland AGB. Finally, we conducted comparative accuracy assessments of both methods across different phenological stages to evaluate their performance differences. Our results demonstrated that SD, which incorporated structural features, could be more precisely estimated ( $R^2 = 0.90$ ,  $nRMSE = 7.92\%$ ,  $Bias\% = 0.01\%$ ) based on hyperspectral data compared to PD ( $R^2 = 0.79$ ,  $nRMSE = 10.19\%$ ,  $Bias\% = -7.25\%$ ), with significant differences observed in their respective responsive spectral bands. PD showed greater sensitivity to shortwave infrared regions, while SD exhibited stronger associations with visible, red-edge, and near-infrared bands. Although both methods achieved comparable overall AGB estimation accuracy (PD-based:  $R^2 = 0.79$ ,  $nRMSE = 10.19\%$ ,  $Bias\% = -7.25\%$ ; SD-based:  $R^2 = 0.82$ ,  $nRMSE = 10.58\%$ ,  $Bias\% = 1.86\%$ ), the SD-based approach effectively mitigated the underestimation of high biomass values caused by spectral saturation effects and also demonstrated superior and more stable performance across different growth



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periods ( $R^2 > 0.6$ ). This work provided concrete physical meaning to the integration of hyperspectral and LiDAR data for grassland AGB monitoring and further suggested the potential of multi-source remote sensing data fusion in estimating grassland AGB. The findings offered theoretical foundations for developing large-scale grassland AGB monitoring models using airborne and spaceborne remote sensing platforms.

**Keywords:** grassland aboveground fresh biomass; planar density; stereoscopic density; hyperspectral data; community volume

## 1. Introduction

Grassland ecosystems serve as critical components of terrestrial biomes, playing indispensable roles in global carbon cycling, biodiversity conservation, and pastoral development [1–3]. Current estimates indicated that grassland occupied approximately 40% of the global terrestrial surface and accounted for 34% of terrestrial carbon stocks [4–6]. Grassland aboveground biomass (AGB) represents a fundamental metric for assessing grassland ecosystem productivity, serving not only as a direct indicator of primary production capacity and ecosystem health, but also as a critical parameter for determining grazing capacity, monitoring grassland degradation, and estimating carbon budgets [5,7–10]. Over recent decades, significant changes in grassland biomass patterns have been observed globally [11], yet conventional ground-based survey methods, despite providing accurate measurements at the plot scale, remain inadequate for meeting the growing demands of large-scale, high-frequency monitoring initiatives. Besides, destructive sampling methods fundamentally preclude the possibility of repeated measurements at identical sampling locations.

The rapid advancement of remote sensing technologies has led to their increasingly widespread application in grassland AGB monitoring. From early multispectral sensors (e.g., Landsat series, MODIS) to recent hyperspectral and active remote sensing systems, remote sensing data have progressively enhanced their contribution to grassland AGB estimation [12–16]. However, optical remote sensing data remain susceptible to atmospheric conditions and cloud cover interference, while exhibiting pronounced saturation effects in high-biomass grassland due to the limited bands [17,18]. Although microwave remote sensing offers all-weather observation capabilities, it demonstrates limited sensitivity for biomass of low-stature vegetation [19]. These inherent limitations have driven the exploration of novel approaches for synergistic inversion using multi-source remote sensing data, with the integration of hyperspectral and Light Detection and Ranging (LiDAR) technologies emerging as particularly promising.

Hyperspectral remote sensing captures vegetation biochemical properties related to biomass (e.g., chlorophyll, water content, cellulose) through fine spectral information across hundreds of continuous narrow bands [20–22], providing novel perspectives for estimating biomass “mass density.” As an active remote sensing technology, LiDAR precisely retrieves three-dimensional vegetation structural information (e.g., canopy height, vertical profiles) by emitting laser pulses and recording return signals [14,23], enabling the quantification of biomass “spatial distribution.” The synergistic use of these technologies theoretically permits more comprehensive and accurate characterization of grassland AGB [24,25]. Machine learning approaches (e.g., random forest, support vector machines) have emerged as the most prevalent solutions for grassland AGB estimation due to their demonstrated capacity to model complex nonlinear relationships [24,26]. But they are usually accompanied by limitations, including poor interpretability and substantial training data requirements. Physically based radiative transfer models (RTMs) have also been employed for grass-

land biomass estimation due to their ability to explicitly establish relationships between canopy properties and spectral characteristics [27,28]. However, enhanced models incorporating structural features remain predominantly applied in forest ecosystems [29,30]. Consequently, establishing effective linkages between these data types for grassland AGB estimation persists as a critical unresolved scientific challenge.

Theoretically, AGB can be expressed as the product of biomass density and vegetation space; this is a conceptual framework that effectively integrates the two dimensions of biomass: mass density and spatial distribution. However, the practical implementation of this theory faces several critical challenges. The primary issue lies in the multidimensional representation of density. Vegetation density can be characterized in two-dimensional space (i.e., biomass per unit area, planar density) or three-dimensional space (biomass per unit volume, stereoscopic density). While hyperspectral data can capture variations in growth status and physicochemical properties among vegetation communities through different spectral bands [22,31,32], its effectiveness in estimating grassland planar density remains uncertain. Furthermore, whether incorporating vertical structural features in stereoscopic density estimation would enhance the performance of hyperspectral data in density monitoring also remains unclear.

Secondly, estimating grassland aboveground biomass using stereoscopic density requires accurate quantification of vegetation volume. While LiDAR data are increasingly being applied to analyze grassland structure [33,34], their measurement accuracy still requires further validation, particularly for grassland with complex canopy structure [35,36]. Consequently, biomass estimation through combining the stereoscopic density and volume must account for error propagation from both density and volume measurements. In contrast, the planar density method primarily relies on area measurements that are essentially unbiased, thus requiring only consideration of planar density estimation errors. Both dimensional approaches exhibit inherent uncertainties in grassland biomass estimation, necessitating systematic accuracy assessments to determine which theoretical framework provides more reliable monitoring results. Furthermore, seasonal monitoring of grassland biomass dynamics can provide continuous data to investigate climate impacts and functional group responses [37–39]; it highlighted the importance of developing a robust model applicable across different phenological stages. Grassland AGB, density, and volume demonstrate asynchronous seasonal variation patterns: rapid volume expansion dominates during green-up with minimal density changes, synchronized increases occur during peak growth, while maturation shows continued density accumulation with stabilized volume. Such phenological heterogeneities often lead to temporal variations in model accuracy. Whether integrated density-volume approaches can effectively mitigate these phenology-induced uncertainties requires further investigation.

To address these research questions, this study will conduct systematic comparative experiments utilizing ground-based spectral reflectance data and terrestrial LiDAR data to evaluate the accuracy differences of hyperspectral remote sensing in monitoring both planar density and stereoscopic density of grassland communities. Grassland aboveground fresh biomass quantification will be further performed based on both planar and stereoscopic density and analyzing their temporal variations throughout the growing season. The specific research objectives include (1) calculating planar density and stereoscopic density of grassland aboveground biomass by integrating ground-measured biomass data with plot area measurements or theoretical true community volume obtained through Monte Carlo simulation and terrestrial LiDAR measurements. (2) developing and comparing predictive models for planar density and stereoscopic density using partial least squares regression based on hyperspectral data and (3) implementing both theoretical approaches (planar density  $\times$  area and stereoscopic density  $\times$  volume) to estimate grassland aboveground

biomass, followed by quantitative evaluation of accuracy differences between these methods and their monthly performance variations. The comparative framework is designed to elucidate the relative capabilities of these approaches for grassland biomass estimation.

## 2. Materials and Methods

This study focused on the performance of two different methodological theories in estimating grassland aboveground fresh biomass. One relying on the product of planar density and grassland coverage, and the other based on the product of stereoscopic density and grassland community volume. The main framework was illustrated in Figure 1. It primarily encompassed (1) the field surveys of grassland community hyperspectral data, terrestrial laser scanning (TLS) data, and biomass; (2) calculation of in situ measured values for planar and stereoscopic densities; (3) along with hyperspectral-based estimation; and finally (4) aboveground biomass computation and accuracy assessment for the two methods.

