



Article

Mapping Shrub Biomass at 10 m Resolution by Integrating Field Measurements, Unmanned Aerial Vehicles, and Multi-Source Satellite Observations

Wenchao Liu ¹, Jie Wang ^{1,*} , Yang Hu ² , Taiyong Ma ³ , Munkhdulam Otgonbayar ⁴ , Chunbo Li ¹, You Li ¹ and Jilin Yang ¹

¹ College of Grassland Science and Technology, China Agricultural University, Beijing 100193, China; sugarvinegar@outlook.com (W.L.); chunboli@cau.edu.cn (C.L.); 13194973225@163.com (Y.L.); jlyang@cau.edu.cn (J.Y.)

² School of Ecology and Environment, Ningxia University, Yinchuan 750021, China; huyang@nxu.edu.cn

³ College of Forestry and Prataculture, Ningxia University, Yinchuan 750021, China; mataiyong506@stu.nxu.edu.cn

⁴ Division of Physical Geography and Environmental Research, Institute of Geography and Geoecology, Mongolian Academy of Sciences, Ulaanbaatar 15170, Mongolia

* Correspondence: jiewang178@cau.edu.cn

Abstract: Accurately estimating shrub biomass in arid and semi-arid regions is critical for understanding ecosystem productivity and carbon stocks at both local and global scales. Due to the short and sparse features of shrubs, capturing the shrub biomass accurately by satellite observations is challenging. Previous studies mostly used ground samples and satellite observations to estimate shrub biomass by establishing a direct connection, which was often hindered by the limited number of ground samples and spatial scale mismatch between samples and observations. Unmanned aerial vehicles (UAVs) provide opportunities to obtain more samples that are in line with the aspects of satellite observations (i.e., scale) for regional-scale shrub biomass estimations accurately with low costs. However, few studies have been conducted based on the air-space-ground-scale connection assisted by UAVs. Here we developed a framework for estimating 10 m shrub biomass at a regional scale by integrating ground measurements, UAV, Landsat, and Sentinel-1/2 observations. First, the spatial distribution map of shrublands and non-shrublands was generated in 2023 in the Helan Mountains of Ningxia province, China. This map had an F1 score of 0.92. Subsequently, the UAV-based shrub biomass map was estimated using an empirical model between the biomass and the crown area of shrubs, which was aggregated at a 10 m × 10 m grid to match the spatial resolution of Sentinel-1/2 images. Then, a regional-scale estimation model of shrub biomass was developed with a random forest regression (RFR) approach driven by ground biomass measurements, UAV-based biomass, and the optimal satellite metrics. Finally, the developed model was used to produce the biomass map of shrublands over the study area in 2023. The uncertainty of the resultant biomass map was characterized by the pixel-level standard deviation (SD) using the leave-one-out cross-validation (LOOCV) method. The results suggested that the integration of multi-scale observations from the ground, UAVs, and satellites provided a promising approach to obtaining the regional shrub biomass accurately. Our developed model, which integrates satellite spectral bands and vegetation indices ($R^2 = 0.62$), outperformed models driven solely by spectral bands ($R^2 = 0.33$) or vegetation indices ($R^2 = 0.55$). In addition, our estimated biomass has an average uncertainty of less than 4%, with the lowest values (<2%) occurring in regions with high shrub coverage (>30%) and biomass production (>300 g/m²). This study provides a methodology to accurately monitor the shrub biomass from satellite images assisted by near-ground UAV observations as well as ground measurements.

Keywords: remote sensing; vegetation mapping; environmental monitoring; UAV; land cover



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1. Introduction

In recent years, more and more attention has been paid to environmental protection and ecosystem restoration due to the impacts of human activities and global climate change [1–4]. As an important vegetation type, shrubs play crucial roles in the conservation and restoration of ecosystems [5–7], such as soil conservation, sand fixation, habitat maintenance, and so on [8–11]. Shrub biomass is a critical measurement indicator to assess shrub growth status and productivity [12,13]. Therefore, accurately estimating shrub biomass is vital for monitoring the dynamics of vegetation growth, assessing ecological functions, and evaluating ecosystem carbon storage at the regional scale [14–16].

Field surveys, as a traditional approach, often have limitations in large-scale monitoring of shrub biomass considering the following factors [17]. Firstly, field surveys need substantial human resources and financial investment and are time-consuming, particularly in areas with intricate topography [18,19]. Secondly, field surveys can only obtain limited samples, making it challenging to fully capture the spatial distributions and temporal patterns of shrubs. Meanwhile, the destructive sampling techniques to quantify shrub biomass may potentially affect the surrounding environment [20]. Furthermore, the biomass of shrubs is influenced by various factors such as vegetation structure, environmental conditions, and climatic variations [21,22]. It is challenging to accurately represent the spatial distributions of shrub biomass at large scales by collecting shrub biomass samples in field surveys.

To address the limitations of conventional field surveys, remote sensing technology has emerged as an efficient tool for estimating shrub biomass [23–25]. For example, satellites can acquire extensive and continuous data with high spatial and temporal resolutions, facilitating large-scale estimation of shrub biomass such as Landsat and Sentinel series [26–28]. Previous studies have applied the combined Sentinel-1/2 satellite images to map the distribution of shrubland biomass from landscape to regional scales [27,28]. However, the performance of utilizing satellite images for shrub biomass estimation is related to selecting suitable satellite metrics [29]. For example, only utilizing the visible and near-infrared bands with wide wavelength ranges makes it challenging to capture the features related to shrub biomass, such as vegetation structure and leaf area index [30]. Therefore, more and more vegetation indices have been used as important indicators for biomass estimation [31]. The vegetation indices are numerical values calculated from spectral bands that can reflect key information about vegetation growth status like chlorophyll content, leaf area index, and other related features [32,33]. However, the sensitivity of existing vegetation indices to shrub biomass varies, and some indices may reach saturation in highly vegetated regions [34]. Therefore, it is still needed to understand the contributions of each vegetation indices or spectral bands to accurately estimate the shrub biomass.

