

Article

Satellite Embedding Features for Grassland Aboveground Biomass Estimation in Complex Mountainous Terrain: A Case Study of the Three Parallel Rivers Region, China

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Highlights

What are the main findings?

- Satellite embeddings improved grassland AGB estimation compared with conventional Sentinel-1, Sentinel-2, and DEM-derived features.
- The Emb-64-based XGBoost model achieved the highest performance, with R^2 values of 0.7949 ± 0.0405 and 0.7660 ± 0.1003 under random five-fold and spatial cross-validation, respectively.

What are the implications of the main findings?

- Satellite embeddings provide a promising high-dimensional representation for mapping vegetation biophysical variables in heterogeneous mountainous landscapes.
- Uncertainty-aware AGB mapping can support grassland productivity assessment, carbon storage estimation, and the identification of areas requiring further field validation.

Abstract

Aboveground biomass (AGB) in grasslands is a key biophysical indicator for evaluating grassland productivity, ecosystem functioning, and carbon storage. However, accurate regional-scale AGB estimation in complex mountainous terrain remains challenging because of fragmented topography, strong environmental gradients, and heterogeneous grassland patches. This study evaluated the applicability of satellite embedding features for grassland AGB estimation in the Three Parallel Rivers region of Yunnan Province, China. Based on 135 field plots surveyed during the 2022 growing season, 64-dimensional annual satellite embedding features were extracted, and a conventional feature system derived from Sentinel-1, Sentinel-2, and DEM data was constructed for comparison. Four feature systems, namely Traditional-9, Traditional-40, Emb-9-PCA, and Emb-64, were evaluated using six regression models, including RF, SVR, GPR, XGBoost, LightGBM, and Elastic Net. Random five-fold cross-validation was used to compare feature systems and model combinations, while spatial cross-validation was further applied to assess model robustness under spatially independent conditions. The results showed that satellite embedding features outperformed conventional remote sensing features. Under random

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five-fold cross-validation, the Emb-64-based XGBoost model achieved the best performance, with an R^2 of 0.7949 ± 0.0405 , an RMSE of 0.1388 ± 0.0191 t/ha, and an MAE of 0.1141 ± 0.0203 t/ha. Under spatial cross-validation, XGBoost retained the highest mean performance, with an R^2 of 0.7660 ± 0.1003 , an RMSE of 0.1417 ± 0.0111 t/ha, and an MAE of 0.1165 ± 0.0124 t/ha. SHAP and Spearman correlation analyses further indicated that important embedding dimensions were associated with AGB and selected conventional environmental variables. Regional mapping showed that predicted grassland AGB ranged from 0.17 to 1.26 t/ha, with a mean value of 0.79 t/ha, and exhibited significant positive spatial autocorrelation. Bootstrap-based uncertainty analysis indicated that higher uncertainty mainly occurred in fragmented mountainous areas, grassland edges, and transition zones. These findings suggest that satellite embedding features provide a promising high-dimensional representation for grassland AGB estimation in complex mountainous landscapes, while their ecological interpretability and transferability still require further investigation.

Keywords: grassland aboveground biomass (AGB); satellite embedding; machine learning; spatial cross-validation; biomass estimation

1. Introduction

Grassland aboveground biomass (AGB) is an important biophysical variable for characterizing grassland productivity, ecosystem function, and changes in carbon stocks. Its accurate estimation is essential for grassland resource management, ecological conservation, regional carbon cycle assessment, and ecosystem service quantification [1,2]. Traditional quadrat harvesting and field surveys can provide reliable point-based observations; however, they are constrained by survey costs, limited spatial coverage, and insufficient temporal continuity, making them inadequate for continuous monitoring and spatial mapping of grassland AGB in complex mountainous regions [3,4]. Therefore, remote sensing-based estimation of grassland AGB has become an important technical approach for regional-scale grassland resource monitoring and ecosystem function assessment [5].

Existing remote sensing studies on grassland AGB estimation have largely relied on manually constructed variables, such as spectral bands, vegetation indices, radar backscatter, texture features, and topographic factors, combined with statistical models or machine learning methods to develop inversion models [6,7]. These conventional remote sensing features have relatively clear physical interpretability; however, they still face substantial limitations in complex mountainous environments. On the one hand, optical vegetation indices are susceptible to cloud contamination, topographic shadowing, and saturation effects in high-biomass areas [8,9]. On the other hand, although SAR and texture features can provide complementary information on vegetation structure and spatial heterogeneity [10], single or limited combinations of explicit variables may be insufficient to fully capture the complex and nonlinear interactions among vegetation conditions, topographic background, hydrothermal gradients, and local habitat conditions [11,12]. This limitation is particularly evident in alpine canyon regions, where grassland AGB is jointly controlled by elevation, aspect, terrain dissection, community composition, and environmental conditions. As a result, similar spectral or radar responses may correspond to different biomass levels, making it difficult for a limited set of explicit remote sensing variables to fully capture the nonlinear variations and spatial heterogeneity of grassland AGB [13,14]. Therefore, AGB estimation in complex mountainous grasslands requires high-dimensional remote sensing representations that can comprehensively integrate multi-source remote sensing observations and environmental background information.

In recent years, remote sensing foundation models and representation learning have provided new feature representations for mapping vegetation biophysical parameters. As a high-dimensional remote sensing representation generated by AlphaEarth Foundations, annual satellite embeddings map multi-source and multi-temporal Earth observation information into a unified latent feature space, thereby providing new input features for representing complex surface conditions and supporting downstream mapping tasks [15]. Previous studies have shown that such features have considerable potential for land-cover identification, environmental monitoring, and automated mapping tasks [16,17]. However, existing studies have mainly focused on the application of satellite embeddings to classification mapping or environmental monitoring, while their applicability to continuous ecological variable estimation, particularly grassland AGB retrieval, remains insufficiently validated [18]. In addition, in mountainous regions characterized by fragmented terrain and complex environmental gradients, high accuracy obtained under random sample partitioning does not necessarily indicate reliable spatial generalization [19]. Therefore, it is necessary to systematically evaluate the representational capacity, model compatibility, and robustness under spatially independent conditions of satellite embeddings for grassland AGB estimation in typical complex mountainous regions.

The Three Parallel Rivers region in Yunnan Province is located on the southeastern margin of the Qinghai–Tibet Plateau and in the core area of the Hengduan Mountains. It is characterized by strong terrain dissection, pronounced elevational gradients, and marked spatial differentiation in hydrothermal conditions and vegetation types. Grassland distribution in this region is jointly controlled by complex topography and local environmental conditions, resulting in substantial spatial heterogeneity in AGB. Therefore, this region provides a representative setting for evaluating the applicability of high-dimensional remote sensing representations to grassland biomass estimation in complex mountainous landscapes [20]. Compared with areas with relatively flat terrain or more homogeneous ecological backgrounds, remote sensing signals in this region are more strongly modulated by topographic effects, environmental gradients, and vegetation heterogeneity. As such, it provides a typical case for comparing the applicability of conventional explicit variables and high-dimensional latent representations in complex mountainous grassland AGB estimation [13,21].

Based on this context, this study used the Three Parallel Rivers region in Yunnan Province as the study area and combined AGB measurements from 135 field plots with the 2022 annual satellite embedding product to evaluate the applicability of satellite embeddings for grassland AGB estimation and mapping in complex mountainous regions. The specific objectives of this study were to: (1) compare the performance of satellite embeddings and conventional multi-source remote sensing features under different feature-system settings; (2) identify the optimal machine learning model for satellite embedding features, evaluate its robustness using spatial cross-validation, and examine the interpretability of important embedding dimensions; and (3) conduct regional-scale grassland AGB mapping and analyze the spatial pattern, spatial autocorrelation, and prediction uncertainty of the results, thereby providing spatial information to support grassland productivity assessment, carbon stock estimation, and ecosystem service evaluation in complex mountainous regions.

2. Methods

2.1. Study Area

This study selected the Three Parallel Rivers region in northwestern Yunnan Province, China, as the study area. The region extends from 98°00' to 100°30'E and from 25°30' to 29°00'N, covering eight counties or county-level cities: Lushui, Fugong, Gongshan, Lanping, Shangri-La, Weixi, Deqin, and Yulong (Figure 1). The area is located on the

southeastern margin of the Qinghai–Tibet Plateau and in the core region of the Hengduan Mountains. The Nujiang, Lancang, and Jinsha rivers incise the landscape nearly parallel in a north–south direction, forming a typical alpine canyon landform. The terrain generally descends in a stepped pattern from the northwest to the southeast, with elevations ranging from approximately 742 to 6431 m and pronounced vertical relief. Influenced by rugged terrain and strong elevational gradients, the climate exhibits distinct vertical zonation. Annual precipitation ranges from approximately 500 to 2000 mm and is mainly concentrated from May to October, resulting in pronounced seasonal and spatial variations in hydrothermal conditions. The complex topography and hydrothermal gradients jointly shape diverse vegetation types and grassland distribution patterns. These environmental conditions contribute to strong spatial heterogeneity in grassland AGB, making the region a representative area for developing and validating remote sensing models for grassland AGB estimation in complex mountainous landscapes.