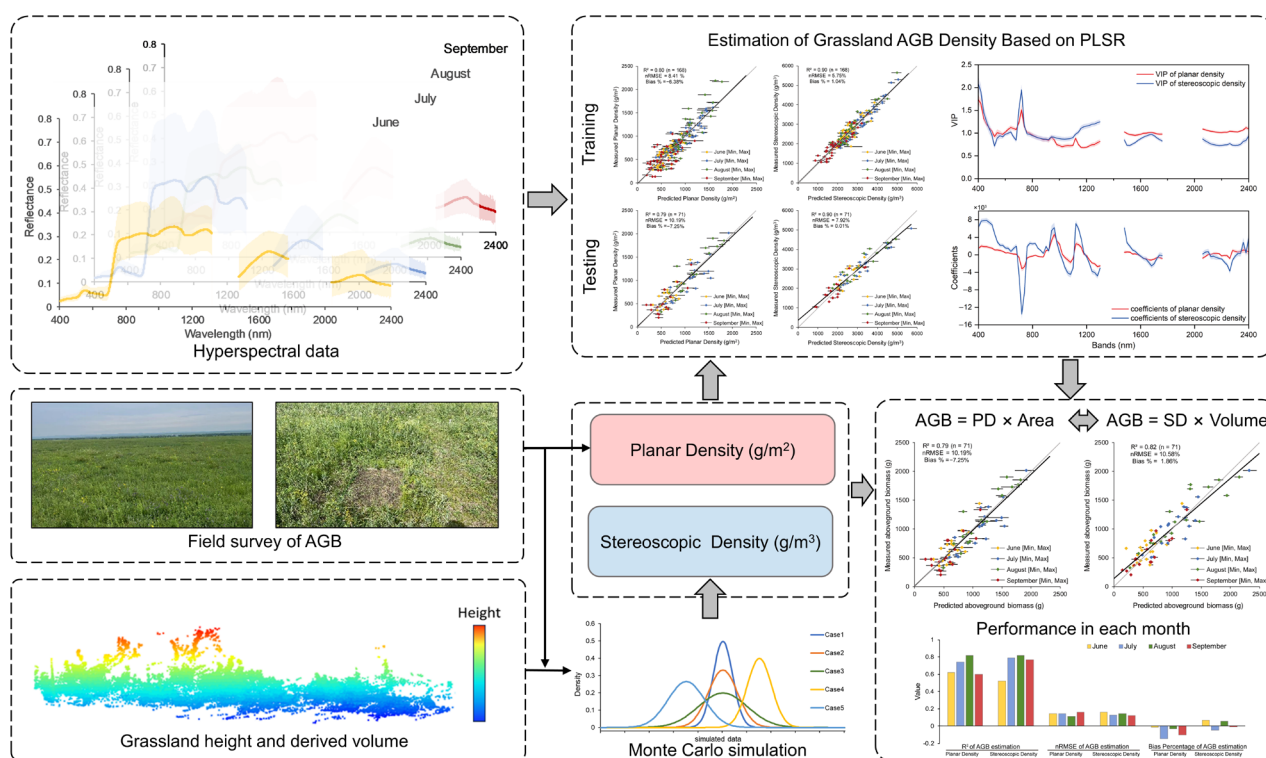


**Figure 1.** Main framework of grassland aboveground fresh biomass estimation.

### 2.1. Study Area

This study was conducted in a representative study area of temperate meadow steppe in Hulun Buir, China (Figure 2). Hulun Buir was the most concentrated and representative region of temperate meadow steppe in China, and various types of meadow steppe ecosystems developed in this region. The meadow steppe forms a narrow strip between the typical steppe zone and the forest belt. The region of field surveys was located at the center of this zone (120°00′00″E, 49°17′18″N). It fell within the temperate semi-humid climatic zone, with an average annual precipitation of 380–400 mm, an average annual temperature of  $-2^{\circ}\text{C}$  to  $-1^{\circ}\text{C}$ , and a humidity of 0.49–0.50. The main grassland community types included *Leymus chinensis* and forb grassland and *Stipa baicalensis* grassland.

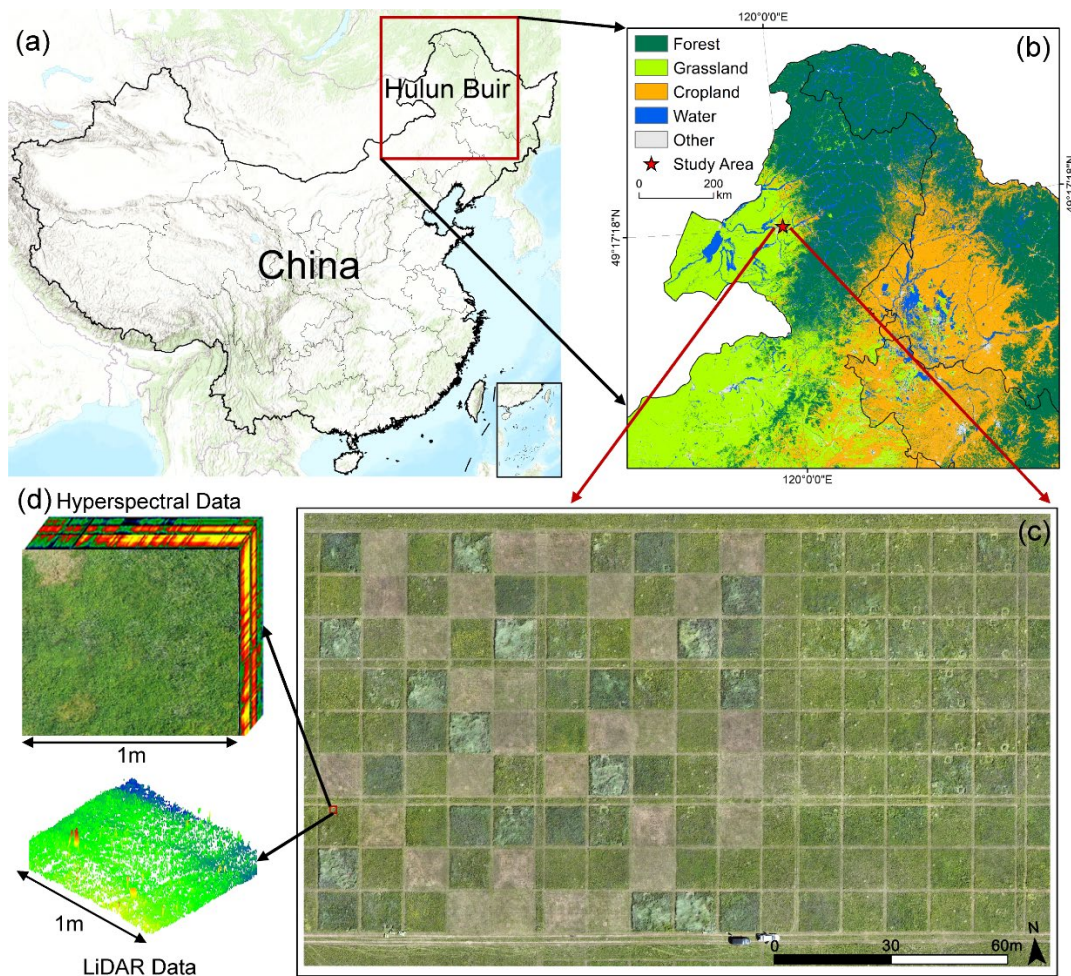


**Figure 2.** Location of study area in China (a), location of the field site in Hulun Buir (b), the mosaiced RGB images of the study area (c), and schematic diagrams of RGB images, hyperspectral data, and TLS data for each plot (1 m × 1 m) (d).

This representative study area comprised 1800 10 m × 10 m experimental plots, among which most plots have been subjected to controlled experiments including fertilization, mowing, grazing, and other activities with different gradients. In this study, 60 plots with distinct fertilization gradients were selected, and these treatments generated plots with varying aboveground biomass gradients. This configuration provides an optimal experimental condition for developing remote sensing monitoring models for estimating grassland aboveground biomass and validating them with in situ measurements.

## 2.2. Field Survey

This study conducted systematic ground-based surveys during the growing season (June to September) of 2023, implementing monthly dynamic monitoring across 60 experimental plots on the research platform. Each plot was pre-established with four standardized 1 m × 1 m quadrats, adopting a rotational sampling approach where one quadrat was comprehensively surveyed each month. At the quadrat level, we synchronously collected three main types of data: vegetation spectral characteristics, vegetation structural parameters, and field-measured data (such as aboveground fresh biomass and maximum height of grassland community). This standardized sampling design ensured strict spatial correspondence and temporal comparability across all data types while maintaining data continuity and representativeness and effectively minimizing vegetation disturbance from repeated sampling. A total of 239 quadrats (1 m × 1 m) were surveyed in the study area,

with 60 quadrats sampled monthly from June to September. But due to data collection constraints, one quadrat was missing in September, resulting in 59 quadrats surveyed that month.

#### 2.2.1. Hyperspectral Data

Hyperspectral data that reflected the vegetation spectral characteristics were acquired by ASD FieldSpec 4 spectrometers (ASD, Inc., Boulder, CO, USA). The spectroradiometer had a spectral range of 350–2500 nm with 1 nm spectral resolution and was equipped with a 25° field-of-view fiber optic probe. For each quadrat, nine consecutive scans (including measurements at three adjacent positions near the quadrat center point and at three similar heights with the probe) were acquired and averaged to ensure complete coverage of each quadrat area while minimizing edge effects and further improving signal-to-noise ratio. Raw spectral data were stored in both digital number (DN) and reflectance formats, with comprehensive metadata including GPS coordinates, measurement timestamps, solar geometry, and instrument configuration parameters. Data preprocessing involved spectral smoothing using Savitzky–Golay filters (5 nm window size) and removal of atmospheric absorption bands (1320–1480 nm and 1780–2040 nm) as well as low signal-to-noise spectral regions (<400 nm and >2400 nm). This standardized approach ensures the acquisition of high-quality spectral data suitable for vegetation characterization and validation of remote sensing products.