In addition to the utilized satellite metrics, the simulation algorithms have been improved gradually in the last decades. Traditionally, statistical regression approaches were employed to estimate biomass by establishing empirical relationships between field-measured biomass and remote sensing variables [35]. However, these models had limitations in capturing complex nonlinear relationships, and the simulation accuracy was affected by the spatial heterogeneity [36]. Over time, several modeling approaches have been developed to enhance the precision of estimating shrub biomass [37–39]. In particular, machine learning methods have become the most used tools due to their superior performance compared to conventional modeling methods [40]. For example, machine learning methods like random forests, support vector machines, and boosted regression trees have been reported with great potential to handle complex and nonlinear relationships in biomass simulations [41,42]. Additionally, machine learning methods can effectively handle large volumes of remote sensing metrics, including multispectral and hyperspectral imagery, which provide rich remote sensing information for accurate biomass estimation across shrublands [40,43,44].

The accuracy of the satellite-based biomass estimation is often affected by two main features of training samples, including (1) the scale mismatch between the limited ground measurement area and the resolution of satellite images [27] and (2) the number of field samples [28]. Unmanned aerial vehicles (UAVs) have advantages to address these issues in shrub biomass estimation [37,45]. UAVs equipped with high-resolution sensors and advanced image processing techniques can capture high spatial resolution remote sensing imagery [46,47]. The high spatial resolutions allow for the capture of finer details of shrub structure and characteristics [48]. This capability is crucial for improving satellite-based biomass estimation by providing high-resolution near-ground observations and bridging the gaps of spatial scales between satellite observations and ground measurements [27,28]. Additionally, they can capture large areas of shrub coverage from a high-altitude perspective, which facilitates the rapid and accurate identification and extraction of shrub objects [37,49–51]. Thus, UAVs can improve workflow efficiency to gather more samples by lowering manpower, saving time, and reducing costs compared to traditional field measurements [52]. However, the studies are still limited to the estimation of shrub biomass at the regional scale by integrating UAV-derived shrub biomass and satellite observations.

This work aimed to propose a framework to estimate shrub biomass over a mountain region by integrating multi-scale data from field measurements, UAV-based biomass estimation, and satellite observations (Sentinel-1/2, Landsat). The Helan Mountains in Ningxia province, China, were selected as the study area. Firstly, the distribution of the shrublands and non-shrublands in the study area was identified by a land cover classification. Secondly, the shrub biomass was estimated based on the UAV images and the in situ measurements by establishing the allometric growth equation between shrub biomass and shrub structure parameters. Finally, the biomass distribution of shrubs was mapped based on the satellite observations using the optimal random forest regression (RFR) model across the Helan Mountains by utilizing the field measurements and UAV-based shrub biomass as samples. The optimal RFR was developed by selecting the sensitive satellite metrics to shrub biomass from the spectral bands, vegetation indices, and backscatter bands from the Landsat and Sentinel-1/2 images. The accuracy of the resultant map was evaluated over various ranges of shrub biomass or shrub coverage. This study provides a methodology to accurately estimate the biomass of shrubs at the satellite scale by incorporating near-ground UAV observations. This approach increases the training samples of shrub biomass and addresses the scale mismatch between ground measurements and satellite observations.

2. Material and Methods

2.1. Study Area

The Helan Mountains are a remnant range of the Kunlun Mountains and are situated at the intersection of the Ningxia Hui Autonomous Region and the Inner Mongolia Autonomous Region. The main peak of the Helan Mountains in Ningxia has an elevation of 3556 m and covers an area of approximately 2100 km². The mean annual temperature in the study area is around -0.8°C , with a mean annual precipitation of about 430 mm (Figure 1).

The study area represents a typical temperate arid mountain region with diverse vegetation types. It is mainly covered by evergreen coniferous forests, deciduous broad-leaved forests, evergreen coniferous shrubs, deciduous broad-leaved shrubs, typical grasslands, and desert grasslands, with slope direction and elevation influencing distribution patterns. Furthermore, the region has several shrub species, including *Amygdalus pedunculata*, *Caragana korshinskii*, and Mongolian almond.