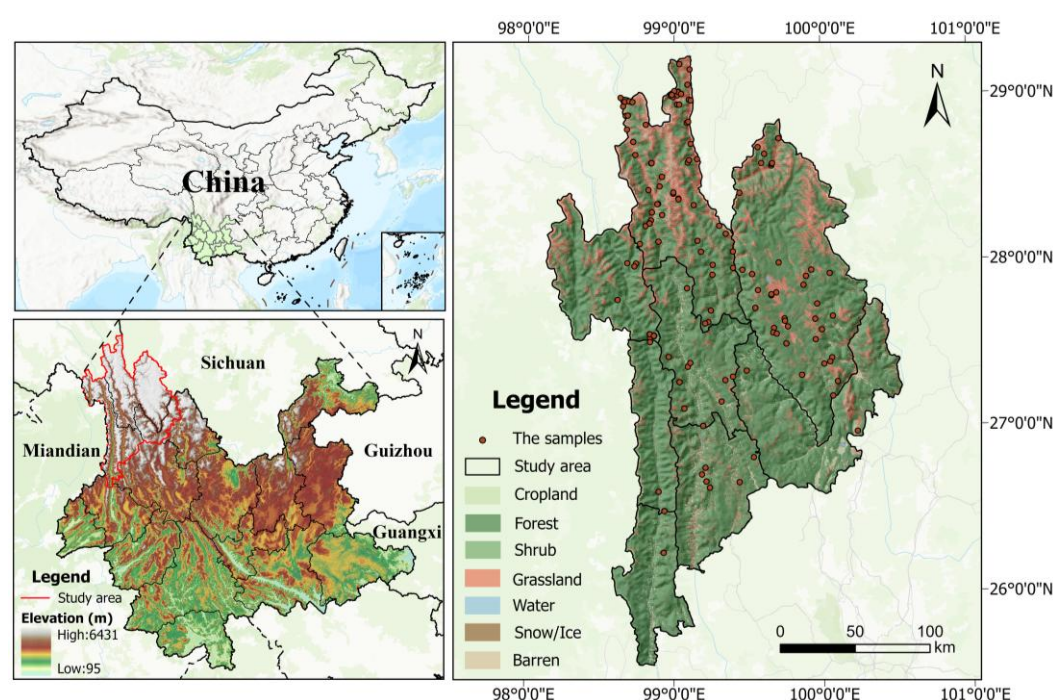


Figure 1. Overview map of the study area.

2.2. Data Collection and Processing

2.2.1. Field Plot Data

Field surveys for grassland AGB were conducted in the study area from July to September 2022, corresponding to the peak growing season of grasslands. An integrated composite plot design was adopted. A total of 135 circular main plots were established, each with a radius of 40 m and an area of approximately 0.5 ha. Plot locations were selected by considering the representativeness of vegetation types, relative homogeneity of community composition, and spatial distribution characteristics, in order to ensure sample representativeness and comparability. During the field survey, basic information including the latitude and longitude of the plot center, elevation, slope, aspect, vegetation coverage, grassland type, vegetation structure, and dominant species was recorded for subsequent spatial registration and analysis.

Within each main plot, three 1 m × 1 m biomass quadrats were established. Aboveground biomass was measured using the quadrat harvesting method. All aboveground vegetation within each quadrat was clipped and collected, impurities were removed, and the samples were oven-dried to a constant weight before dry mass measurement. The

mean dry mass of the three biomass quadrats was used to represent the plot-level above-ground biomass and was converted to aboveground biomass per unit area (t/ha). Finally, AGB observations from 135 plots were obtained and used for subsequent modeling analysis. Descriptive statistics of plot-level AGB are presented in Table 1.

Table 1. Results of statistical analysis of biomass in sample plots.

Number of Samples	Minimum Value (t/ha)	Maximum Value (t/ha)	Mean Value (t/ha)	Standard Deviation (t/ha)	Variance ((t/ha) ²)
135	0.085	1.51	0.69	0.31	0.10

2.2.2. Satellite Embedding Data

This study used the Annual Satellite Embedding dataset generated by AlphaEarth Foundations as a high-dimensional remote sensing representation. AlphaEarth Foundations is a geospatial embedding model designed for Earth observation tasks. It integrates multi-source and multi-temporal Earth observation information and maps spatial, temporal, and observational contexts into a unified latent feature space, thereby generating general-purpose geospatial representations for surface mapping and monitoring tasks [15]. According to the Google Earth Engine dataset description, the Satellite Embedding dataset is generated by AlphaEarth Foundations and integrates multiple streams of Earth observation data, including optical, radar, and LiDAR observations. Its embedding representations are analysis-ready and can be used for downstream tasks such as classification, regression, and change detection [22]. The dataset provides an annual embedding vector for each pixel, summarizing surface conditions and their spatiotemporal characteristics within a given year.

Unlike conventional explicit-variable modeling approaches that rely on manually constructed spectral indices, radar backscatter, texture features, or topographic factors, Satellite Embedding represents integrated surface information in the form of multidimensional latent vectors. Individual embedding dimensions generally do not correspond to single physical quantities; rather, they jointly constitute axes in the latent feature space. Therefore, this study used the Annual Satellite Embedding dataset as a high-dimensional remote sensing representation to evaluate its applicability for grassland AGB estimation in complex mountainous regions.

The annual Satellite Embedding dataset was obtained through the Google Earth Engine (GEE) platform under the dataset ID GOOGLE/SATELLITE_EMBEDDING/V1/ANNUAL. The official data catalog is available at: https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL (accessed on 12 March 2026). Because the field survey of grassland AGB in the study area was conducted from July to September 2022, the 2022 annual Satellite Embedding product was selected for feature extraction to match the field survey year. This product provides an annual-scale integrated representation, and its temporal-scale difference from peak-growing-season field measurements is further discussed in Section 4.5. The product has a spatial resolution of 10 m, and each pixel contains 64 embedding bands, denoted as A00–A63.

To match the satellite embedding features with the spatial scale of the field plots, circular buffers with a radius of 40 m were generated around the center points of the 135 plots, and the mean value of each embedding band within each buffer was calculated. This processing step helped reduce the influence of single-pixel noise, plot positioning errors, and local spatial heterogeneity on feature extraction. As a result, each plot was assigned a 64-dimensional satellite embedding feature vector, and all 64 embedding bands were used as predictor variables in the subsequent machine learning models. To further examine the influence of feature dimensionality on model comparison, a PCA-

reduced embedding feature set was also constructed for comparison with conventional feature sets, as described in Section 2.4.

2.2.3. Conventional Remote Sensing Data

To construct the conventional remote sensing feature system, Sentinel-1 radar data, Sentinel-2 multispectral data, and a digital elevation model (DEM) were selected as the primary data sources. Unlike the Annual Satellite Embedding product, the conventional remote sensing variables were mainly extracted from July to September 2022 to represent peak-growing-season surface conditions corresponding to the field survey period.

Sentinel-1 is an important C-band synthetic aperture radar (SAR) data source from the European Space Agency (ESA) Copernicus Programme. It provides all-weather and day-and-night Earth surface observation capabilities, making it suitable for extracting surface information in regions with frequent cloud cover and complex terrain. In this study, the COPERNICUS/S1_GRD product available on the Google Earth Engine (GEE) platform was used. Images acquired over the study area from July to September 2022 in Interferometric Wide Swath (IW) mode, with VV and VH dual polarization and a spatial resolution of 10 m, were selected for analysis. The VV, VH, and VV/VH backscatter features were extracted. In addition, neighborhood mean features and gray-level co-occurrence matrix (GLCM) texture features were derived from the VV and VH images to characterize local spatial heterogeneity and surface structure.

Sentinel-2 is a multispectral optical remote sensing mission under the European Space Agency (ESA) Copernicus Programme. It consists of the Sentinel-2A and Sentinel-2B satellites, provides relatively high temporal resolution, and includes 13 spectral bands covering the visible, near-infrared, and shortwave infrared regions. In this study, the Sentinel-2 Level-2A surface reflectance product available on the GEE platform was used for the period from July to September 2022. To ensure image quality, scenes with cloud cover lower than 10% were selected, and all selected bands were resampled to a spatial resolution of 10 m for feature extraction. Cloud-affected observations were further reduced during image compositing in GEE. Spectral bands and vegetation indices were then extracted to describe grassland spectral reflectance, vegetation vigor, and canopy conditions during the growing season.

The DEM data were derived from the Shuttle Radar Topography Mission (SRTM) global elevation product provided by the United States Geological Survey (USGS), with an original spatial resolution of 30 m. To ensure consistency with Sentinel-1, Sentinel-2, and Satellite Embedding features, the DEM was resampled to 10 m on the GEE platform, and topographic factors including elevation, slope, and aspect were subsequently extracted. These variables were included because terrain strongly affects vegetation distribution, hydrothermal conditions, and grassland productivity in complex mountainous regions.

2.2.4. Grassland Mask Data

To constrain the spatial extent of regional-scale grassland AGB inversion, the 2022 Global Pasture Watch (GPW) 30 m grassland probability product was used to generate a grassland mask. Pixels with a grassland probability greater than 0.6 were defined as grassland and resampled to the same spatial resolution as the inversion results using the nearest-neighbor method. After regional prediction, the grassland mask was applied to the final results to ensure that the AGB estimates were restricted to grassland areas.

2.3. Research Methods

In this study, field-measured grassland AGB was used as the response variable, and grassland AGB estimation models were developed based on satellite embedding features and conventional remote sensing features, respectively. First, field survey data and multi-source remote sensing data were integrated, and plot-level features were extracted using the mean values within 40 m buffers to construct the modeling dataset. Second, different feature systems were constructed, including selected conventional features, full conventional features, PCA-reduced satellite embedding features, and original satellite embedding features, to compare their predictive performance under different dimensionality settings. Third, machine learning models, including RF, SVR, GPR, XGBoost, LightGBM, and Elastic Net, were developed, and random five-fold cross-validation was used to compare the predictive performance of different feature systems and model combinations. On this basis, spatial cross-validation was further conducted for the optimal satellite embedding feature system to evaluate the robustness of the optimal model under spatially independent conditions. Finally, the optimal model was used for regional-scale grassland AGB mapping, and a grassland mask was applied to spatially constrain the prediction results. The final predictions were then used to analyze the spatial pattern, spatial autocorrelation, and prediction uncertainty of grassland AGB. The technical route is shown in Figure 2.