#### 2.2.2. Terrestrial Laser Scanning Data

Terrestrial Laser Scanning (TLS) was applied to acquire high-fidelity 3D structural data from 1 m × 1 m grassland quadrats. The acquisition system consisted of a Trimble TX8 terrestrial laser scanner (1500 nm wavelength) with a nominal ranging accuracy of ±2 mm at 100 m distance. It also features an expansive scanning range of 360° in the horizontal plane and 317° in the vertical plane, enabling comprehensive omnidirectional 3D data acquisition that captures complete geometric information of each grassland quadrat with full coverage. Each grassland quadrat was characterized by a dense point cloud dataset exceeding 1 million individual points, ensuring sub-centimeter resolution of vegetation structural parameters. Moreover, to facilitate precise segmentation of individual quadrat data, we installed 80 cm high-reflectance targets at each corner point while ensuring minimal interference with LiDAR acquisition through strategic placement and material selection.

#### 2.2.3. Field-Measured Data

Following the acquisition of hyperspectral data and terrestrial laser scanning (TLS) measurements, we conducted comprehensive vegetation surveys within each 1 m × 1 m quadrat. The investigation commenced with systematic documentation of species composition. Maximum canopy height of each quadrat was precisely measured using a tape with a precision of 5 mm, with the specific measurement location recorded relative to quadrat boundaries in June and August. And then, a standardized harvest protocol was implemented: all vegetation within each quadrat was clipped at ground level, and all vegetation samples were weighed in situ using a high-precision electronic balance (accuracy ± 0.01 g). The process of biomass collection was generally completed within 15 min to minimize water loss, thereby reducing the experimental error in monitoring the grassland fresh weight in this study to the greatest extent. The distribution of grassland biomass was shown in Supplementary Figure S1.

### 2.3. Estimation of Grassland Structural Parameters

#### 2.3.1. Grassland Canopy Height and Derived Community Volume

Prior to deriving canopy height and derived volume, the TLS point clouds underwent a standardized preprocessing workflow comprising three key steps: (1) quadrat-based segmentation, (2) noise removal, and (3) ground point classification. The  $1\text{ m} \times 1\text{ m}$  grassland quadrat point clouds were extracted based on the high-reflectance targets at each corner point using CloudCompare software v2.12.2. Noise removal was performed through statistical outlier, where points exhibiting mean nearest-neighbor distances exceeding  $\mu + 5\sigma$  ( $\mu$ : global mean distance;  $\sigma$ : standard deviation) were eliminated. Ground and vegetation points were classified from the denoised point cloud data using a local minimum-based approach. In this study, the point cloud within each  $1\text{ m} \times 1\text{ m}$  quadrat was first partitioned into grid cells ( $1\text{ cm} \times 1\text{ cm}$ ) with the lowest 1% of points in each grid cell classified as ground. Moreover, to account for ground return absence in dense canopy areas (>90% cover), points exceeding the 2nd percentile of the ground point elevation distribution were reclassified as non-ground.

For each  $1\text{ cm} \times 1\text{ cm}$  grid cell, the maximum height value was extracted from the classified point cloud data. These gridded maximum heights were statistically analyzed and compared with field-measured canopy maximum heights for accuracy assessment. Additionally, each grid cell was conceptualized as a volumetric pixel (voxel) with dimensions of  $1\text{ cm} \times 1\text{ cm} \times h$ . Considering the minimal area of individual voxels, we adopted the maximum height within each voxel as the  $h$  for volume calculation of grassland quadrat rather than the mean height. The total vegetation volume ( $V$ ) within each sampling quadrat was then calculated by summing the products of height and area for all voxels. In particular, for grid cells containing only ground points, their height was considered to be 0.

#### 2.3.2. Theoretical Community Volume from Monte Carlo Simulation

Monte Carlo simulation is a numerical computational method based on random sampling, which approximates solutions to mathematical, physical, or engineering problems through repeated stochastic sampling. It is particularly suitable for scenarios where analytical solutions are difficult to obtain or when dealing with high-dimensional and highly complex systems. The core principle relies on the Law of Large Numbers, ensuring that the frequency of random events converges to their theoretical probability as the sample size increases. By generating a large number of random samples, the method simulates possible states of the system to estimate target quantities (e.g., expected values, probability distributions).

In this study, grassland community volumes derived from Terrestrial Laser Scanning data were used as the observational samples. The observed discrepancy between TLS-derived maximum height and field-measured maximum height provided the statistical foundation for Monte Carlo simulation. The simulation was repeated 10,000 times to converge on a theoretical true value of grassland community volume. This derived volume was subsequently applied to calculate the three-dimensional stereoscopic density of the grassland community.

### 2.4. Calculation of Planar Density and Stereoscopic Density

Based on field-measured grassland biomass data, combined with quadrat area and derived vegetation community volume, this study introduced two quantitative indicators, planar density (PD) and stereoscopic density (SD), to analyze the grassland aboveground biomass distribution characteristics from both two-dimensional and three-dimensional perspectives, respectively.

Planar density (*PD*) was usually defined as the ratio of grassland aboveground biomass (*AGB*) to the plot area (*A*), calculated as

$$PD = \frac{AGB}{A} \quad (1)$$

Since this study employed 1 m × 1 m standard quadrats, the planar density is numerically equivalent to biomass per unit area (g/m<sup>2</sup>).

Stereoscopic density (*SD*) further incorporated vertical structure by calculating the ratio of grassland aboveground biomass to community volume, characterizing biomass distribution in three-dimensional space:

$$SD = \frac{AGB}{V} \quad (2)$$

where *V* represents the theoretical true total vegetation community volume (m<sup>3</sup>) within the quadrat obtained from TLS data. The stereoscopic density (g/m<sup>3</sup>) can effectively capture biomass distribution patterns along the vertical dimension.

By employing these two metrics, we assessed how effectively remote sensing can capture grassland biomass distribution patterns at the scale of quadrats from both planar and stereoscopic perspectives and further evaluated the performance of these indicators in estimating grassland biomass.

## 2.5. Grassland Aboveground Biomass Density Estimation

To evaluate the performance of hyperspectral data in estimating grassland aboveground biomass density, we used Partial Least Squares Regression (PLSR) to establish remote sensing estimation models linking quadrat-level hyperspectral information with corresponding planar density (*PD*) and stereoscopic density (*SD*) measurements. PLSR is a robust multivariate statistical technique particularly suited for analyzing datasets with multicollinearity and high-dimensional predictors, making it ideal for processing hyperspectral data with numerous narrow bands. Compared with the machine learning, the PLSR modeling approach (1) effectively reduced data dimensionality while preserving maximum covariance between spectral predictors and density response variables, (2) mitigated overfitting issues common in high-dimensional regression analyses, and (3) intuitively reflected the physical correlation between different spectral bands and vegetation density by analyzing band weights or loadings. For each density metric (*PD* and *SD*), we developed separate PLSR models using field-measured density values as dependent variables and spectral reflectance resampled to 20 nm spectral resolution (reducing the correlation of adjacent wavebands and data complexity) from 400 to 2400 nm (Except for the removed water vapor absorption bands) as independent variables.

Prior to model construction, we partitioned the dataset into training (*n* = 168, 70%) and testing (*n* = 71, 30%); the training set was utilized for PLSR model development, while the testing set served as an independent validation sample to objectively assess prediction accuracy. During PLSR model development, we first determined the optimal number of components through a rigorous selection process using the cross-validated predictive residual sum of squares (PRESS) criterion. This approach systematically identifies the most parsimonious model that minimizes prediction error while avoiding overfitting. Moreover, to enhance model stability and reliability, we also implemented an intensive validation procedure consisting of 50 iterations of tenfold cross-validation. The final predictive model was derived by averaging results across all iterations, thereby reducing random variation associated with single data partitions and ensuring robust model performance while maintaining generalizability to new observations.

## 2.6. Accuracy Assessment

Following the prediction of planar density (PD) and stereoscopic density (SD), we derived the aboveground biomass (AGB) estimates by multiplying the predicted density values with their corresponding ground-measured areas (for PD) or volumes (for SD). These estimated AGB values were then systematically compared against field-measured biomass. Model performance, or prediction accuracy, was quantitatively assessed through three complementary metrics: (1) Coefficient of determination ( $R^2$ ) for quantifying the proportion of variance explained by the models and indicating the strength of the linear relationship between predicted and observed values; (2) normalized root mean square error ( $nRMSE$ ) for expressing prediction errors relative to the mean observed value across different magnitudes; (3) bias percentage ( $Bias\%$ ) for assessing systematic over- or under-estimation trends in the predictions.