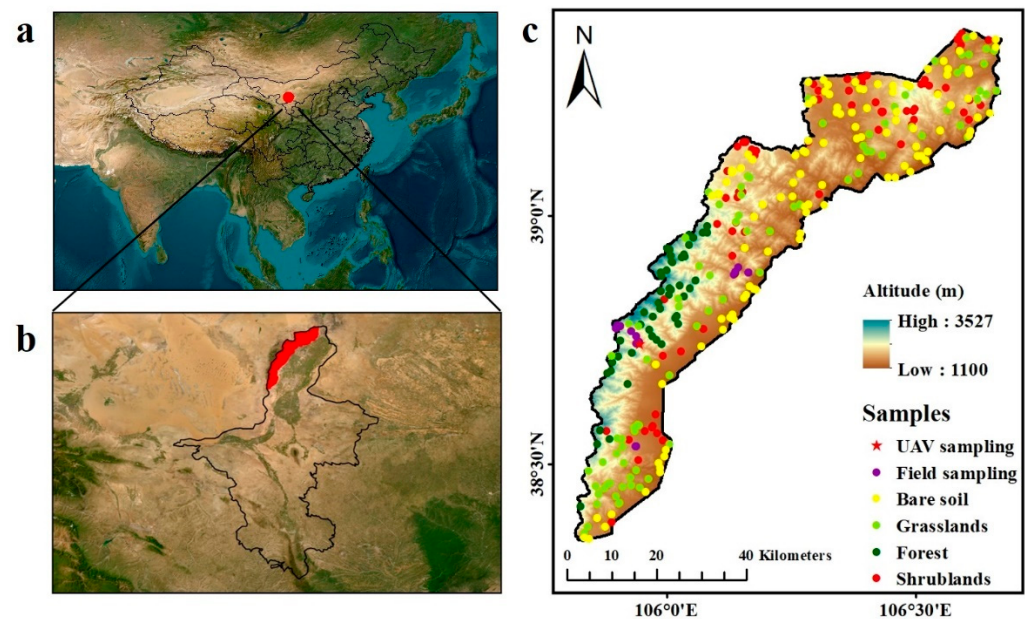


Figure 1. (a,b) Locations of the Helan Mountain in China and Ningxia province, and (c) the distribution of ground truth samples from field measurements, UAV, and visual interpretation.

2.2. Data

2.2.1. Landsat and Sentinel-1/2 Data and Pre-Processing

Our study utilized all available Landsat 8/9, Sentinel-2, and Sentinel-1 satellite images from late July to early August 2023. These satellite datasets were accessed through Google Earth Engine (GEE). Landsat-8 Operational Land Imager (OLI) and Landsat-9 OLI-2 data were utilized, which include visible, infrared, and shortwave infrared bands with a spatial resolution of 30 m. This study also used Sentinel-2 multispectral instrument (MSI) Level-2A products, which provide red-edge band data additionally at 10 m compared to Landsat. Sentinel-1 provides dual-polarization C-band Synthetic Aperture Radar (SAR) observations operating at 5.405 GHz (C band), including vertical receive (VV) and horizontal receive (VH) bands. Thus, our dataset includes three visible bands, three red-edge bands, one near-infrared band, two shortwave infrared bands, and two radar bands.

The spatial resolution of the Landsat 8/9 image was resampled to 10 m with the bilinear method in GEE to match the spatial resolution of the Sentinel-2. To identify the quality of the satellite images, the pixel-wise quality control operation images were processed by using the quality assurance (QA) band and CFMask algorithm [53]. Due to some differences in bandwidth between MSI, OLI, and ETM+ sensors, the band reflectance values were then matched among the three sensors to construct reliable time series by the ordinary least squares regression method proposed by Roy (2016) [54]. Thus, the harmonized Landsat/Sentinel-2 datasets were generated.

With the harmonized Landsat/Sentinel-2 datasets, various vegetation indices that are sensitive to shrub biomass were calculated [27] to select the optimal predictor variables for constructing the model. In total, 28 vegetation indices were selected and then computed on the GEE platform (Table 1).

Table 1. Vegetation indices (VIs) for the estimates of shrub biomass in this study. R = red; G = green; B = blue; RE = RedEdge1; NIR = near-infrared; SWIR1 = shortwave infrared 1; SWIR2 = shortwave infrared 2. ρ represents the band of NIR, $\sigma = 0.5 \times (\text{NIR} + \text{red})$.

No.	Index	Formula
1	Normalized difference vegetation index [55]	$\text{NDVI} = \frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}}$
2	Enhanced vegetation index 1 [56]	$\text{EVI} = \frac{2.5 \times (\text{NIR}-\text{R})}{\text{NIR}+6 \times \text{R}-7.5 \times \text{B}+1}$
3	Land surface water index [57]	$\text{LSWI} = \frac{\text{NIR}-\text{SWIR1}}{\text{NIR}+\text{SWIR1}}$
4	Difference vegetation index [58]	$\text{DVI} = \text{NIR} - \text{R}$
5	Green normalized difference vegetation index [59]	$\text{GNDVI} = \frac{\text{NIR}-\text{G}}{\text{NIR}+\text{G}}$
6	Vegetation index green [60]	$\text{VIgreen} = \frac{\text{G}-\text{R}}{\text{G}+\text{R}}$
7	Infrared simple ratio [61]	$\text{ISR} = \frac{\text{NIR}}{\text{SWIR1}}$
8	Moisture stress index [62]	$\text{MSI} = \frac{\text{SWIR1}}{\text{NIR}}$
9	Ratio vegetation index [63]	$\text{RVI} = \frac{\text{R}}{\text{NIR}}$
10	Simple ratio [64]	$\text{SR} = \frac{\text{NIR}}{\text{R}}$
11	Enhanced vegetation index 2 [65]	$\text{EVI}_2 = \frac{2.5 \times (\text{NIR}-\text{R})}{\text{NIR}+2.4 \times \text{R}+1}$
12	Modified simple ratio [66]	$\text{MSR} = \frac{\frac{\text{NIR}}{\text{R}}-1}{\sqrt{\frac{\text{NIR}}{\text{R}}+1}}$
13	Optimized soil-adjusted vegetation index [67]	$\text{OSAVI} = (1+L) \times \frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}+L}$, L was set to 0.16
14	Renormalized difference vegetation index [68]	$\text{RDVI} = \frac{\text{NIR}-\text{R}}{\sqrt{\text{NIR}+\text{R}}}$
15	Soil adjusted vegetation index [69]	$\text{SAVI} = (1+L) \times \frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}+L}$, L = 0.5
16	Soil adjusted vegetation index 2 [70]	$\text{SAVI}_2 = \frac{\text{NIR}}{\text{NIR}+\frac{b}{a}}$, b was set to 0.025 and a to 1.25
17	Stress-related vegetation index 1 [71]	$\text{STVI}_1 = \frac{\text{SWIR1} \times \text{R}}{\text{NIR}}$
18	Stress-related vegetation index 2 [71]	$\text{STVI}_2 = \frac{\text{NIR}}{\text{SWIR2} \times \text{R}}$
19	Stress-related vegetation index 3 [71]	$\text{STVI}_3 = \frac{\text{NIR}}{\text{SWIR1} \times \text{R}}$
20	Red edge normalized difference vegetation index [72]	$\text{RENDVI} = \frac{\text{NIR}-\text{RE}}{\text{NIR}+\text{RE}}$
21	Anthocyanin reflectance index [73]	$\text{ARI} = \frac{1}{\text{G}} - \frac{1}{\text{RE}}$
22	Vogelmann red edge index [74]	$\text{VREI} = \frac{\text{NIR}}{\text{RE}}$
23	Radar ratio vegetation index	$\text{Ratio} = \frac{\text{VV}}{\text{VH}}$
24	Radar difference vegetation index	$\text{Difference} = \text{VV} - \text{VH}$
25	Radar normalized difference vegetation index (RNDVI)	$\text{RNDVI} = \frac{\text{VV}-\text{VH}}{\text{VV}+\text{VH}}$
26	Near-infrared reflectance of vegetation [75]	$\text{NIRv} = \left(\frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}} - C \right) \times \rho$ (C = 0.08)
27	kernel (NDVI) [76]	$\text{kNDVI} = \tanh\left(\left(\frac{\text{NIR}-\text{R}}{2\sigma}\right)^2\right)$
28	Normalized difference phenology index [77]	$\text{NDPI} = \frac{\text{NIR}-(0.74 \times \text{R}+0.26 \times \text{SWIR1})}{\text{NIR}+(0.74 \times \text{R}+0.26 \times \text{SWIR1})}$