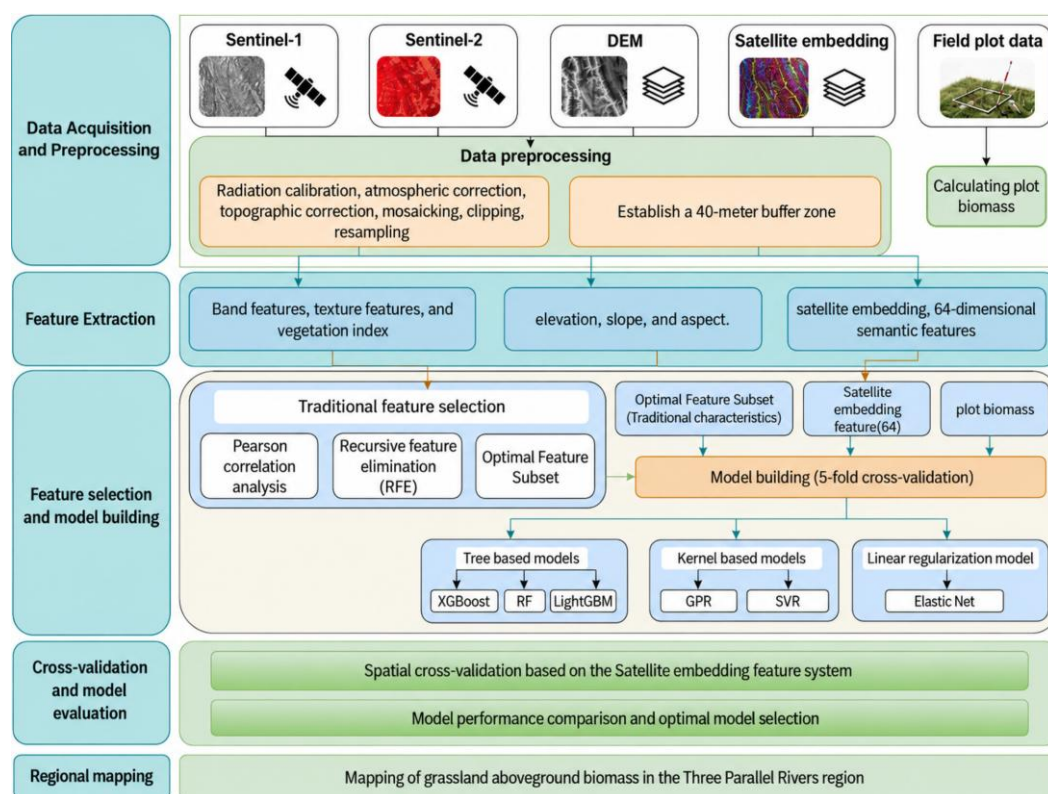


Figure 2. Technical route.

Feature Extraction

Two types of input variables were constructed in this study: satellite embedding features and conventional remote sensing features. For the satellite embedding feature system, the 2022 annual Satellite Embedding product was obtained through the GEE platform. Considering that the field survey was mainly conducted from July to September 2022, the 2022 annual product was selected to match the field survey year. A circular buffer with a radius of 40 m was generated around the center point of each field plot, and

the mean values of the 64 embedding dimensions within each buffer were calculated as plot-level input variables.

For the conventional remote sensing feature system, candidate variables were extracted from Sentinel-1, Sentinel-2, and DEM data (Table 2). Sentinel-1 features mainly represented radar backscatter, vegetation structure, and local spatial heterogeneity; Sentinel-2 features characterized grassland spectral responses, vegetation vigor, and moisture-related conditions; and DEM-derived variables reflected topographic gradients and environmental background effects. To ensure spatial-scale consistency between satellite embedding features and conventional remote sensing variables, all conventional variables were extracted using the same 40 m buffer-based mean approach as that used for the satellite embedding features.

Table 2. Candidate features derived from conventional remote sensing data.

Data Source	Feature Category	Variable Names
Sentinel-1	Backscatter coefficients	VV, VH, VV/VH
	GLCM texture features	VV_Mean, VV_Variance, VV_Homogeneity, VV_Dissimilarity, VV_Entropy, VV_Contrast, VV_SecondMoment, VV_Correlation; VH_Mean, VH_Variance, VH_Homogeneity, VH_Dissimilarity, VH_Entropy, VH_Contrast, VH_SecondMoment, VH_Correlation
	Spectral reflectance bands	B2, B3, B4, B5, B6, B7, B8, B8A
Sentinel-2	Vegetation indices	NDVI, GNDVI, RVI, EVI, DVI, SAVI, MSAVI, OSAVI
	Shortwave infrared bands	B11, B12
DEM	Topographic variables	Elevation, Slope, Aspect

Note: VV and VH represent vertical transmit–vertical receive and vertical transmit–horizontal receive Sentinel-1 polarizations, respectively. GLCM denotes gray-level co-occurrence matrix. B2–B8A, B11, and B12 are Sentinel-2 spectral bands. NDVI, GNDVI, RVI, EVI, DVI, SAVI, MSAVI, and OSAVI are vegetation indices. Detailed descriptions of all candidate variables are provided in Table S1.

2.4. Feature Selection and Dimensionality Reduction

To reduce redundancy and multicollinearity among the candidate conventional remote sensing features and improve model stability, a two-stage feature selection procedure was applied. First, pairwise correlation analysis was conducted using the Pearson correlation coefficient. When the absolute correlation coefficient between two features exceeded 0.90, the feature showing a stronger correlation with grassland aboveground biomass (AGB) was retained, whereas the less correlated feature was removed. Subsequently, recursive feature elimination (RFE) with random forest as the base estimator was used to select key predictors from the correlation-filtered feature set [23]. RFE has been widely used for remote sensing feature optimization because it iteratively removes variables with relatively low contributions and reduces feature redundancy [24,25]. The optimal number of features was determined through cross-validation, and the final selected conventional feature set was used for subsequent modeling.

For the satellite embedding feature system, the original 64-dimensional satellite embedding features were directly used as model inputs without preliminary feature selection. Satellite embeddings are high-dimensional latent representations generated through representation learning, and individual dimensions generally do not correspond to explicit surface attributes. Their information content is more likely encoded by the joint structure of the multidimensional feature space. Therefore, direct univariate feature selection may weaken the integrity of the learned representation.

To address the potential influence of unequal feature dimensionality on model comparison, two additional feature settings were constructed. First, all 40 candidate conventional variables were retained without feature selection to form the full conventional feature set. Second, principal component analysis (PCA) was applied to the 64-dimensional satellite embedding features, and the first nine principal components were retained to form a PCA-reduced embedding feature set. Thus, four feature systems were compared in this study: selected conventional features, full conventional features, PCA-reduced satellite embedding features, and original satellite embedding features.

2.5. Model Parameter Optimization

To compare the responses of different modeling approaches to satellite embedding features and conventional remote sensing features, this study selected random forest (RF), XGBoost, and LightGBM as tree-based ensemble learning methods, support vector regression (SVR) and Gaussian process regression (GPR) as kernel-based methods, and Elastic Net as a regularized linear model to develop grassland aboveground biomass (AGB) estimation models. These models have been widely applied in remote sensing-based AGB estimation because of their ability to handle multi-source remote sensing variables, nonlinear relationships, and complex ecological responses [26,27]. Among them, tree-based ensemble models are effective in capturing nonlinear relationships and feature interactions, SVR and GPR are suitable for nonlinear regression under small-sample conditions, and Elastic Net provides variable shrinkage and regularization in high-dimensional feature spaces [28].

Hyperparameter tuning for each model was conducted using grid search under the five-fold cross-validation framework. Candidate hyperparameter combinations were evaluated based on cross-validation performance, and the configuration with the best cross-validation performance was selected for subsequent model training and performance comparison. For RF, the main tuned parameters included the number of trees, maximum tree depth, minimum samples required for node splitting, minimum samples per leaf, and the number of features considered at each split. For XGBoost, the learning rate, tree depth, number of estimators, subsampling ratio, column sampling ratio, minimum child weight, and gamma were tuned. For LightGBM, the learning rate, number of estimators, column sampling ratio, tree depth, minimum child samples, number of leaves, subsampling ratio, and L1/L2 regularization terms were considered. For SVR, the radial basis function kernel was used, and the penalty parameter C, kernel coefficient gamma, and epsilon-insensitive loss parameter were tuned. For GPR, a composite kernel consisting of a constant kernel, radial basis function kernel, and white-noise kernel was used, and the alpha and normalize_y parameters were considered. For Elastic Net, the regularization strength, L1/L2 mixing ratio, intercept fitting, and selection strategy were considered. The selected hyperparameter settings of each regression model are reported in Table 3.

Table 3. Selected hyperparameter settings of the regression models.

Model	Selected Hyperparameter Settings
RF	n_estimators = 400; max_depth = 5; min_samples_split = 2; min_samples_leaf = 1; max_features = 0.7
XGBoost	n_estimators = 600; max_depth = 2; learning_rate = 0.01; subsample = 0.9; colsample_bytree = 0.8; min_child_weight = 4; gamma = 0
LightGBM	learning_rate = 0.01; n_estimators = 600; colsample_bytree = 0.85; max_depth = 3; min_child_samples = 5; num_leaves = 15; reg_alpha = 0.0; reg_lambda = 0.0; subsample = 0.7
SVR	kernel = rbf; C = 2.0; epsilon = 0.1; gamma = 0.01
GPR	kernel = ConstantKernel(1.0) × RBF(length_scale = 1.0) + WhiteKernel(noise_level = 1.0); alpha = 0.0001; normalize_y = False

Elastic Net	alpha = 0.01; l1_ratio = 0.95; fit_intercept = True; selection = random
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Note: RF, SVR, GPR, XGBoost, LightGBM, and Elastic Net denote random forest, support vector regression, Gaussian process regression, extreme gradient boosting, light gradient boosting machine, and elastic net regression, respectively. Hyperparameter tuning was conducted using grid search under the five-fold cross-validation framework.

2.6. Cross-Validation and Model Evaluation

Given the limited sample size and strong spatial heterogeneity of the study area, this study adopted a dual validation strategy combining random cross-validation and spatial cross-validation to evaluate model predictive performance and spatial generalization ability. First, random five-fold cross-validation was used as the baseline validation strategy to compare different models and feature systems. Specifically, all samples were randomly partitioned into five mutually exclusive subsets. In each iteration, one subset was used as the validation set, and the remaining four subsets were used for model training. This procedure was repeated five times, and the results from all folds were averaged to evaluate the overall model performance.

Considering that random partitioning may produce overly optimistic accuracy estimates due to the spatial proximity of field plots, spatial cross-validation was further conducted for the optimal satellite embedding feature system [19,29,30]. Specifically, plot longitude, latitude, and elevation were used to construct three-dimensional spatial groups. Elevation was included because the study area is characterized by strong topographic gradients, and grassland AGB may vary along elevation gradients. Before clustering, longitude, latitude, and elevation were standardized using z-score normalization to reduce the influence of scale differences among these variables. KMeans clustering was then applied to divide the 135 samples into 10 spatial groups. GroupKFold was used to conduct five-fold spatial cross-validation, ensuring that samples from the same spatial group were assigned exclusively to either the training set or the validation set in each fold. The number of field plots in each spatial group is provided in Table S2. This design was intended to reduce spatial dependence between training and validation samples and provide a more stringent evaluation of model spatial transferability.

Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Among these metrics, R^2 indicates the explanatory power of the model, whereas RMSE and MAE quantify the magnitude of prediction errors. The formulas are as follows:

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

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

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

where y_i is the observed grassland AGB of the i -th sample, $\hat{y}_i$ is the corresponding predicted value, $\bar{y}$ is the mean observed grassland AGB, and n is the total number of samples.

2.6.1. Prediction Uncertainty Estimation

To characterize the uncertainty of regional-scale grassland AGB predictions, a Bootstrap resampling strategy was applied to construct an ensemble based on the final XGBoost model. Based on the fixed 10 three-dimensional spatial groups defined in Section 2.6, spatial groups were sampled with replacement for 50 bootstrap iterations. After each resampling iteration, the model was retrained and a corresponding regional-scale grassland AGB prediction was generated. For each pixel, the 5th percentile (P05) and 95th percentile (P95) were calculated from the 50 predictions, and their difference (P95 – P05) was used to represent the width of the 90% prediction interval. In addition, the mean and standard deviation of the predicted values were calculated for each pixel to characterize the central tendency, dispersion, and spatial uncertainty of the regional predictions.

2.6.2. Spatial Autocorrelation Analysis

Moran's I is a global statistic widely used to measure spatial autocorrelation and to determine whether a spatial variable exhibits clustered, dispersed, or random distribution patterns [31]. In recent years, this index has also been widely applied in analyses of remote sensing-based ecological quality, vegetation distribution, and biomass spatial patterns [32]. Its value generally ranges from –1 to 1. A Moran's I value greater than 0 indicates positive spatial autocorrelation, suggesting that similar values tend to be spatially clustered; a value less than 0 indicates negative spatial autocorrelation, suggesting that high and low values tend to be spatially adjacent; and a value close to 0 indicates an approximately random spatial distribution. In this study, global Moran's I was used to analyze the spatial autocorrelation characteristics of the final grassland AGB prediction results, and Moran scatter plots were further used to identify the spatial clustering patterns of the predictions [33]. The formula is as follows:

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (4)$$

where n is the number of spatial units included in the analysis; (x_i) and (x_j) denote the predicted grassland AGB values at locations (i) and (j), respectively; $(\bar{x})$ is the mean predicted value across all spatial units; and (w_{ij}) is the element of the spatial weight matrix; and (S_0) is the sum of all spatial weights.

3. Results

3.1. Selection of Conventional Remote Sensing Features

To reduce redundancy and multicollinearity among the candidate conventional remote sensing variables, Pearson correlation analysis was first used for correlation-based filtering, followed by recursive feature elimination (RFE) with random forest as the base learner to further select key predictors. The Pearson correlation analysis showed strong correlations among several spectral bands, vegetation indices, and texture features, indicating information redundancy among the candidate conventional variables. The Pearson correlation matrix of the candidate conventional features is provided in Figure S1. After correlation filtering, the number of candidate features was reduced from 40 to 20.

Based on the correlation-filtered feature set, RFE was further applied to optimize the retained variables. According to the cross-validation results, nine features were finally selected as the input variables for the conventional remote sensing feature system. The selected variables included three Sentinel-1 features, four Sentinel-2 features, and two DEM-derived topographic variables, namely VH, VV_Contrast, VH_Contrast, B4, B12, EVI, RVI, Elevation, and Slope (Table 4). These variables covered radar backscatter and texture information, optical spectral and vegetation-index information, and topographic gradient

information, and were used to construct the Traditional-9 feature system for subsequent model comparison.

Table 4. Selected conventional remote sensing variables.

Data Source	Selected Variable	Description
Sentinel-1	VH	VH-polarized backscatter coefficient
	VV_Contrast	GLCM contrast of VV polarization
	VH_Contrast	GLCM contrast of VH polarization
Sentinel-2	B4	Red band
	B12	Shortwave infrared 2 band
	EVI	Enhanced Vegetation Index
	RVI	Ratio Vegetation Index
DEM	Elevation	Elevation derived from DEM
	Slope	Slope derived from DEM

3.2. Comparison of Feature Systems and Model Performance

3.2.1. Performance Comparison Among Feature Systems

To compare the predictive performance of different feature systems, four feature settings were evaluated under the random five-fold cross-validation framework: Traditional-9, Traditional-40, Emb-9-PCA, and Emb-64. Traditional-9 represented the selected conventional feature set obtained in Section 3.1, whereas Traditional-40 retained all 40 candidate conventional remote sensing variables. Emb-9-PCA consisted of the first nine principal components derived from the original 64-dimensional satellite embedding features using PCA and was used as a dimension-matched embedding feature system for comparison with Traditional-9. Emb-64 represented the original 64-dimensional satellite embedding feature set.

The predictive performance differed among the four feature systems (Table 5). Emb-64 achieved the highest overall performance, with XGBoost producing an R^2 of 0.7949 ± 0.0405 , an RMSE of 0.1388 ± 0.0191 t/ha, and an MAE of 0.1141 ± 0.0203 t/ha. Emb-9-PCA ranked second among the four feature systems, with GPR producing an R^2 of 0.6940 ± 0.0675 , an RMSE of 0.1688 ± 0.0188 t/ha, and an MAE of 0.1360 ± 0.0167 t/ha. For Traditional-9, RF achieved the best performance, with an R^2 of 0.5104 ± 0.1602 , an RMSE of 0.2123 ± 0.0370 t/ha, and an MAE of 0.1741 ± 0.0291 t/ha. For Traditional-40, XGBoost showed the best performance, with an R^2 of 0.4476 ± 0.2385 , an RMSE of 0.2247 ± 0.0505 t/ha, and an MAE of 0.1842 ± 0.0412 t/ha. Among the four feature systems, Emb-64 achieved the highest R^2 and the lowest RMSE and MAE. The Emb-9-PCA feature system also showed higher predictive performance than Traditional-9 under the same number of input features. The full results for all six models under the four feature systems are provided in Table S3.

Table 5. Comparison of model performance across different feature systems.

Feature System	Features	Best Model	R^2	RMSE (t/ha)	MAE (t/ha)
Emb-64	64	XGBoost	0.7949 ± 0.0405	0.1388 ± 0.0191	0.1141 ± 0.0203
Emb-9-PCA	9	GPR	0.6940 ± 0.0675	0.1688 ± 0.0188	0.1360 ± 0.0167
Traditional-9	9	RF	0.5104 ± 0.1602	0.2123 ± 0.0370	0.1741 ± 0.0291
Traditional-40	40	XGBoost	0.4476 ± 0.2385	0.2247 ± 0.0505	0.1842 ± 0.0412

Note: Traditional-9 and Traditional-40 denote the selected nine conventional variables and all 40 conventional variables, respectively. Emb-9-PCA and Emb-64 denote the first nine principal components and the original 64-dimensional satellite embedding features, respectively. Values are reported as mean $\pm$ standard deviation from random five-fold cross-validation.

3.2.2. Observed vs. Predicted AGB

The observed–predicted relationships of the best-performing models are shown in Figure 3. The Emb-64-based XGBoost model showed the closest agreement with the 1:1 reference line, followed by the Emb-9-PCA-based GPR model. The Traditional-9-based RF and Traditional-40-based XGBoost models showed more dispersed scatter patterns. The scatter patterns were consistent with the performance ranking (Table 5).

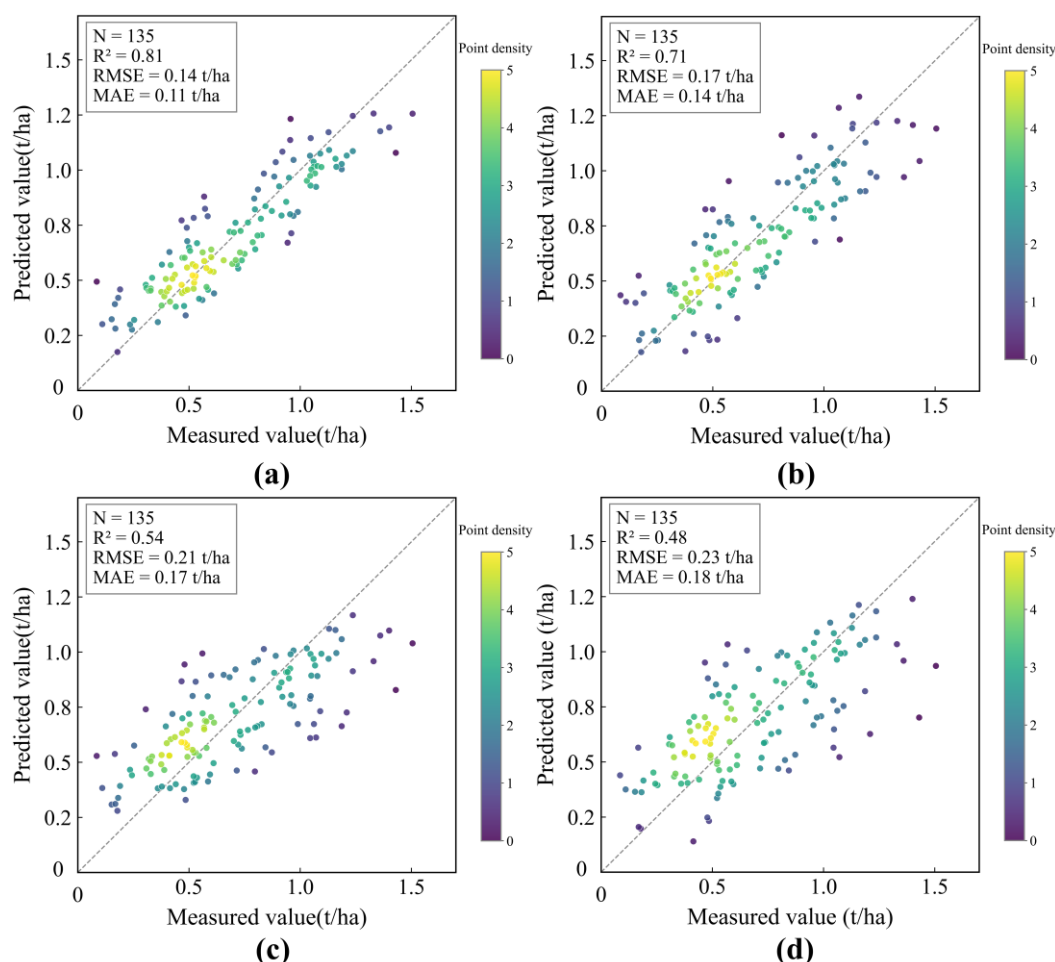


Figure 3. Observed vs. predicted AGB for the best-performing models. (a) Emb-64 + XGBoost; (b) Emb-9-PCA + GPR; (c) Traditional-9 + RF; (d) Traditional-40 + XGBoost. The dashed line represents the 1:1 reference line, and point colors indicate local point density. The metrics were calculated from pooled out-of-fold predictions.