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

$$nRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2}}{y_{max} - y_{min}} \quad (4)$$

$$Bias\% = \frac{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)}{\bar{y}} \quad (5)$$

where  $y_i$  represented the observed value (actual measurement) of sample  $i$ , while  $\hat{y}_i$  denoted the corresponding predicted value generated by the model. The mean of all observed values ( $\bar{y}$ ) served as a critical reference point for evaluating model performance.  $y_{max}$  and  $y_{min}$  were the maximum and minimum observed values.

## 3. Results

### 3.1. Characterization of Spectral and Density

#### 3.1.1. Variations in Spectral Reflectance

The mean values and coefficients of variation (CV) of reflectance spectra from June to September, along with the aggregated values across all months, were presented in Figure 3. The results demonstrated significant monthly differences in the average spectral reflectance of grassland community canopy. In July, the canopy exhibited notably higher mean reflectance in the near-infrared region beyond the red-edge band compared to other months. Conversely, September and June showed higher reflectance in the specific near-infrared (beyond 1200 nm) and shortwave infrared regions. The complete reflectance spectra of all samples for each month (from June to September) were displayed in Supplementary Figure S2.

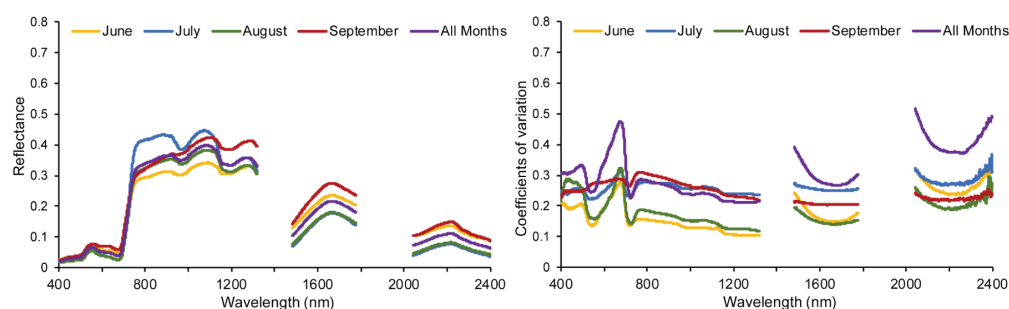


**Figure 3.** Mean canopy reflectance and coefficient of variation (CV) of reflectance for four months (June to September) as well as all months.

Regarding spectral variability, the CV analysis revealed greater differences between months (mean CV =  $0.31 \pm 0.08$ ) than within individual months, especially in the visible (CV = 0.48, band = 675 nm) and shortwave infrared regions (CV = 0.52, band = 2041 nm). July and September exhibited particularly higher variability (mean CV =  $0.26 \pm 0.02$  and  $0.26 \pm 0.03$ ) compared to June and August (mean CV =  $0.18 \pm 0.06$  and  $0.18 \pm 0.05$ ). The observed spectral pattern could be attributed to the phenological differences among different grassland communities. July represents the vegetation growth peak with vigorous photosynthetic activity, while September marks the onset of senescence. Interspecific growth divergence becomes particularly pronounced during these critical phenological transition periods, which likely contributed to the observed spectral heterogeneity.

### 3.1.2. Estimation of Grassland Height

Given the ease and accuracy of field measurements for grassland maximum community height, we employed it as the validation benchmark to evaluate the precision of TLS-derived canopy height information. Ground-based measurements of maximum grassland height in June and August demonstrated strong agreement with TLS-derived estimates ( $R^2 = 0.82$ , nRMSE = 10.15%; Figure 4a). However, systematic underestimation was also observed in TLS measurements (mean maximum height was  $56.4 \pm 13.4$  cm) compared to field observations (mean maximum height was  $57.7 \pm 13.9$  cm) (Figure 4b). The height-dependent bias was evident with progressive underestimation for taller canopies, particularly for grassland exceeding 60 cm (Figure 4c).

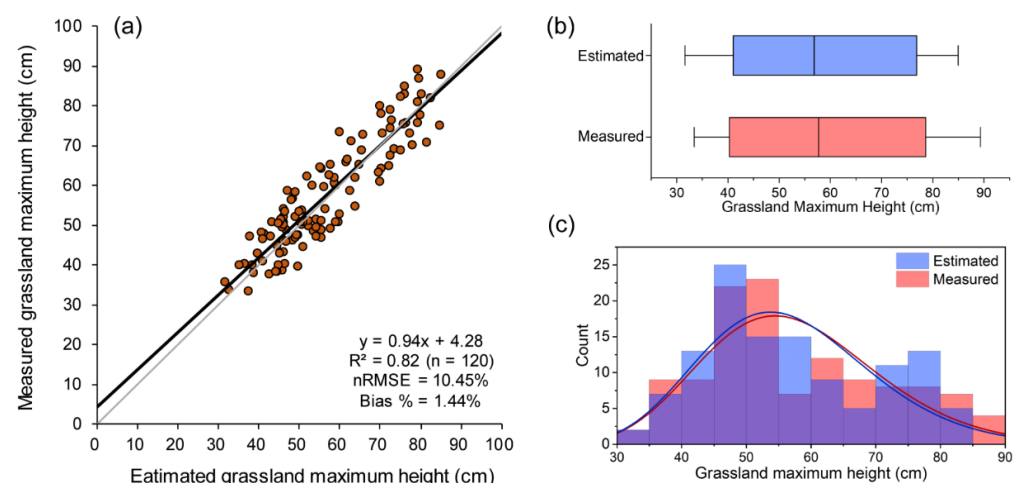


**Figure 4.** Accuracy assessment of terrestrial laser scanning (TLS) for grassland canopy maximum height estimation. (a) Validation between TLS-derived and field-measured maximum heights with 1:1 reference line; (b) variation in measured and estimated grassland maximum height shown as boxplots (central line: mean; box limits: 10th–90th percentiles; whiskers:  $1.5 \times$  interquartile range); (c) frequency histograms of field-measured and TLS-estimated maximum heights with Gamma distribution fits (solid curves).

Precision assessments for June and August yielded consistently high predictive accuracy, with  $R^2$  at 0.80 in August and 0.74 in June (Supplementary Figure S3). Although there was substantial growth in mean maximum plant height from 51.01 cm (June) to 64.35 cm (August), the TLS-derived estimates could maintain a strong correlation with field measurements. It demonstrated robust performance of TLS in estimating maximum vegetation height across different phenological stages throughout the growing season, which supported its reliability for deriving subsequent volumetric assessments of grassland communities.

### 3.1.3. Grassland Community Volume Estimation and Simulation

Based on TLS-derived canopy height, we estimated monthly plant community volumes for all grassland plots from June to September using a minimum voxel accumulation approach (Supplementary Figure S4). Our results revealed significant seasonal variations in grassland community volume, with August exhibiting the highest mean volume ( $0.36 \pm 0.09 \text{ m}^3$ ) and June showing the lowest volume ( $0.23 \pm 0.06 \text{ m}^3$ ). However, considering the systematic underestimation in TLS height measurements led to correspondingly low volume estimates. We therefore applied Monte Carlo simulations to reconstruct bias-corrected true volumes based on the TLS-derived volume by incorporating the relationship between TLS-derived and field-measured grassland heights. The relationship between simulated and TLS-measured grassland canopy volumes exhibited similar patterns to those observed between field-measured and TLS-derived canopy heights (Figure 5). Notably, the simulated volumes demonstrated systematically higher values (mean =  $0.31 \pm 0.09 \text{ m}^3$ ) compared to TLS measurements (mean =  $0.29 \pm 0.09 \text{ m}^3$ ) (Figure 5b). Their frequency distributions were clearly similar, as shown in Figure 5c. This consistent pattern was maintained throughout the growing season from June to September, where simulated volumes consistently exceeded TLS measurements across all monthly comparisons (Supplementary Figure S4).

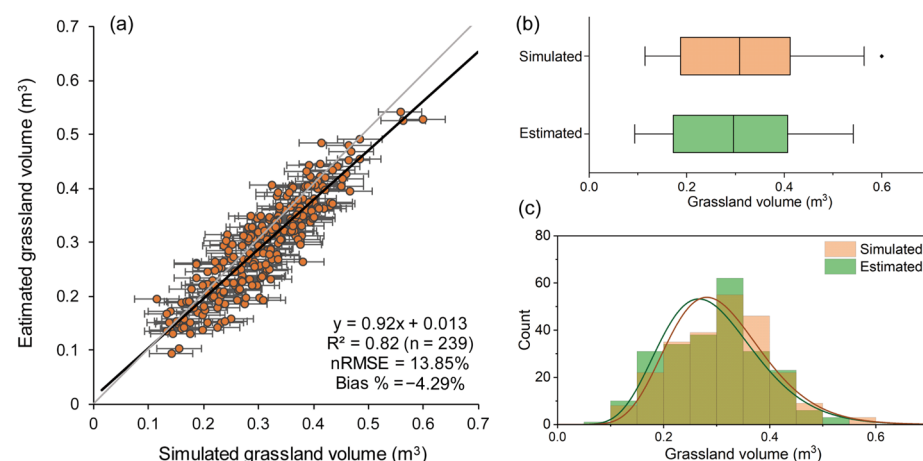


**Figure 5.** Comparison between TLS-derived and simulated grassland canopy volume. (a) Correlation between TLS-derived and simulated grassland canopy volume with 1:1 reference line; (b) Variation in estimated and simulated grassland canopy volume shown as boxplots (central line: mean value; box limits: 10th–90th percentiles; whiskers:  $1.5 \times$  interquartile range); (c) Frequency histograms of TLS-estimated and simulated grassland canopy volume with Gamma distribution fits (solid curves).