2.2.2. Land Cover Data for Shrubland Mapping

The European Space Agency (ESA) WorldCover dataset provides global 10 m land cover types, which was based on Sentinel-1/2 images with 11 land cover types [78]. 500 samples were generated randomly, and the land cover type of each sample point was acquired. Then, the classification accuracy of each sample was examined by visual interpretation using high-resolution Google Earth images and field photographs taken in April, July, and August 2023. In this study, an area with more than 10% shrub cover was classified as shrubland based on the MODIS land cover dataset [79]. Finally, a total of 354 samples were obtained, including 97 shrublands, 86 grasslands, 112 barren lands, and

59 forests. These samples were randomly separated into training and validation points at a 7:3 ratio and used for shrubland mapping.

2.2.3. Field Measurement and UAV Images

Two comprehensive field surveys were conducted in the Helan Mountains in late April 2023 and late July to early August 2023. 13 individual shrubs were selected randomly from the study area for destructive sampling and measurement of structural parameters. The samples included the dominant species with different plant sizes to ensure the representativeness of the samples in the study area. Structural parameters include shrub length (CL), width (CW), height (CH), crown area (CA), and volume (CV). The shrub samples were then dried in an oven at 70 °C for 48 h and weighed to obtain the biomass data (Table 2). These measurements were used to develop the optimal allometric growth equation for estimating shrub biomass.

Table 2. Field samples, including structural parameters and biomass data of each shrub.

ID	CL (m)	CW (m)	CH (m)	CA (m ²)	CV (m ³)	Number of Branches	Single Branch Biomass (g)	Single Plant Biomass (g)
1	1.62	1.02	1.34	1.3	1.74	6	487.81	2926.88
2	1.74	1.55	1.83	2.12	3.88	13	243.91	3170.79
3	1.26	1.02	0.73	1.01	0.74	33	40.95	1351.46
4	0.72	0.58	0.5	0.33	0.16	1	183.43	183.43
5	0.51	0.48	0.45	0.19	0.09	1	513.86	513.86
6	1.15	0.96	0.84	0.87	0.73	10	134.43	1344.3
7	0.42	0.42	0.6	0.14	0.08	1	185.91	185.91
8	1.63	1.58	0.74	2.02	1.5	9	226.38	2037.45
9	0.88	0.99	1	0.68	0.68	9	121.95	1097.58
10	1.96	2.08	1.32	3.2	4.23	40	38.48	1539.07
11	1.32	1.47	1.11	1.52	1.69	15	144.95	2174.3
12	1.05	0.98	0.59	0.81	0.48	3	495.86	1487.58
13	0.89	0.68	0.75	0.48	0.36	5	51.95	259.77

In addition, 24 sampling plots with each size of 10 m × 10 m were chosen to measure the structural parameters of each shrub. The sampling plots were evenly distributed throughout the study area. Shrub cover within the plots ranged from low to high. By utilizing the previously fitted allometric growth equation, the total shrub biomass for each plot can be calculated.

In late April 2023, a UAV image of the Helan Mountain region was acquired using a DJI Phantom 4 Pro V2.0 (a UAV from DJI China). The image covered a large area of 588 m × 196 m, with a spatial resolution of 0.06 m. The Phantom 4 Pro V2.0 UAV provides six bands, including true color (RGB), blue, green, red, red edge, and near-infrared (NIR).