3.3. Spatial Cross-Validation Performance

Given that Emb-64 achieved the best overall performance among the four feature systems, spatial cross-validation was further performed for the six regression models using the Emb-64 feature system. Under spatial cross-validation, XGBoost achieved the highest mean predictive performance, with an R^2 of 0.7660 ± 0.1003 , an RMSE of 0.1417 ± 0.0111 t/ha, and an MAE of 0.1165 ± 0.0124 t/ha (Table 6). LightGBM yielded the second-best performance, with an R^2 of 0.7372 ± 0.1045 , an RMSE of 0.1510 ± 0.0162 t/ha, and an MAE of 0.1232 ± 0.0151 t/ha. The other models exhibited lower predictive performance under spatial cross-validation, with mean spatial R^2 values ranging from 0.6203 to 0.6636.

The comparison between random five-fold cross-validation and spatial cross-validation showed that the R^2 values of most models decreased when spatial independence between training and validation samples was considered (Figure 4). Based on pooled out-of-fold predictions, XGBoost showed the smallest performance difference between the

two validation strategies, with R^2 values of 0.81 and 0.80 under random five-fold and spatial cross-validation, respectively. LightGBM also showed comparable performance between the two validation strategies, with corresponding R^2 values of 0.79 and 0.77. In contrast, RF showed a more pronounced decrease, with R^2 declining from 0.77 under random five-fold cross-validation to 0.66 under spatial cross-validation. These results indicate that the Emb-64-based XGBoost model retained relatively robust predictive performance under spatially independent validation and was therefore selected as the final model for regional-scale grassland AGB mapping, spatial autocorrelation analysis, and prediction uncertainty assessment.

Table 6. Model performance under random five-fold and spatial cross-validation.

Model	Random 5-Fold R^2	Spatial R^2	Spatial RMSE (t/ha)	Spatial MAE (t/ha)
XGBoost	0.7949 $\pm$ 0.0405	0.7660 $\pm$ 0.1003	0.1417 $\pm$ 0.0111	0.1165 $\pm$ 0.0124
LightGBM	0.7801 $\pm$ 0.0461	0.7372 $\pm$ 0.1045	0.1510 $\pm$ 0.0162	0.1232 $\pm$ 0.0151
RF	0.7601 $\pm$ 0.0672	0.6203 $\pm$ 0.1184	0.1829 $\pm$ 0.0205	0.1512 $\pm$ 0.0162
Elastic Net	0.7328 $\pm$ 0.0829	0.6481 $\pm$ 0.1781	0.1723 $\pm$ 0.0152	0.1423 $\pm$ 0.0150
SVR	0.7305 $\pm$ 0.0730	0.6636 $\pm$ 0.1529	0.1698 $\pm$ 0.0153	0.1361 $\pm$ 0.0156
GPR	0.7262 $\pm$ 0.0721	0.6533 $\pm$ 0.1468	0.1724 $\pm$ 0.0097	0.1398 $\pm$ 0.0137

Note: Random five-fold R^2 values are reported as the mean $\pm$ standard deviation from random five-fold cross-validation. Spatial R^2 , RMSE, and MAE values are reported as the mean $\pm$ standard deviation across spatial cross-validation folds.

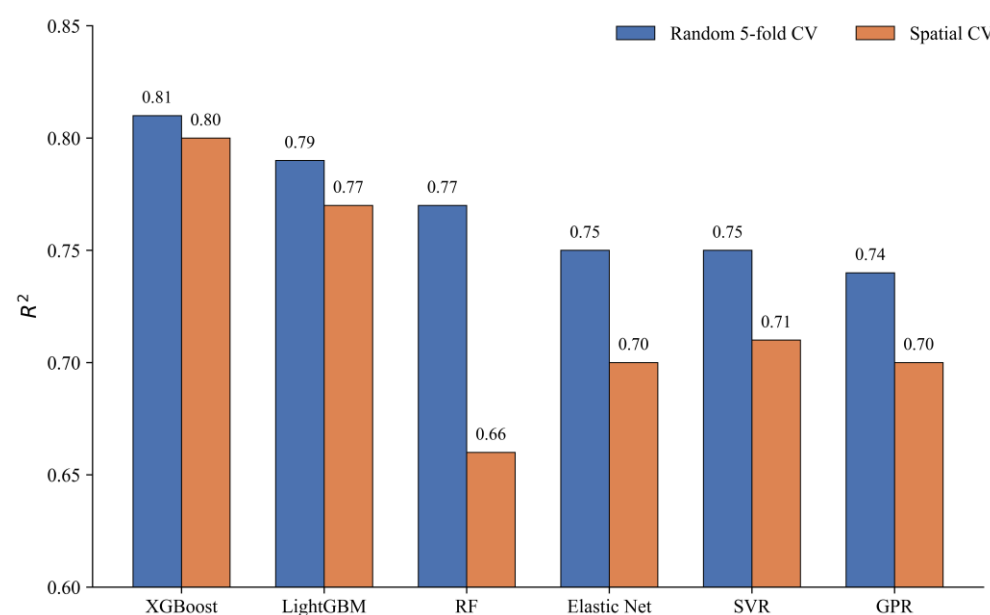


Figure 4. Comparison of pooled out-of-fold R^2 between random five-fold cross-validation and spatial cross-validation using the Emb-64 feature system. The R^2 values were calculated from pooled out-of-fold predictions.

3.4. Interpretation of Important Embedding Features

To evaluate the contribution of satellite embedding features to the Emb-64-based XGBoost model, SHAP analysis was conducted (Figure 5). The mean absolute SHAP values showed that A05 had the largest contribution, followed by A56, A06, A51, and A34. The SHAP summary plot further showed distinct SHAP value distributions among the selected embedding dimensions.

Spearman correlation analysis was further conducted between the important embedding dimensions and selected variables, including AGB and the nine conventional variables.

bles selected in Section 3.1 (Figure 6). The results showed that the important embedding dimensions exhibited different correlation patterns with AGB, topographic variables, spectral bands, vegetation indices, and radar-derived variables. Among the selected embedding dimensions, A05 showed the strongest correlation with AGB, whereas A56 showed relatively high positive correlations with EVI and RVI. Other embedding dimensions showed varying correlations with spectral, topographic, and radar-derived variables. The full correlation results between the important embedding dimensions, AGB, and all candidate conventional variables are provided in Figure S2. The ecological interpretation of these relationships is further discussed in Section 4.2.

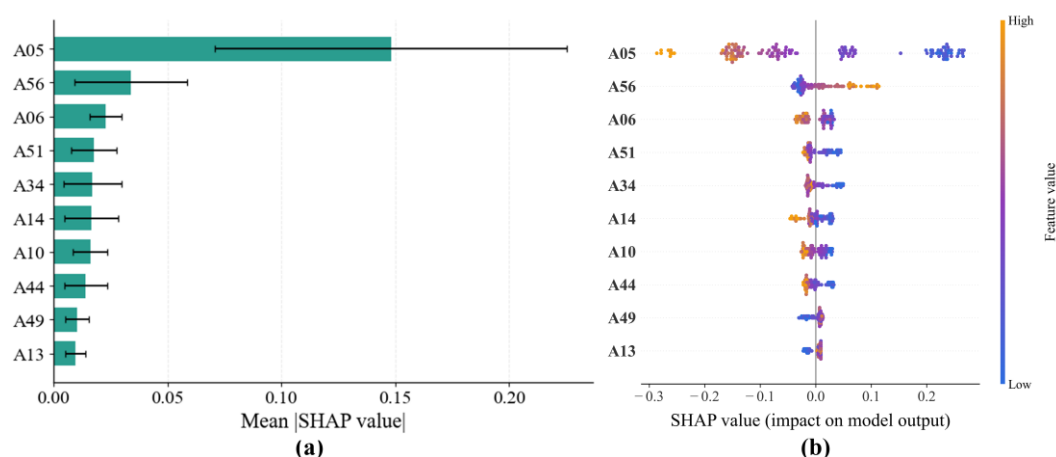


Figure 5. SHAP-based interpretation of important embedding dimensions in the Emb-64-based XGBoost model. (a) Mean absolute SHAP values of the top 10 embedding dimensions; (b) SHAP summary plot of the same dimensions.