### 3.1.4. Planar Density and Stereoscopic Density

Using field-measured biomass data combined with sampling area ( $1 \text{ m} \times 1 \text{ m}$ ) and simulated theoretical community volume, we calculated both planar density and stereoscopic density for grassland communities. Their frequency distributions and value ranges are presented in Figure 6. The results demonstrated that SD exhibits a substantially wider distribution range ( $1047.02\text{--}5642.39 \text{ g/m}^3$ , mean =  $2636.48 \text{ g/m}^3$ ) compared to PD ( $139.59\text{--}2191.40 \text{ g/m}^2$ , mean =  $830.72 \text{ g/m}^2$ ), suggesting greater variability in three-dimensional biomass allocation patterns. It also further demonstrated that SD exhibited superior discriminative capacity for fresh aboveground biomass compared to PD. Our monthly comparative analysis (from June to September) revealed that while both PD and stereoscopic density SD showed synchronous fluctuations in mean values corresponding to grassland growth patterns (Supplementary Figure S5), SD consistently maintained a significantly broader dynamic range throughout the observation period.

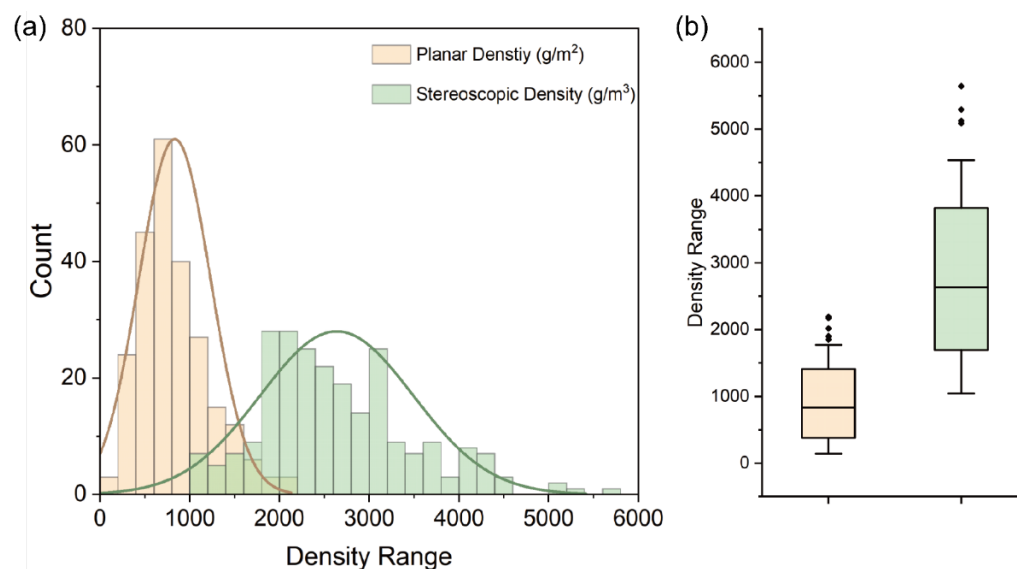


**Figure 6.** Comparative analysis of grassland density metrics. (a) Frequency distributions with Gamma fitting (solid curves) for planar density (PD) and stereoscopic density (SD), and (b) Value range comparison (boxes: 10th–90th percentiles; central line: mean value; whiskers:  $1.5 \times \text{IQR}$ ).

### 3.2. Model Performance of Planar Density (PD) and Stereoscopic Density (SD)

#### 3.2.1. Accuracy of Planar Density and Stereoscopic Density

Based on quadrat-scale canopy reflectance data, both planar density and stereoscopic density of grassland AGB were predicted with high accuracy (Figure 7). Comparative results demonstrated superior performance in SD estimation ( $R^2 = 0.90$ ,  $\text{nRMSE} = 5.75\%$ ,  $\text{Bias}\% = 1.04\%$ ) compared to PD ( $R^2 = 0.80$ ,  $\text{nRMSE} = 8.41\%$ ,  $\text{Bias}\% = -6.38\%$ ), with this pattern being consistently maintained in independent testing dataset validations (SD:  $R^2 = 0.90$ ,  $\text{nRMSE} = 7.92\%$ ,  $\text{Bias}\% = 0.01\%$ ; PD:  $R^2 = 0.79$ ,  $\text{nRMSE} = 10.19\%$ ,  $\text{Bias}\% = -7.25\%$ ). However, both of the metrics displayed considerable deviations for high values. We found pronounced underestimation for PD estimation at values exceeding  $1500 \text{ g/m}^2$  in both the training and testing datasets. SD predictions also exhibited larger deviations for high-density samples ( $>4000 \text{ g/m}^3$ ) in the testing dataset, though SD showed closer agreement with measured values across most samples.

Comprehensive analysis also revealed significant differences in the performance of planar density and stereoscopic density estimation across each month from June to September (Supplementary Tables S1 and S2). The results from both the training and testing datasets demonstrated that SD consistently achieved superior predictive accuracy than PD, particularly during peak growing seasons ( $R^2 > 0.90$ ). Besides, we also found that both PD and SD exhibited clear seasonal variability in estimation accuracy, with improved performance during the peak growing season (July–August) compared to other months. But SD demonstrated more stable bias characteristics ( $-3.59\%$  to  $3.13\%$ ), suggesting better robustness to seasonal vegetation changes. In contrast, PD exhibited consistent underestimation biases across all months, with particularly severe underestimation in July ( $-14.50\%$ ).

#### 3.2.2. Coefficients and Variance Importance Projection of Wavebands

The relative contributions of spectral bands to the estimation of PD and SD were evaluated through the model coefficients and Variable Importance Projection (VIP) values from the PLSR model. Distinct relative spectral contribution patterns across the entire spectral range for PD and SD estimation were identified (Figure 8). SD exhibited significantly greater variability in model coefficients with extreme values occurring at  $720 \text{ nm}$  and  $460 \text{ nm}$  compared to PD with smaller fluctuations. Although both PD and SD shared

relative peak VIP values at 400 nm and 740 nm, their spectral importance profiles diverged substantially. SD showed consistently higher VIP values in most visible and near-infrared regions, while PD demonstrated higher VIP performance in shortwave infrared.

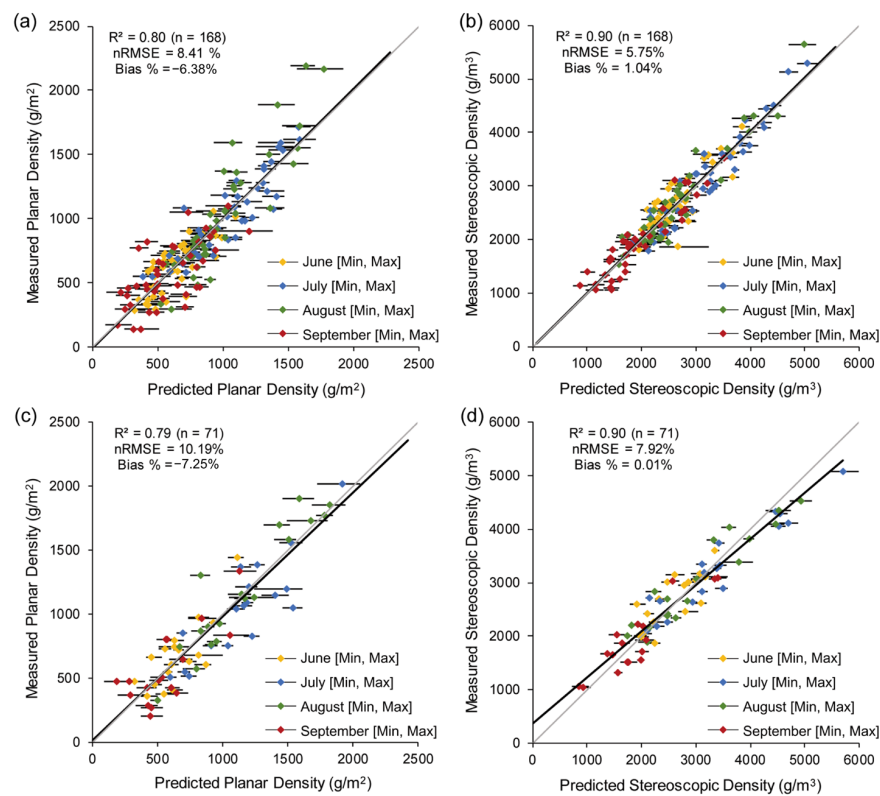


**Figure 7.** Measured vs. estimated planar density (a,c) and stereoscopic density (b,d) with grassland canopy spectra using partial least squares regression for both the training and testing datasets.