2.2.4. Auxiliary Datasets

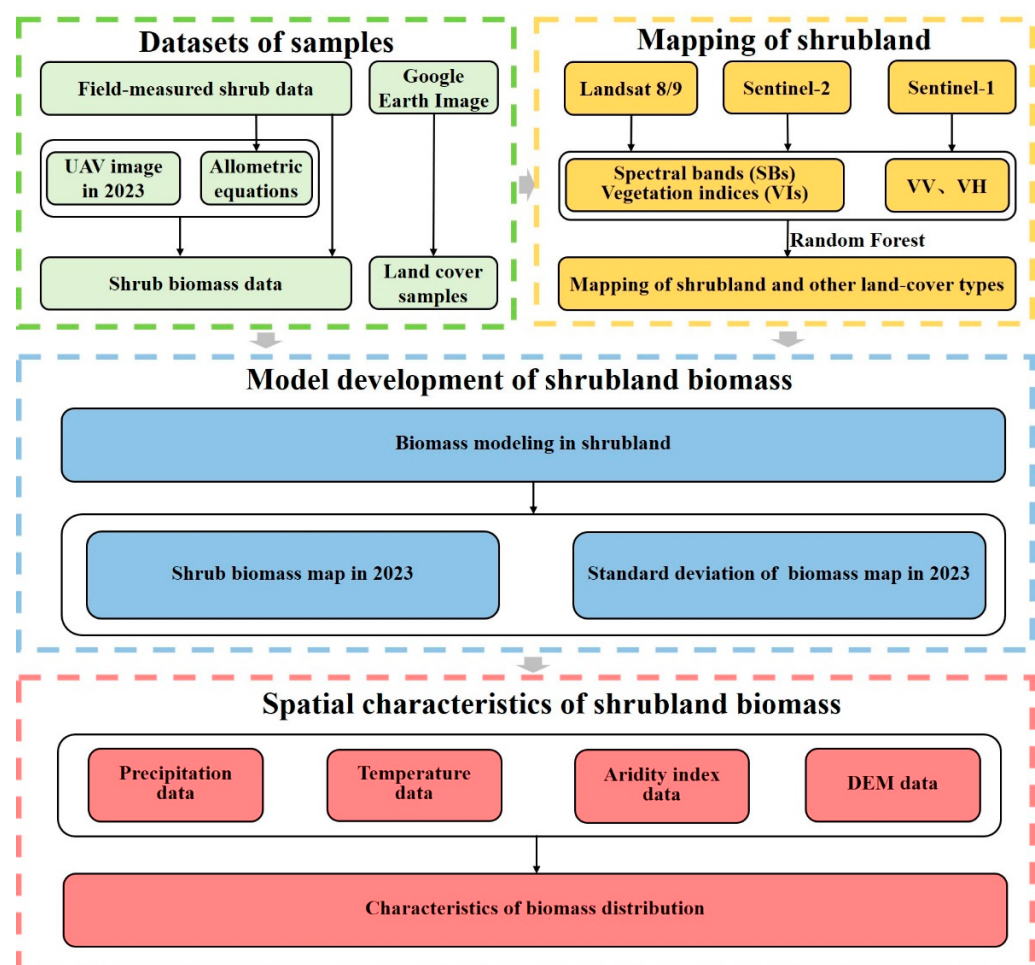
Precipitation, temperature, aridity index, and elevation datasets were used in this study (Table 3). The precipitation data were obtained using the 1 km monthly precipitation dataset for China (1901–2022) [80], with a spatial resolution of 1 km. The temperature data were a 1 km monthly mean temperature dataset for China (1901–2022) [81]. Two datasets provide monthly average precipitation and temperature. Since the two datasets provided the most recent climate variables in 2022, the mean values of monthly precipitation and temperature from 2000 to 2022 were used to analyze the spatial distribution characteristics of shrub biomass. The 1 km aridity index data were the global aridity index and potential evapotranspiration (ET₀), which calculated the aridity index based on the mean annual precipitation and evapotranspiration [82]. The lower the values, the more severe the drought conditions. The elevation data were obtained from the 30 m NASA SRTM Digital Elevation dataset [83]. These datasets were obtained through the GEE platform.

Table 3. Auxiliary datasets used in this study.

Influencing Factor	Dataset Name	Spatial Resolution
Precipitation	1 km monthly precipitation dataset for China (1901–2022)	1 km
Air temperature	1 km monthly mean temperature dataset for China (1901–2022)	1 km
Aridity index	Global aridity index and potential evapotranspiration (ET0) Climate Database v2	1 km
Elevation	NASA SRTM Digital Elevation	30 m

2.3. Methods

Figure 2 shows the workflow for shrub biomass estimation. It includes four main procedures. (1) A diverse ground sample dataset was constructed based on field surveys, ground measurements, UAVs, and Google Earth images. The dataset included samples of land cover types, shrub structure parameters, and shrub biomass. (2) The distribution map of shrublands was generated by land cover classification. (3) The shrub biomass map was generated for the Helan Mountains in 2023 by developing the optimal estimation model based on multi-scale data from ground, UAV, and satellite imagery. Here, the optimal model for shrub biomass estimation was built by comparing different RFR models driven by various combinations of predictor variables, including spectral bands, spectral vegetation indices, and backscatter bands (VV and VH). (4) The spatial distribution characteristics of the shrub biomass were analyzed comprehensively. Each of the steps is described in detail in the subsequent paragraphs.

**Figure 2.** The workflow for estimating biomass of shrubland.

2.3.1. Shrub and Non-Shrub Mapping in the Study Area

The study area is mainly covered by four land cover types, including forest, bare soil, grassland, and shrubland, based on the field survey. For shrubland mapping, the time series of 11 spectral bands were acquired corresponding to our collected 354 samples (Section 2.2.2). The data from these 11 spectral bands were acquired from all available Landsat 8/9, Sentinel-2, and Sentinel-1 satellite imagery in late July to early August 2023 based on the GEE platform, and included three visible (RGB), three red-edge, one near-infrared (NIR), two shortwave infrared (SWIR), and two radar (VV, VH) bands. The spectral bands and the associated land cover type of each sample were then inputted into the random forest (RF) model.