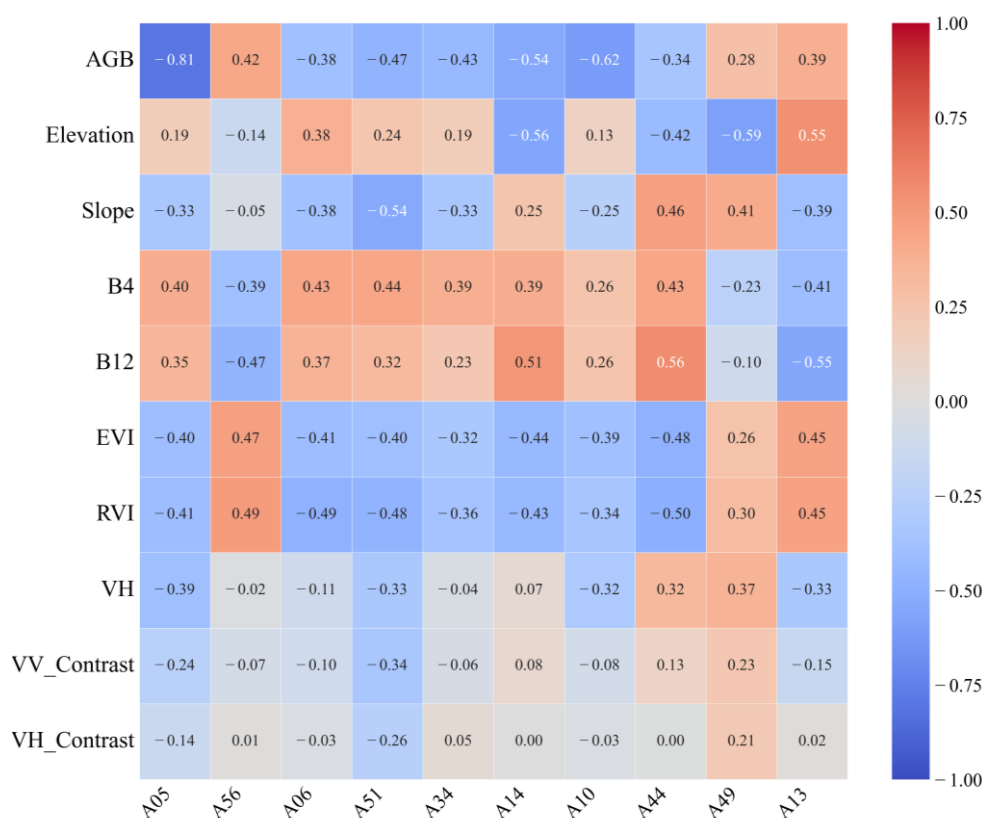


Figure 6. Spearman correlations between the top 10 important embedding dimensions, AGB, and selected conventional variables. Cell values represent Spearman correlation coefficients.

3.5. Spatial Autocorrelation of Predicted Grassland AGB

To evaluate the spatial autocorrelation of the predicted grassland AGB, global Moran's I was calculated, and a Moran scatter plot was generated. The results showed significant positive spatial autocorrelation, with a Moran's I of 0.654, a Z-score of 173.70, and a permutation test p -value of 0.001. The Moran scatterplot showed that high–high and low–low clusters accounted for 44.8% and 38.9%, respectively, together representing 83.7% of the spatial units (Figure 7).

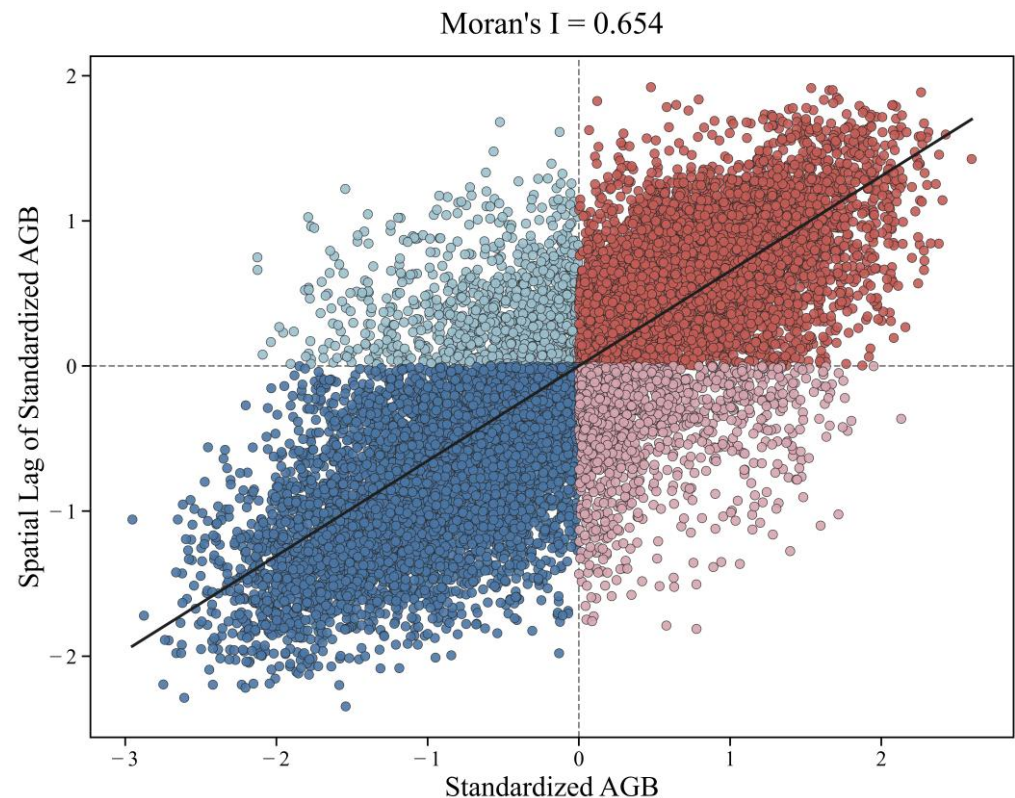


Figure 7. Moran scatter plot of predicted grassland AGB. The dashed lines indicate zero reference lines, the solid line represents the fitted Moran's I relationship, and colors denote Moran quadrant types.

3.6. Spatial Pattern and Prediction Uncertainty of Grassland AGB

The regional-scale prediction results obtained using the final XGBoost model showed that the predicted grassland AGB in the Three Parallel Rivers area ranged from 0.17 to 1.26 t/ha, with a mean value of 0.79 t/ha (Figure 8). High-AGB areas were mainly distributed in belt-like or patch-like patterns in the northern and eastern parts of the study area and in some mountainous grassland regions. Medium-AGB areas were widely distributed and constituted the dominant spatial background of regional grassland AGB. Low-AGB areas occurred mainly as scattered patches in regions with sparse grassland cover or fragmented spatial patterns. The enlarged views further showed fine-scale spatial variation of grassland AGB in mountainous areas and grassland patch mosaics.

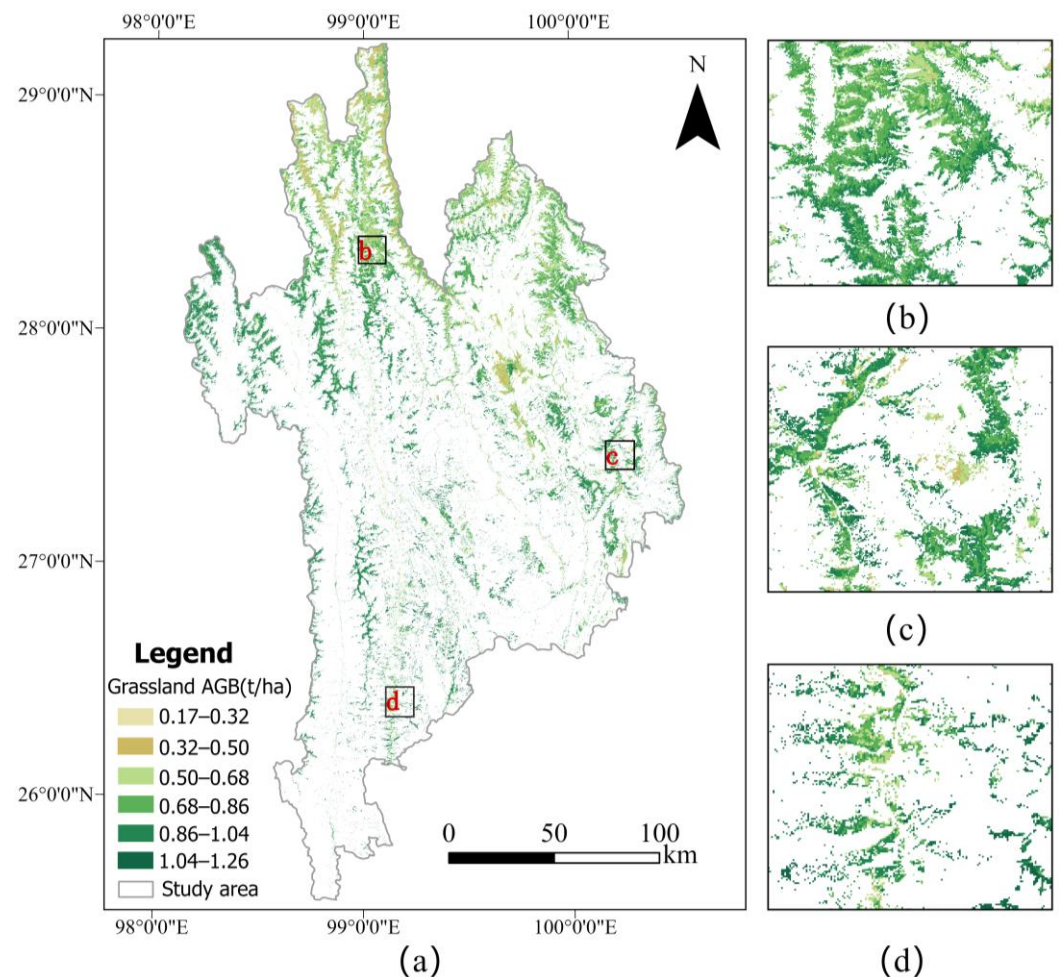


Figure 8. Spatial distribution of predicted grassland AGB in the Three Parallel Rivers area. (a) Regional-scale prediction map; (b) low-AGB area; (c) medium-AGB area; (d) high-AGB area. The red boxes and letters in panel (a) indicate the locations of the enlarged areas shown in panels (b–d).

Bootstrap uncertainty analysis showed spatial heterogeneity in grassland AGB prediction uncertainty (Figure 9). The 0.12–0.20 t/ha uncertainty class accounted for the largest proportion, at 61.35%, followed by the 0.20–0.29 t/ha and 0.05–0.12 t/ha classes, which accounted for 21.88% and 14.64%, respectively. The higher uncertainty classes, 0.29–0.39 t/ha and 0.39–0.49 t/ha, accounted for smaller proportions, at 2.08% and 0.06%, respectively. Spatially, higher prediction uncertainty was mainly distributed in mountainous fragmented areas, grassland edges, and patch transition zones, whereas lower uncertainty was observed in areas with more continuous grassland distribution.