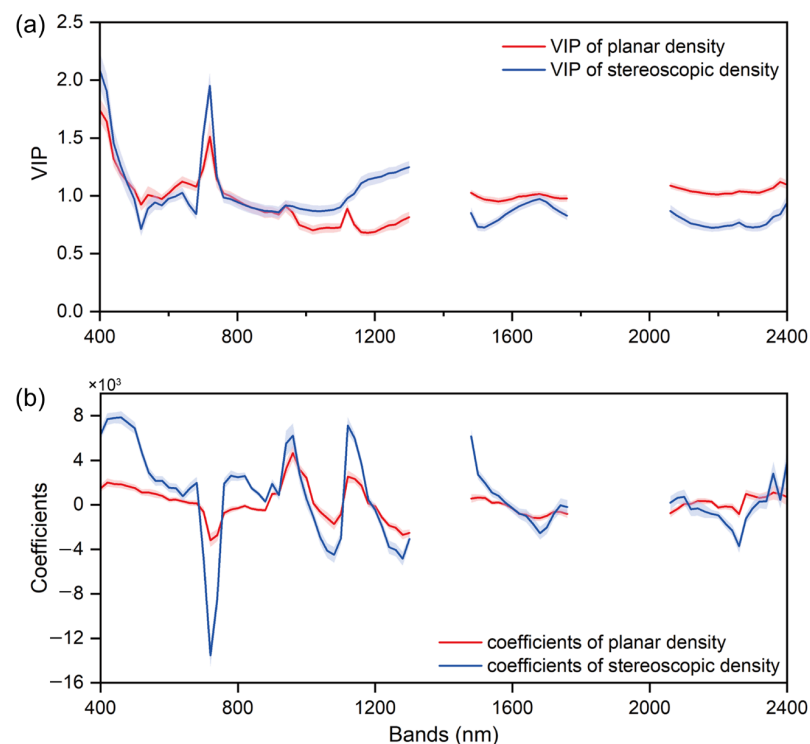


**Figure 8.** PLSR spectral coefficients (a) and variance influences projection (VIP) (b) of the 50 iterations and their average in the training mode. The solid line represents the average of 50 iterations, while the shaded area indicates the value range across these iterations.

### 3.3. Estimating Grassland Aboveground Biomass Based on PD and SD

#### 3.3.1. Validation of AGB Estimation

By integrating spectral reflectance-derived planar density and stereoscopic density with field-measured area and volume data, we achieved robust estimation of grassland aboveground fresh biomass. As shown in Figure 9, both approaches demonstrated comparable accuracy when validated against independent biomass testing data (PD-derived:  $R^2 = 0.79$ , nRMSE = 10.19%; SD-derived:  $R^2 = 0.82$ , nRMSE = 10.58%). However, PD-based biomass estimation exhibited persistent saturation effects, systematically underestimating high biomass values exceeding 1500 g, although the overall estimation was on the high side (Bias% = −7.25%). The estimation based on SD and volume was free from saturation and showed a smaller estimation bias (Bias% = 1.86%), but it showed increased deviations for biomass exceeding 1500 g/m<sup>2</sup> (Supplementary Figure S6).

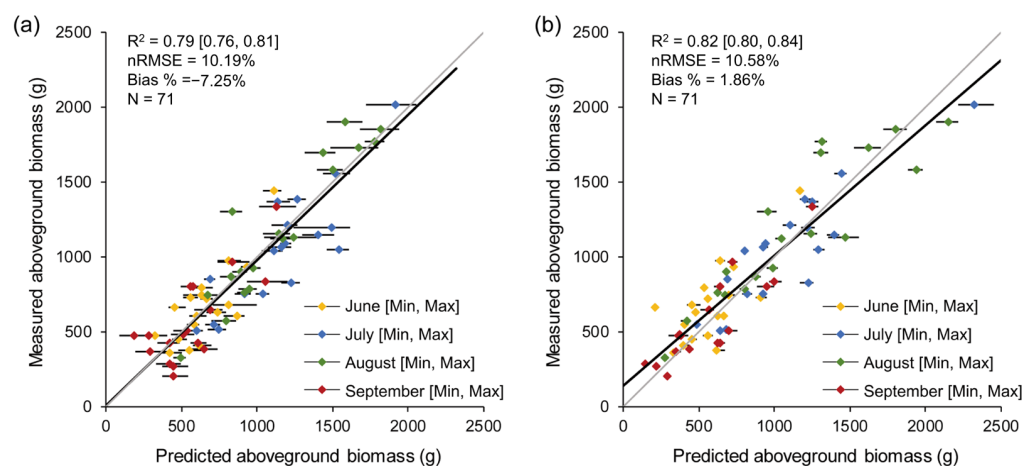


**Figure 9.** Measured vs. estimated grassland aboveground biomass based on planar density (a) and stereoscopic density (b) for testing datasets.

#### 3.3.2. Accuracy Differences Among Various Months

Overall, both estimation methods based on PD and SD demonstrated reasonable accuracy ( $R^2 > 0.6$ ) across most months, except for SD-based estimation in June ( $R^2 = 0.52$ ). The PD-based approach showed larger inter-month variability in accuracy, indicating stronger temporal dependence, while SD-based estimates maintained more stable performance from July to September ( $R^2$  ranged from 0.77 to 0.82). The nRMSE values were comparable between two methods, ranging from 11.12% to 16.03% for PD-based grassland biomass estimation and 12.44–15.87% for SD-based. Notably, PD estimates consistently overestimated biomass across all months with substantial variation in bias percentage (−1.4% to −14.5%), whereas SD estimates exhibited smaller and more stable bias percentage patterns (−4.39% to 6.95%).

## 4. Discussion

This study successfully established a data-driven model for monitoring both planar density and stereoscopic density of grassland communities across an entire growing season using in-situ hyperspectral remote sensing, ultimately achieving accurate estimation and validation of aboveground fresh biomass through the integration of area and volume measurements. Our findings provided dual insights: firstly, we elucidated the capacity of hyperspectral data to characterize grassland community features across different dimensions, revealing distinct spectral response patterns corresponding to vertical and horizontal vegetation structures. More significantly, we pioneered a simple semi-mechanistic approach by fusing geometric features (area/volume) with spectral information for biomass

estimation. In contrast to vegetation indices and scattering feature-based remote sensing methods [18,24,40], which suffered from poorly interpretable feature weighting issues, the proposed approach directly correlated the variation of grassland physical structure with biomass accumulation processes. This framework explicitly elucidated the mechanistic basis of grassland biomass formation while ensuring traceability of estimation results to specific vegetation structural parameters and underlying physiological processes. Consequently, it could facilitate mechanistic analysis and process-based modeling of key drivers influencing grassland productivity, such as precipitation-mediated canopy volume expansion and nitrogen deposition-induced modulation of tissue density.

#### 4.1. PLSR Model Performance of Density Prediction

Independent validation accuracy demonstrated that grassland biomass stereoscopic density incorporating vertical structural characteristics could be more effectively estimated through hyperspectral reflectance compared to planar density (Figure 7). Fundamentally, the spectral reflectance characteristics of vegetation canopy resulted from the combined effects of three-dimensional structural attributes (e.g., leaf layer count, gap fraction), observation geometry (e.g., sun-sensor angles), and leaf biochemical properties (e.g., chlorophyll, water content) [41,42]. PD estimation neglected vertical structural influences, relying solely on two-dimensional projected information, which proved inadequate for distinguishing certain grassland community scenarios. For instance, a tall-sparse canopy with low SD and a short-dense canopy with high SD might exhibit similar PD values. Our results also revealed that SD demonstrated a greater value range than PD (Figure 6). Besides, for vertically stratified communities (e.g., grass-forb mixtures), photosynthetically active tissues from different species and heights contributed differentially to spectral signatures [43,44]. Furthermore, we also observed underestimation of high AGB in PD monitoring, primarily due to dominant spectral saturation effects, a well-documented limitation in vegetation index-based biomass estimation [12,45,46]. But this phenomenon was substantially mitigated in SD results. It suggested that coupling structural characteristics of vegetation communities could effectively mitigate spectral saturation thresholds and demonstrate stronger explanatory power for AGB estimation in grassland communities that exceeded critical coverage thresholds.