RF is a widely used machine-learning method that combines the characteristics of decision trees and randomness [84,85]. It demonstrates good skills in handling large-scale and high-dimensional datasets and is also able to evaluate each feature's significance in terms of selecting important features. 70% of the samples were used to train the RF model, and the remaining samples (30%) were used to validate the performance of classification. The mapping result was evaluated by the metrics of accuracy, recall, and F1-score (Equations (1)–(3)). Python (version 3.11) and the scikit-learn library (version 1.5.1) were used for the model development and accuracy calculation. Thus, a detailed land cover map including shrublands and other land cover types has been generated over the study area based on the RF model and multi-source satellite images.

$$\text{Accuracy} = \frac{(\text{True Positives} + \text{True Negatives})}{(\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives})} \quad (1)$$

$$\text{Recall} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Negatives})} \quad (2)$$

$$\text{F1 score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (3)$$

2.3.2. Estimation of Shrub Biomass at the Individual Level

The structural parameters of shrubs closely reflect their growth status and biomass accumulation, making them important indicators for estimating shrub biomass. By conducting field measurements of shrub length, width, and height, the shrub's crown area and volume can be calculated, both of which are positively correlated with shrub biomass [56]. Generally, shrub crown area (CA) and volume directly reflect biomass values. The crown area represents the horizontal structure of the shrub, while the volume represents its horizontal and vertical structural characteristics [56]. Studies have shown a linear link between the biomass of shrubs and CA [56].

Then allometric equations were established for shrub development. Seven samples were utilized in each iteration to fit the canopy area (CA) and crown volume (CV), with the remaining six samples being used for validation. A total of $5 \times C_{13}^7$ iterations were conducted, using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) as accuracy assessment criteria. The final selected allometric equations for shrub biomass estimation based on area and volume are as follows:

$$\text{AGB} = e^{(7.3+0.41 \times \ln(\text{CV}))} \quad (4)$$

$$\text{AGB} = 1060.93 \times \text{CA} \quad (5)$$

2.3.3. Estimation of Shrub Biomass at the UAV Plot Level

UAVs can provide a convenient approach to estimating shrub biomass at the plot level and alleviate the estimation uncertainty caused by the spatial mismatch between ground sampling and satellite observations [56]. In this study, we innovatively explored the feasibility of sample generation methods in remote sensing biomass inversion by combining

ground survey and UAV rather than using only one of them. Specifically, as for the UAV-based sampling method, by leveraging the true color UAV image, we first identified the shrub based on an RF classification (RF) model (Figure 3a). The shrub ($N = 106$) and non-shrub ($N = 229$) samples were collected by visual interpretation of the UAV imagery using a random sampling approach. The RGB band values of each sample in the UAV imagery were extracted as input features for building the RF model. Thus, a binary image of shrub and non-shrub (i.e., the shrub and non-shrub pixels) in the UAV image was produced at the UAV level (spatial resolution about 0.06 m). The model fitness showed that all the accuracy, recall, and F1 score of the UAV-based shrub map exceeded 0.9.

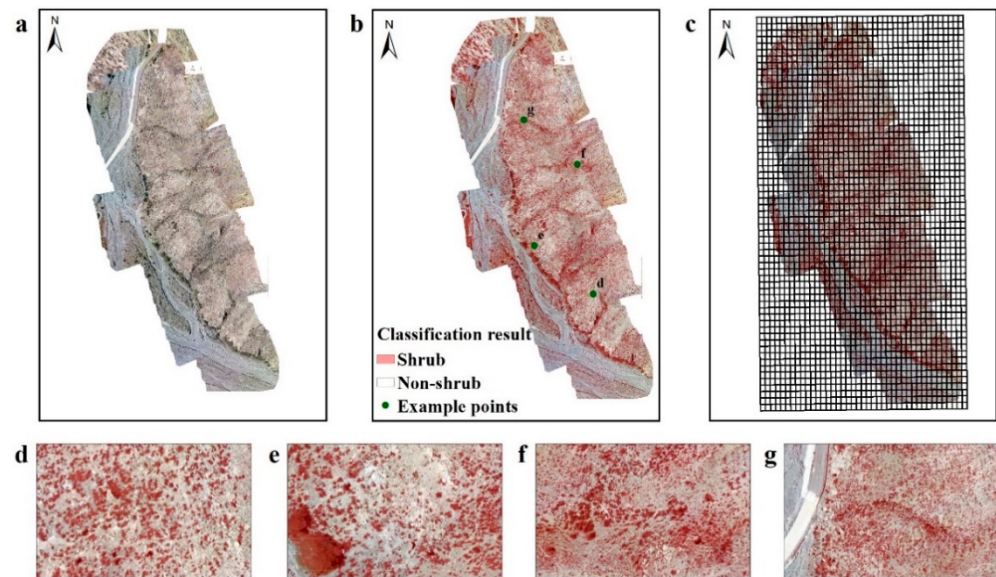


Figure 3. (a) The original unmanned aerial vehicle (UAV) image. (b) The classified map of shrublands. (c) The fishnet constructed based on the UAV imagery. (d–g) The zoomed-in views of four sample points in (b).