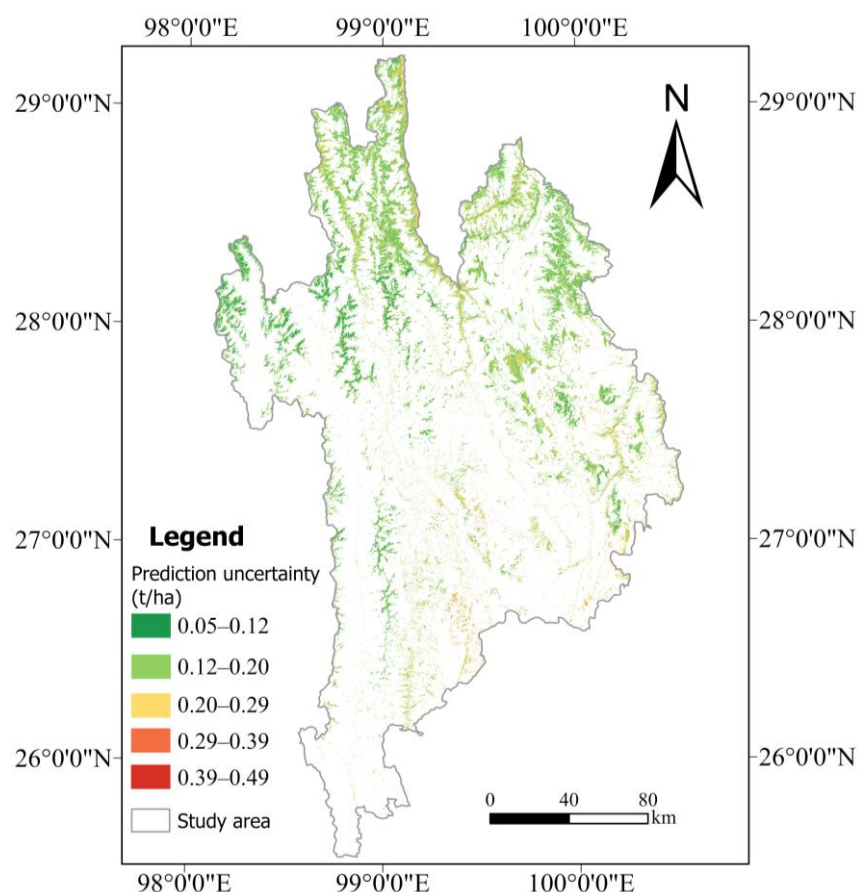


Figure 9. Spatial distribution of grassland AGB prediction uncertainty.

4. Discussion

4.1. Representation Capacity of Satellite Embedding Features

Remote sensing estimation of grassland AGB in complex mountainous terrain is affected by the combined influences of vegetation structure, topographic gradients, environmental heterogeneity, and grassland patch fragmentation. Conventional remote sensing variables, such as spectral bands, vegetation indices, radar backscatter, texture features, and topographic factors, provide physically interpretable predictors, but their individual or limited combinations may be insufficient to fully characterize the nonlinear and spatially heterogeneous responses of grassland AGB in alpine canyon landscapes. Previous studies have reported that optical vegetation indices may suffer from saturation effects under dense or heterogeneous vegetation conditions, whereas radar and texture features can provide complementary but still partial information on vegetation structure and surface heterogeneity [10,34]. In this context, high-dimensional remote sensing representations generated by Earth science foundation models and self-supervised representation learning provide a new way to integrate multisource Earth observation information into a unified latent feature space [15,34,35].

The comparison among feature systems with different dimensionality settings provides further insight into the representation capacity of satellite embedding features. Emb-64 achieved the highest overall predictive performance, with an R^2 of 0.7949 ± 0.0405 , whereas Emb-9-PCA still reached an R^2 of 0.6940 ± 0.0675 after reducing the original 64-dimensional embedding features to nine principal components. In contrast, Traditional-9 and Traditional-40 achieved lower R^2 values of 0.5104 ± 0.1602 and 0.4476 ± 0.2385 , respectively. These results suggest that the performance gain of satellite embedding features was not simply a consequence of using more input variables. Instead, the advantage was more

likely associated with the information structure preserved in the learned latent representation.

The stronger performance of the embedding-based feature systems suggests that satellite embeddings may retain integrated information from multisource and multitemporal Earth observations that is difficult to represent using a limited set of manually constructed variables. In complex mountainous grasslands, AGB variation is jointly controlled by spectral responses, vegetation vigor, terrain gradients, moisture-related conditions, and local surface heterogeneity. A latent representation learned from large-scale Earth observation data may therefore provide a more compact and comprehensive description of these coupled conditions [36]. However, this does not imply that conventional remote sensing variables are unimportant. Conventional variables remain essential for ecological interpretation, mechanism analysis, and comparison with existing remote sensing-based AGB estimation studies. Therefore, satellite embedding features should be regarded as a complementary high-dimensional representation rather than a direct replacement for physically interpretable variables. Under the current study area, sample conditions, and validation framework, the results indicate that satellite embeddings provided stronger representational capacity for grassland AGB estimation, while their broader transferability still requires further validation.

4.2. Interpretability of Important Embedding Dimensions

Although satellite embedding features improved grassland AGB estimation, their latent nature makes dimension-level interpretation more challenging than that of conventional remote sensing variables. Unlike spectral bands, vegetation indices, radar backscatter, texture features, or DEM-derived variables, individual embedding dimensions are learned axes in a multidimensional representation space and generally do not correspond to predefined physical or ecological quantities [15,22,34]. Therefore, the interpretation of important embedding dimensions should be based on their contribution to model predictions and their quantitative associations with known environmental variables, rather than assigning direct physical meanings to individual dimensions.

The SHAP analysis showed that the Emb-64-based XGBoost model was primarily influenced by a limited number of embedding dimensions, with A05, A56, A06, A51, and A34 ranking as the most important contributors. TreeSHAP provides an effective framework for interpreting tree-based ensemble models by quantifying the contribution of each feature to model predictions [37], and similar XGBoost–SHAP frameworks have been applied in remote sensing-based AGB estimation to improve model interpretability [38]. In this study, the concentration of high SHAP values in several embedding dimensions indicates that the predictive information in the satellite embedding representation was not uniformly distributed across all 64 dimensions. Instead, the model relied more strongly on a subset of latent dimensions that were more closely associated with AGB variation.

The Spearman correlation analysis further provided quantitative evidence for the relationships between important embedding dimensions and conventional environmental variables. Among the important dimensions, A05 showed the strongest absolute correlation with AGB, while A56 showed relatively high positive correlations with vegetation-index variables such as EVI and RVI. Other important dimensions exhibited varying correlations with spectral bands, radar-derived texture features, and topographic factors. These associations suggest that the important embedding dimensions were related to multiple types of information relevant to grassland AGB estimation, including vegetation conditions, spectral responses, surface structural heterogeneity, and terrain gradients. This interpretation is consistent with previous studies showing that vegetation indices can characterize vegetation vigor and canopy greenness [8], radar backscatter and texture features can provide information on vegetation structure and spatial heterogeneity [10], and

topographic factors can strongly influence remote sensing signals and vegetation distribution in mountainous regions [20]. At the same time, the known saturation and sensitivity limitations of conventional optical vegetation indices under dense or heterogeneous vegetation conditions [39] may partly explain why latent embedding features can provide additional information beyond manually constructed variables.

Nevertheless, these relationships should be interpreted cautiously. Correlation analysis does not establish causality, and a single satellite embedding dimension may encode mixed information from multiple spectral, structural, temporal, and environmental signals. Therefore, A05 should not be interpreted as a direct biomass indicator, nor should A56 be regarded as a direct substitute for vegetation indices. Instead, the SHAP and correlation analyses provide indirect but quantitative evidence that the satellite embedding space contains information associated with AGB variation and related environmental gradients. This improves the ecological interpretability of the embedding-based model while acknowledging that the physical meanings of individual latent dimensions remain inherently indirect. Future studies should further examine whether these embedding–environment relationships remain stable across different years, grassland types, and geographic regions, which would be important for assessing the transferability of satellite embedding-based AGB estimation frameworks.

4.3. Model Adaptability, Nonlinearity, and Spatial Robustness

The performance differences among models indicate that the predictive advantage of satellite embedding features was also influenced by model architecture. Satellite embedding dimensions are learned latent variables rather than independently designed physical predictors, and their predictive information may be expressed through nonlinear combinations and interactions among dimensions. Tree boosting models, such as XGBoost and LightGBM, are well suited to this type of feature structure because they can iteratively capture nonlinear relationships, threshold effects, and high-order feature interactions [40]. This may explain why XGBoost and LightGBM consistently achieved the best performance under both random five-fold cross-validation and spatial cross-validation. In contrast, Elastic Net assumes a primarily linear relationship between predictors and AGB, while SVR and GPR may be more sensitive to sample size, feature distribution, and spatial shifts in high-dimensional settings. These differences suggest that the effectiveness of satellite embedding features depends not only on their representation capacity but also on their compatibility with model structures capable of capturing nonlinear ecological responses.

The spatial cross-validation results provided a more stringent evaluation of model robustness than random five-fold cross-validation. Random partitioning may produce overly optimistic accuracy estimates when nearby field plots share similar environmental and spectral conditions, whereas spatial cross-validation evaluates model performance under more spatially independent validation conditions [19,29,30]. In this study, most models showed reduced R^2 values under spatial cross-validation, indicating that spatial sample partitioning increased the difficulty of prediction. Nevertheless, the Emb-64-based XGBoost model retained the highest mean spatial cross-validation performance, and LightGBM ranked second. The relatively small difference between random and spatial pooled out-of-fold R^2 values for XGBoost further suggests that this model maintained comparatively stable predictive ability under spatially independent validation.

The increased standard deviation of R^2 under spatial cross-validation also indicates that model performance varied among spatial folds. This variability is expected in the Three Parallel Rivers region, where field plots are distributed across strong elevation gradients, fragmented grassland patches, and heterogeneous environmental conditions. Therefore, the spatial cross-validation results should not be interpreted as eliminating all

overfitting risk, but rather as providing a more rigorous internal test of spatial generalization. The relatively stable performance of XGBoost under this validation strategy supports its selection as the final model for regional-scale grassland AGB mapping. However, external validation across additional regions, years, and grassland types remains necessary to further evaluate the transferability of the satellite embedding-based modeling framework.