As demonstrated by the partial least squares regression model coefficients and VIP values (Figure 8), we compared the sensitive band differences between planar density and stereoscopic density across the full spectral range between 400 and 2400 nm. The higher VIP values for SD estimation in visible and near-infrared bands indicated that hyperspectral data preferentially captured vertical structural variations through these spectral regions, while the estimation of PD relied more on shortwave infrared (SWIR) bands and was primarily associated with absorption features related to biomass components such as leaf area mass, water content, cellulose, and lignin that predominantly occurred in SWIR wavelengths [47–49]. Compared to PD, SD exhibited more pronounced coefficients at specific individual bands and demonstrated greater coefficient variability across the full spectral range. This pattern suggested that structure-informed SD estimation depended more heavily on particular spectral bands to detect vertical biomass distribution differences. For instance, red-edge bands (700–750 nm) were less affected by vertical structural variations in retrieving leaf area index and related parameters [47–49], which directly correlated with both vegetation density and biomass, and consequently received higher weights in the SD estimation model. In contrast, the PD model attenuated vertical variation information, and it might require consideration of more spectral bands to explain differences among sample plots with similar biomass density, resulting in relatively stabilized coefficients.

#### 4.2. New Perspectives on Grassland Aboveground Biomass Estimation

Building upon the high-accuracy monitoring results of both planar density and stereoscopic density and further combining with fixed plot areas and vegetation volumes derived from terrestrial LiDAR, we successfully predicted fresh aboveground biomass in the test dataset (Figure 9). In practice, horizontal features such as vegetation coverage could be accurately monitored through hyperspectral data and derived vegetation indices [50,51]. Therefore, for PD estimation, we employed plot area rather than vegetation coverage area, which aligned with the conventional definition of aboveground biomass as the total weight of plant aboveground parts per unit area. Given our fixed plot size (1 m × 1 m), AGB estimation based on area and PD was essentially equivalent to direct biomass estimation using hyperspectral data. The accuracy achieved based on PD using hyperspectral data were comparable to previous research employing machine learning algorithms with spectral-derived and LiDAR-derived features for aboveground biomass estimation [25]. It is more likely attributed to monitoring scale considerations. Ground or near-ground observations typically offered higher spatial resolution than spaceborne remote sensing data, also enabling more precise matching with field plots and capturing finer spectral characteristics [24,52]. Furthermore, spectral features and their derivatives also could partially characterize vegetation structural features [45,53], which might somewhat diminish the independent contribution of structural parameters. Additionally, our hyperspectral-based estimation results outperformed traditional approaches relying on vegetation indices in the previous studies, which often exhibited pronounced saturation effects [18].

The accuracy of AGB estimation by combining stereoscopic density and volume approximated that of direct AGB prediction (Figure 9), but the uncertainty in the proposed AGB estimation model (Stereo Density × Volume) was found to originate from two distinct sources: the error in SD estimation and the error in volume measurement. A first-order error propagation analysis demonstrated that these components contributed unequally to the total uncertainty in AGB estimation, with approximately 57.1% attributable to volume and 42.9% to SD. This finding indicated that volume measurement constituted the dominant source of error in the approach. However, precise estimation of grassland structural parameters using LiDAR remained challenging, particularly for large-scale monitoring with UAV or spaceborne platforms [19,35,54]. For example, the height of grassland canopy was often underestimated, and the underestimation was more significant for the average height compared to the maximum height. However, the estimation of maximum height was also affected by noise and other factors. Therefore, which structural indicator, such as average height, median height, or percentile height, could better reflect the information of grassland community volume still needed further exploration in combination with measured data? This observation error largely explained why structural features typically contribute less to biomass estimation than spectral features for large-scale remote sensing applications [26,46], despite their potential to enhance monitoring accuracy [12]. Some studies had attempted grassland biomass estimation using solely LiDAR-derived features [23,55], but these approaches predominantly relied on statistical relationships (e.g., regression fitting) without explicit modeling of vegetation structure-biomass conversion mechanisms. Vegetation changes manifested not only structurally but also physiologically, such as increased carbon-based compounds (e.g., cellulose, lignin) through photosynthesis or higher leaf mass per area (LMA), which might occur without significant structural alterations. The approach by combining stereoscopic density and volume uniquely accommodated both physiological trait variations and structural information, effectively capturing biomass-induced changes across these two dimensions. It demonstrated particular advantages for structurally complex, high-density grassland communities, especially in addressing the common underestimation of high AGB. These findings provided a novel

approach for accurately estimating the AGB of heterogeneous grassland by synergizing hyperspectral (biochemical characteristics) and LiDAR data (structural features), alleviating the limitations of traditional remote sensing methods that focus solely on two-dimensional characteristics of grassland communities. However, attention should also be paid to the AGB estimation errors caused by SD and volume. In the future, combined with optimized experimental design, using multi-sensor synchronous observations to obtain benchmark true values and meanwhile reducing sample distribution bias through stratified sampling to quantify the contributions of SD and volume errors to AGB estimation. Additionally, machine learning models could be applied to explore the nonlinear interaction effects between errors, providing a theoretical basis for targeted optimization of AGB estimation.

#### 4.3. Reliable Prediction Across Months

The temporal dynamics of grassland AGB during the growing season served as both a crucial indicator of ecosystem productivity changes and carbon sequestration function as well as a central component for investigating grassland community carbon-water cycle coupling and their responses to climate change [37,56,57]. Utilizing time-series spectral reflectance data across an entire growing season, we monitored grassland community density and biomass, demonstrating that a single cross-seasonal model could yield accurate seasonal dynamic monitoring results (Supplementary Tables S1 and S2, Figure 10). This indicated that temporal variations of vegetation spectra and inter-community spectral variability shown in our study (Figure 3, Supplementary Figure S2) could sufficiently capture the changes in both PD and SD across different phenological stages (Supplementary Figure S5). Although both methods achieved acceptable accuracy ( $R^2 > 0.6$ ) for most months, June and September showed relatively inferior performance in density and biomass estimation. This could be attributed to lower vegetation coverage in June causing soil spectral interference [58], while the result in September was more affected by vegetation senescence [59].

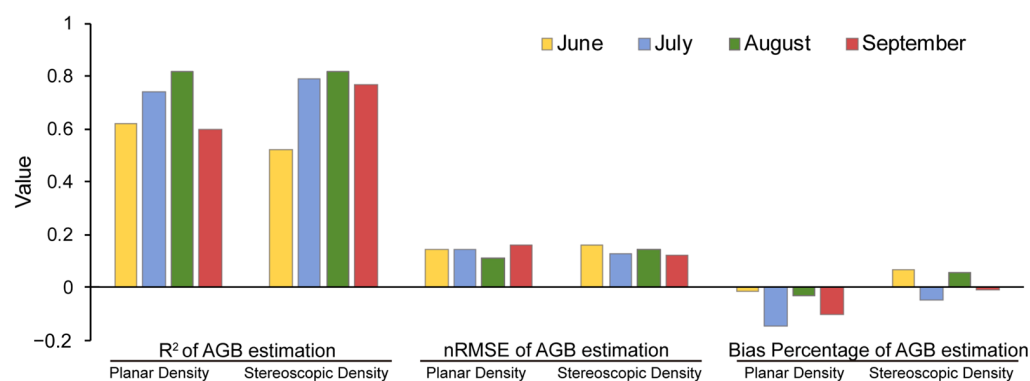


**Figure 10.** Comparison of estimation accuracy of grassland aboveground biomass based on planar density and stereoscopic density for each month from June to September.

The spatiotemporal variations in spectral reflectance could first be attributed to the differences in physiological traits [60]. For example, water content and dry matter primarily influenced shortwave infrared bands, while pigment concentrations predominantly affected visible regions [61,62]. Second, our study revealed the temporal changes in structural traits (Supplementary Figure S4), which also significantly altered community spectral characteristics [63]. However, PD was predominantly influenced by variations in physiological traits, whereas SD mainly represented a combined effect of both physiological traits and structural characteristics. This explained why SD consistently demonstrated superior accuracy to PD across all monthly measurements, as PD failed to account for structural parameters.

Comparatively, SD-based AGB estimation also demonstrated more stable performance across monthly dynamics than PD-based approaches (Figure 10). PD-based estimation exhibited systematic underestimation with fluctuating bias magnitude throughout all months. This persistent underestimation likely stemmed from inadequate modeling of the nonlinear relationship between PD and biomass. Specifically, at higher biomass levels, PD exhibited reduced sensitivity to actual biomass variation, causing systematic underestimation in model outputs. In contrast, SD-based estimation showed higher and more stable accuracy from July to September, suggesting SD could capture core biomass-related characteristics (e.g., structural parameters, coverage) better during peak growth. The relatively lower accuracy in June might be attributed to the vegetation green-up period, during which the correlation between SD and biomass had not yet stabilized. However, our results demonstrated that the structural prediction bias in June remained consistent with August (Supplementary Figure S3). This indicated that the estimation errors of AGB in June primarily originated from spectral-based density estimation inaccuracies rather than structural parameters.