Then, the grids with a size of $10\text{ m} \times 10\text{ m}$ were created by using the above UAV-based shrub and non-shrub map to match the spatial resolution of the satellite images we used in this study. This process was conducted using the “create fishnet” function in ArcMap 10.4. The grids were perfectly aligned with the pixel boundaries of the satellite image (Figure 3c). Within each grid, the crown area (CA) of shrubs was calculated by counting the shrub pixels in the UAV image. Third, the total shrub biomass within each grid was estimated by applying a CA-related biomass allometric equation ($\text{AGB} = 1060.93 \times \text{CA}$ ($R^2 = 0.9$); Equation (5)) [56]. In addition, to reduce the impacts caused by rugged terrain and clouds, the grids with black or bright backgrounds, steep slopes, or clouds were removed. At last, a total of 86 UAV-based samples were obtained for further biomass estimation.

2.3.4. Satellite-Based Modeling of Shrub Biomass at the Regional Level

Two methods for satellite-based biomass estimation at the regional level, the random forest regression (RFR) model and the leave-one-out cross-validation (LOOCV) method, were employed. The RFR model calculates the final score as the mean score of all decision trees rather than through voting, resulting in better predictive performance and higher accuracy than the RF model [86]. With the LOOCV method, the RFR model was trained N times ($N = 89$), where $N-1$ samples were used for training and the remaining sample was used for testing. The model with the highest accuracy was selected as the final output that was used to make full use of the samples [27].

It should be noted that the model’s performance is not positively impacted by every feature. Certain characteristics may cause little variations in samples, which might reduce the classification accuracy. Thus, the combination of multiple feature variables may have

the problem of data redundancy and complex computation. Accordingly, the optimization of multidimensional features is important for improving model performance [87–89]. To select the optimal features.

Three models were constructed with the RFR algorithm driven by three different satellite feature combinations: (1) the VV, VH, and spectral bands (SB), (2) the vegetation indices (VI), and (3) all available variables (SBVI). The accuracy of different combinations was calculated based on the R-squared (R^2) and root mean squared error (RMSE). Finally, the best model and its corresponding optimal feature combination could be identified for shrub biomass estimation. Two Python libraries (RFECV and KFold) based on scikit-learn library (version 1.5.1) were used in this study. The RFECV package was employed for constructing different combinations of features, and the KFold package was used for cross-validation.

2.3.5. Regional Implementation of the Satellite-Based Shrub Biomass Model

Through the LOOCV model, the distribution maps of shrubland biomass were obtained at 10 m spatial resolution with a total number of 89. The mean value map of the 89 shrubland biomass distribution maps was calculated as the final resultant map. Moreover, a map of standard deviation (SD) was generated for shrubland biomass to present the potential uncertainty based on the 89 shrubland biomass distribution maps. Subsequently, the uncertainty of the resultant biomass map was analyzed along with the magnitudes of shrubland biomass and coverage. To obtain the shrubland coverage map, the land cover map in Section 2.3.1 was classified and aggregated into the shrubland and non-shrubland maps. The shrubland and non-shrubland pixels were assigned into 1 and 0, respectively. Here, the non-shrubland included the forest, bare soil, and grassland types. This 10 m binary map was resampled into a shrubland coverage map at a spatial resolution of 1 km by the mean method. Then, the relationship between the SD map and the shrubland coverage map was examined at 1000 m by a spatial overlay analysis.

2.3.6. Spatial Characteristics of the Shrub Biomass

To examine the geographical patterns of shrub biomass, the resultant shrub biomass map was overlaid with different datasets of precipitation, temperature, aridity index, and elevation (Table 3). Then, the spatial distributions of shrub biomass along with the gradients of different environmental factors can be analyzed.

3. Results

3.1. Mapping of Shrubland and Other Land Cover Types

A land cover map for the Helan Mountains in 2023 was created by using an RF model constructed with 11 remote sensing features. Four land cover types have been identified, including forest, barren lands, grasslands, and shrublands. Figure 4 displays the result map, where only the shrublands were used for biomass estimation. It can be observed that shrublands are predominantly distributed in the southeastern plains and northeastern parts, while forests dominate the southwestern region. Additionally, there is relatively less grassland and more barren land in the study area, which can be attributed to the overall climate type being a typical temperate arid climate with low rainfall. The accuracy assessment on the shrubland and non-shrubland map was shown in Table 4, presenting an overall classification accuracy of 0.91, a recall of 0.92, and an F1 score of 0.92.

Table 4. Shrubland and non-shrubland classification accuracy assessment results.