4.4. Spatial Pattern and Uncertainty Implications of Grassland AGB Mapping

The regional-scale AGB mapping results showed clear spatial heterogeneity in the Three Parallel Rivers region, with the coexistence of local high-AGB patches and extensive medium- to low-AGB areas. Higher AGB values were mainly distributed in the northern and eastern parts of the study area and in some mountainous grassland regions, whereas medium- and low-AGB areas formed the dominant spatial background. This spatial pattern is consistent with the alpine canyon geomorphological setting of the study area, where strong elevation gradients, fragmented terrain, hydrothermal differentiation, and local habitat variation jointly influence grassland growth conditions. Previous studies have also shown that vegetation biomass in mountainous regions is commonly regulated by environmental gradients and local habitat heterogeneity [41].

The significant positive spatial autocorrelation of predicted grassland AGB further indicated that the regional mapping results retained spatially organized patterns rather than random spatial variation. The high–high and low–low clustering types accounted for most spatial units, suggesting that similar AGB values tended to be spatially aggregated. In complex mountainous landscapes, such spatial organization may reflect the combined effects of terrain constraints, vegetation patch continuity, and environmental gradients. Spatial statistical methods such as Moran's I and local spatial association analysis have been widely used to characterize clustering patterns of ecological and environmental variables and to support the interpretation of regional-scale spatial patterns [42]. Therefore, the spatial autocorrelation result provides additional statistical support for the mapped AGB pattern.

Prediction uncertainty provides complementary information for evaluating the reliability of regional-scale grassland AGB mapping. In this study, higher prediction uncertainty was mainly distributed in mountainous fragmented areas, grassland edges, and patch transition zones, whereas lower uncertainty was observed in areas with more continuous grassland distribution. These spatial differences suggest that prediction uncertainty was higher in areas with stronger environmental heterogeneity, more complex land-cover boundaries, or less stable relationships between input features and AGB. Uncertainty quantification has been increasingly emphasized in remote sensing retrieval of biophysical variables because it helps identify where model outputs are more reliable and where caution is needed in interpretation and application [43]. Therefore, high-uncertainty areas should not be regarded as invalid predictions, but rather as regions where the AGB estimates require more careful interpretation in combination with local environmental conditions and additional field information.

The joint analysis of predicted AGB distribution, spatial autocorrelation, and prediction uncertainty improves the practical value of the regional AGB map. Areas with relatively low uncertainty and coherent spatial patterns may provide more reliable information for grassland productivity assessment and carbon stock estimation, whereas fragmented mountainous areas and grassland transition zones should be treated as priority areas for future sampling and model refinement. This uncertainty-aware mapping framework can therefore support both regional-scale grassland resource assessment and the identification of locations where further field validation is most needed.

4.5. Limitations, Temporal Mismatch, and Future Transferability

Although this study demonstrated the potential of satellite embedding features for grassland AGB estimation in complex mountainous terrain, the results should be interpreted within several limitations. First, model development and regional mapping were based on 135 field plots collected from a single study region and one survey year. The Three Parallel Rivers region is characterized by fragmented terrain, strong elevation gradients, heterogeneous grassland patches, and complex local environmental conditions. Under such conditions, the current sample size and spatial coverage may still be insufficient to fully represent transition zones, rare grassland conditions, and extreme AGB values. Therefore, the prediction results are more suitable for characterizing regional-scale spatial patterns of grassland AGB than for reconstructing fine-scale local variation with high precision.

Second, a temporal-scale difference exists between the annual satellite embedding product and the field AGB measurements. The 2022 annual satellite embedding features represent integrated surface conditions over the full year, whereas the field AGB measurements and conventional remote sensing variables mainly correspond to the peak growing season from July to September. The annual embedding representation may provide useful information by integrating multi-temporal surface conditions, but it may also contain signals from periods outside the peak biomass season. This temporal mismatch could affect the comparison between annual latent representations and growing-season explicit variables, particularly for fast-growing grassland ecosystems with strong seasonal dynamics. Future studies should further compare annual, seasonal, and phenology-specific embedding representations to evaluate how temporal aggregation influences grassland AGB estimation.

Third, although spatial cross-validation and Bootstrap-based uncertainty analysis were used to evaluate model robustness, they cannot fully replace external independent validation. Spatial cross-validation provides a more stringent internal evaluation than random partitioning and reduces the risk of overly optimistic accuracy estimates caused by spatial dependence among nearby samples [19,29,30]. However, model transferability across different regions, years, grassland types, and climatic conditions remains to be tested. Similarly, Bootstrap-based uncertainty analysis provides useful information on the spatial reliability of the prediction map, but it does not fully account for all possible sources of uncertainty, such as field measurement errors, remote sensing preprocessing uncertainties, grassland mask errors, and model structural uncertainty [43,44].

Finally, the ecological interpretation of satellite embedding dimensions remains indirect. The SHAP and Spearman correlation analyses provided quantitative evidence that important embedding dimensions were associated with AGB and selected conventional environmental variables. However, individual embedding dimensions are latent features and should not be directly equated with explicit physical or ecological variables. Future studies should further investigate the stability of embedding–environment relationships across years and regions and combine embedding analysis with field ecological traits, phenological metrics, topographic gradients, and hydrothermal variables. Expanding field sample size, improving the coverage of transition zones and extreme AGB conditions, and conducting independent cross-region and cross-year validation will be necessary to improve the robustness, interpretability, and general applicability of satellite embedding-driven models for grassland AGB estimation in complex mountainous regions.

5. Conclusions

This study evaluated the applicability of satellite embedding features for grassland AGB estimation in the Three Parallel Rivers region of Yunnan Province, China. Based on 135 field plots and 2022 satellite embedding features, four feature systems and six regres-

sion models were compared. Spatial cross-validation, SHAP analysis, Spearman correlation analysis, regional-scale AGB mapping, spatial autocorrelation analysis, and Bootstrap-based uncertainty assessment were further conducted. The main conclusions are as follows:

- (1) The original 64-dimensional satellite embedding feature system showed the highest predictive performance among the four feature systems. The Emb-64-based XGBoost model achieved an R^2 of 0.7949 ± 0.0405 , an RMSE of 0.1388 ± 0.0191 t/ha, and an MAE of 0.1141 ± 0.0203 t/ha under random five-fold cross-validation. The Emb-9-PCA feature system also outperformed Traditional-9 under the same number of input features, whereas Traditional-40 did not improve model performance relative to the selected conventional feature system. These results suggest that the advantage of satellite embedding features was not solely attributable to higher dimensionality but was also related to the information structure preserved in the learned latent representation.
- (2) Under spatial cross-validation, the Emb-64-based XGBoost model retained the highest mean predictive performance among the six models, with an R^2 of 0.7660 ± 0.1003 , an RMSE of 0.1417 ± 0.0111 t/ha, and an MAE of 0.1165 ± 0.0124 t/ha. The comparison between random and spatial cross-validation indicated that XGBoost maintained relatively stable predictive performance under spatially independent validation. These results support the use of XGBoost as the final model for regional-scale grassland AGB mapping in this study.
- (3) The SHAP analysis identified several important satellite embedding dimensions, with A05 showing the largest contribution, followed by A56, A06, A51, and A34. Spearman correlation analysis further showed that these important embedding dimensions were associated with AGB and selected conventional variables. These results provide quantitative evidence for improving the interpretability of the embedding-based model, although individual embedding dimensions should still be regarded as latent features rather than direct physical or ecological variables.
- (4) The regional-scale mapping results showed that predicted grassland AGB ranged from 0.17 to 1.26 t/ha, with a mean value of 0.79 t/ha. The predicted AGB exhibited significant positive spatial autocorrelation, with a Moran's I of 0.654, indicating spatial clustering of similar AGB values. Bootstrap-based uncertainty analysis showed that most grassland areas were characterized by low to moderate prediction uncertainty, whereas higher uncertainty mainly occurred in fragmented mountainous areas, grassland edges, and transition zones.

Overall, the results indicate that satellite embedding features provide a promising high-dimensional representation for grassland AGB estimation in complex mountainous regions. Rather than replacing conventional remote sensing variables, satellite embeddings can serve as a complementary representation that enhances predictive performance while retaining links to conventional environmental information. Nevertheless, this study was based on one study area, one survey year, and 135 field plots. Future studies should further evaluate the transferability and robustness of satellite embedding-based AGB estimation across different regions, years, grassland types, and independent validation datasets.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18142348/s1>, Table S1: Description of candidate conventional remote sensing variables; Table S2: Number of field plots in each spatial group used for spatial cross-validation; Table S3: Full model performance of all six models under different feature systems; Figure S1: Pearson correlation matrix of candidate conventional remote sensing variables. Red and blue ellipses indicate positive and negative correlations, respectively, and the color intensity and el-

lipse shape represent the strength of the correlation; Figure S2: Spearman correlation heatmap between the top 10 important embedding dimensions, AGB, and all candidate conventional variables. The color scale represents Spearman correlation coefficients, ranging from −1 to 1.

Author Contributions: Conceptualization, W.L. and H.Z.; methodology, W.L. and Q.S.; software, W.L., H.Z. and B.Z.; validation, W.L., Q.S.; formal analysis, W.L. and T.H.; investigation, W.L. and Q.S.; resources, Q.S., X.R. and J.L.; data curation, Q.S.; writing—original draft preparation, W.L.; writing—review and editing, W.L., Q.S., Y.W. and X.W.; visualization, Q.S.; supervision, Q.S., B.Z., Y.W. and R.W.; project administration, W.L. and Q.S.; funding acquisition, Q.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The satellite embedding data, Sentinel-1, Sentinel-2, and DEM data used in this study were obtained through the Google Earth Engine platform (available online: <https://earthengine.google.com/>, accessed on 18 February 2026). Relevant actual measurement data can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AGB	Aboveground biomass
DEM	Digital Elevation Model
GEE	Google Earth Engine
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SHAP	SHapley Additive exPlanations
PCA	Principal component analysis
RFE	Recursive feature elimination
GLCM	Gray-level co-occurrence matrix
OOF	Out-of-fold
SRTM	Shuttle Radar Topography Mission

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