While we revealed the combined effects of biomass density and structural features on AGB estimation, we did not quantify their respective contributions to estimation errors, particularly regarding synchronous or asynchronous variations of these traits across phenological stages. This limitation somewhat constrained model interpretability, and it should be further explored in the future.

#### 4.4. Limitations and Future

Our study developed a semi-mechanistic remote sensing approach for grassland AGB estimation by integrating stereoscopic density with structural volume at the three-dimensional scale, but several critical scientific questions warrant further investigation. First, our research primarily focused on plot-scale measurements, but data acquisition remained time-consuming, particularly for terrestrial LiDAR requiring high point cloud density. Additionally, information loss-induced errors also posed non-negligible challenges [35,36]. Structure-from-motion (SfM) photogrammetry using cameras might offer a viable alternative [64], though its field accuracy requires further validation. Scaling this approach for extensive grassland AGB mapping presented even greater challenges. Besides, although hyperspectral data have proven indispensable for grassland monitoring at leaf and canopy scale [20,22], their application to satellite-based studies still demanded additional research.

Currently, stepwise scaling approaches by integrating ground-UAV-satellite data have been widely adopted [24], but the effects of spatial resolution on spectral data and the representation of satellite-derived features on structural information should be considered [19,54,65], which might significantly impact the final AGB estimation at the large scale. Besides, the hyperspectral data used in our study represented the spectral characteristics at the whole-community level. Comparatively, imaging spectroscopy data can inherently provide finer-scale vegetation density information at the pixel scale. When integrated with LiDAR data, this combination enabled more precise detection of intra-community spatial heterogeneity and consequently higher-accuracy monitoring of grassland AGB.

Spectral range and band quantity equally critically influenced AGB and related parameter estimation accuracy [66–68]. Our study employed 400–2400 nm hyperspectral data for density retrieval, but not all spectral bands contributed equally to the model performance, with only specific wavelengths exhibiting significant predictive power (Figure 8). Therefore, we advocated for systematically balancing spectral range, band number, and model accuracy to achieve efficient grassland AGB estimation. According to the results of the coefficients and variance importance projection of wavebands (Figure 8), it sug-

gested that the B6 band in Sentinel-2 data might play a more important role; the specific identification of the band still requires further analysis and demonstration based on the future study. For instance, deep learning algorithms could extract the most discriminative low-dimensional features from hyperspectral data [69], followed by transferring these optimized spectral features to multispectral sensors by building the characteristic relationships. This could effectively address the cost constraints of hyperspectral data in large-scale applications and further establish a scalable theoretical foundation for upscaling to Sentinel-2 and Landsat-series optical satellite data. Beyond the influence of remote sensing data, inherent differences existed in both structural and spectral characteristics across grassland types (e.g., typical steppe vs. meadow steppe) and management regimes (e.g., grazing vs. enclosure) [70,71], making ecosystem heterogeneity another critical influencing factor. Our study was geographically limited to a small region. Although different fertilization treatments enhanced data heterogeneity, the environmental and meteorological conditions remained homogeneous. Notably, previous research demonstrated that when grassland conditions were not represented in the training and calibration datasets, the uncertainty of trait parameter estimation using spectral data would increase significantly [22]. Therefore, future research should not only develop innovative scaling methods to bridge the plot-to-region gap but also validate these approaches across broader ecosystem types, incorporating environmental and climatic gradients. This dual strategy was essential for evaluating methodological generalizability and robustness, ultimately enabling the development of more reliable, cross-scale remote sensing monitoring frameworks. In addition, we found that the estimation bias of high-biomass samples is relatively large (Supplementary Figure S6). This may be because the insufficient number of samples limits the model's ability to capture extreme values, which is consistent with the consensus in ecological modeling that extreme value samples determine the model's boundary capabilities [72]. Therefore, to make up for this deficiency, future studies can increase targeted sampling in potential distribution areas of high biomass (such as low-lying humid meadows and long-term enclosed protected areas) to raise the proportion of high-biomass samples in the total samples, ensure the completeness of biomass gradient coverage, and verify the monitoring accuracy in the high-biomass sample interval. Methodologically, our PLSR implementation could not provide explicit uncertainty estimates, whereas Gaussian process regression (GPR) [22,73] and neural networks [74] offered superior capabilities in this regard. By precisely determining whether the errors originated from density estimation, structural parameterization, or their interaction effects, we could achieve more targeted model calibration and refinement.

Finally, our cross-phenological data-driven model successfully monitored seasonal AGB dynamics (Figure 10), but it required temporally matched spectral, structural, and grassland AGB data. Nowadays, most existing studies concentrate on temporal extrapolation methods based on single-time-phase modeling while overlooking the impact mechanisms of seasonal environmental disturbances on aboveground biomass (AGB) estimation, such as soil moisture fluctuations in spring and litter coverage impacts in autumn. Further investigating the capacity of the method combining density and volume to capture non-linear seasonal changes of AGB and analyzing its temporal transferability were essential for developing a simpler and more stable grassland AGB estimation model. Advancing biomass monitoring frameworks at a three-dimensional scale with cross-spatiotemporal optimization might enable a paradigm shift from static empirical estimation to dynamic mechanistic monitoring and further provide next-generation technical support for global grassland carbon sink assessment.

## 5. Conclusions

Our study proposed a remote sensing-based estimation method for grassland above-ground fresh biomass with explicit physical interpretation across the full growing season by integrating hyperspectral-derived density and LiDAR-derived volume. The estimation of stereoscopic density demonstrated superior accuracy with  $R^2$  at 0.90 and temporal stability ( $R^2$  over 0.80 in July, August, and September) compared to planar density. Although the subsequent estimation results of grassland AGB based on planar density and stereoscopic density, respectively, demonstrated comparable accuracy (PD-based:  $R^2 = 0.79$ , SD-based:  $R^2 = 0.82$ ), the superior density prediction was somehow tempered by volume estimation inaccuracy. The SD-based approach incorporating vegetation volume effectively alleviated the spectral saturation effect prevalent in the spectral-based biomass estimation model. Moreover, a cross-seasonal modeling strategy using time-series spectral and LiDAR data achieved consistent grassland AGB predictions with moderate to high accuracies from July to September ( $R^2$  ranged from 0.77 to 0.82). These results also further elucidated fundamental differences in temporal stability between grassland biomass estimation approaches based on stereoscopic density and planar density, revealing critical divergence in their phenological dynamics and highlighting the potential for developing temporally generalizable models in grassland aboveground fresh biomass monitoring.

The contribution of this study lay in establishing a three-dimensional stereoscopic density estimation model using hyperspectral remote sensing and further integrated vegetation volume parameters to achieve precise grassland aboveground fresh biomass prediction and cross-temporal dynamic monitoring. This work explored a new semi-mechanistic remote sensing approach for grassland AGB estimation based on remote sensing and provided technical support for the multiple consecutive observations of the grassland AGB in the same plot without destructive sampling. Future research should focus on extending its applicability across diverse grassland types and management regimes and also scaling up this framework using multi-source and multi-scale data. Such advancements will be critical for enabling operational AGB monitoring accuracy and improving assessments of grassland ecosystem function and carbon sequestration potential at regional to global scales with consistent long-term temporal coverage.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs17173038/s1>, Figure S1. The distribution of grassland biomass; Figure S2. Mean grassland canopy reflectance with range from June to September; Figure S3. Accuracy assessment of terrestrial laser scanning (TLS) for grassland canopy maximum height estimation. (a) Validation between TLS-derived and field-measured maximum heights with 1:1 reference line in June; (b) Validation between TLS-derived and field-measured maximum heights with 1:1 reference line in August; (c) variation in measured and estimated grassland maximum height in June and August shown as boxplots (central line: mean; box limits: 10th–90th percentiles; whiskers:  $1.5 \times$  interquartile range); Figure S4. Variation in estimated and simulated grassland volume from June to September shown as boxplots (central line: mean; box limits: 10th–90th percentiles; whiskers:  $1.5 \times$  interquartile range); Figure S5. Variation in planar density and stereoscopic density from June to September shown as boxplots (central line: mean; box limits: 10th–90th percentiles; whiskers:  $1.5 \times$  interquartile range); Figure S6. Comparison of measured and estimated grassland aboveground biomass based on planar density and stereoscopic density for four ranges (<500 g; 500–1000 g; 1000–1500 g; >1500 g). Table S1. Performance of planar density and stereoscopic density based on hyperspectral data for each month from June to September in training dataset; Table S2. Performance of planar density and stereoscopic density based on hyperspectral data for each month from June to September in testing dataset.

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writing—original draft preparation, C.X. and D.Z.; writing—review and editing, C.X. and D.Z.; supervision, Z.Z., Y.Z. (Yuan Zeng), Y.Z. (Yujin Zhao) and B.W. All authors have read and agreed to the published version of the manuscript.

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