Accuracy Index	Accuracy	Recall	F1 Score
Value	0.91	0.92	0.92

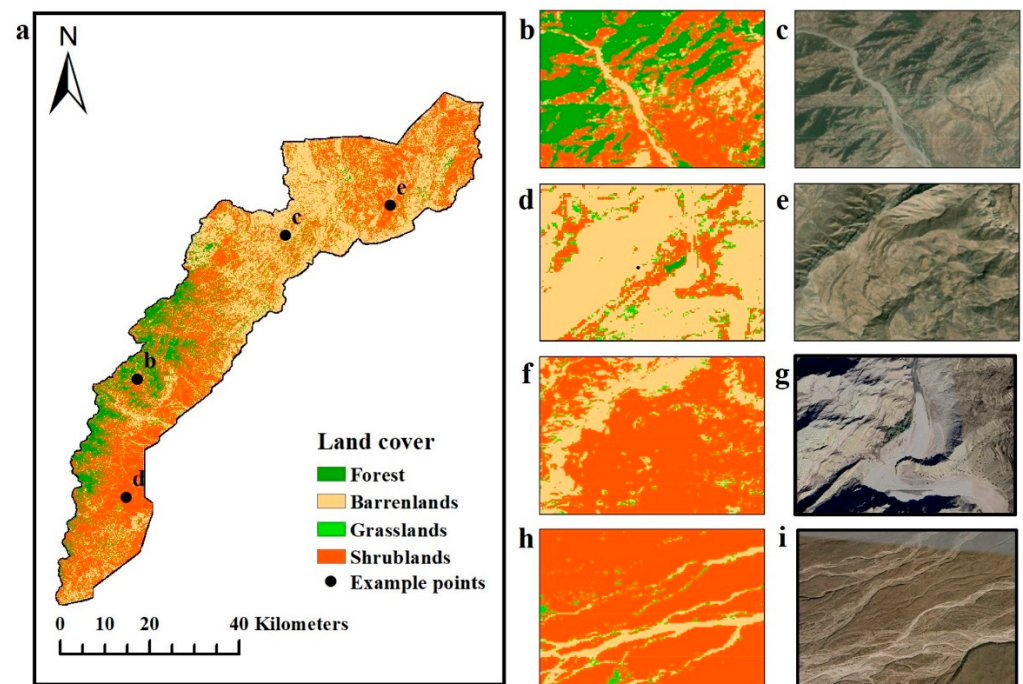


Figure 4. (a) The shrublands and other land over types of Helan Mountain, China, in 2023. (b–i) The zoom-in views of four example regions in the resultant map and the Google Earth images.

3.2. Selection of the Best Satellite-Based Biomass Model Based on Variable Importance Analysis

Three models driven by different features were conducted: VV, VH, and spectral bands (SB), another with only vegetation indices (VI), and a third with all available features (SBVI). The RFECV and KFold packages were used to determine the optimal variables for each model. The best variables for each model are shown in Table 5. The R^2 and RMSE for each of the three models are shown in Figure 5. The results suggested that the SBVI model achieved the best performance with R^2 of 0.62, which was higher than that of the SB model ($R^2 = 0.33$) and VI model ($R^2 = 0.55$). Therefore, the SBVI model was selected as the final model for estimating shrub biomass in the following studies. It also showed that a significant number of vegetation indices related to the near-infrared (NIR) band (e.g., DVI, SAVI2) are incorporated into the model, indicating the high correlation of NIR-based vegetation indices for shrub biomass.

Table 5. Model feature selection results.

Model	Features
SB	Blue, Red, NIR, SWIR2
VI	EVI, DVI, GNDVI, SAVI2, Ratio, RNDVI
SBVI	DVI, SAVI2, VH, VV

The accuracy was assessed based on shrub biomass samples across different groups of shrub coverages and biomass (Figure 6a). The ratio of RMSE to mean shrub coverage was calculated to present the error of one percent coverage of shrub (EOPC) [90]. EOPC decreases with the increase in shrub coverage. Similarly, the ratio of RMSE to mean biomass was calculated to present the error of one unit biomass (EOUB) (Figure 6b). EOUB decreases along with the increase in shrub biomass. The lowest values of R^2 were observed within the range of 20–30% shrub coverage ($R^2 = 0.3$) and 200–300 g/m² shrub biomass ($R^2 = 0.19$). These results indicate the estimation accuracy is relatively lower in the moderate shrub coverage and biomass ranges than that in the high and low levels.

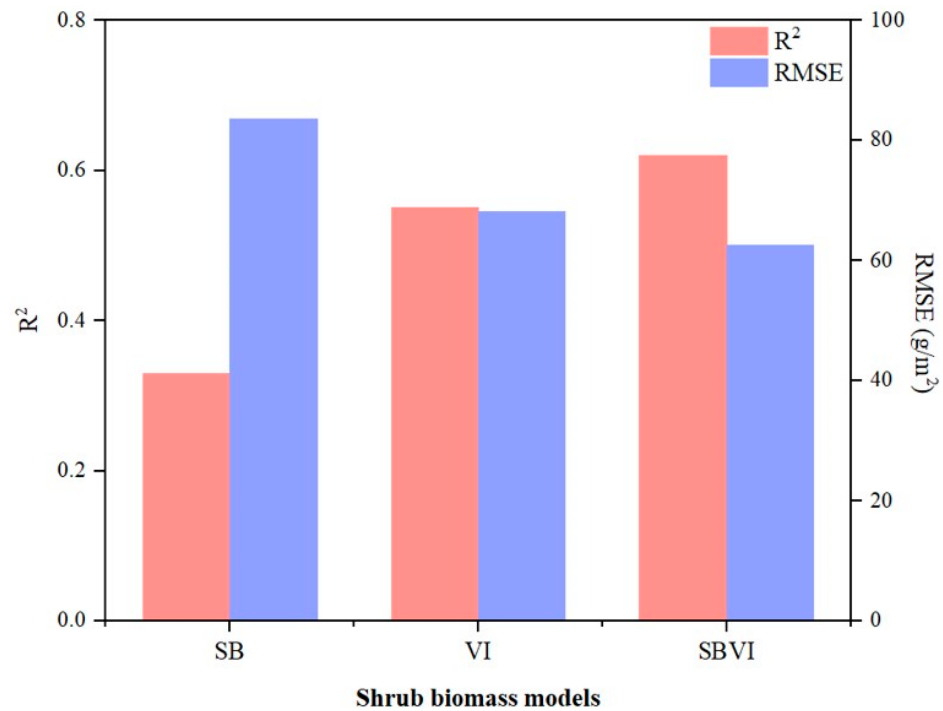


Figure 5. The comparison of accuracy among the three models. The x-axis represents three models driven by the basic bands (SB), the vegetation indices (VI), and the combination of the basic bands and vegetation indices (SBVI). Their performance is evaluated using R^2 and RMSE.

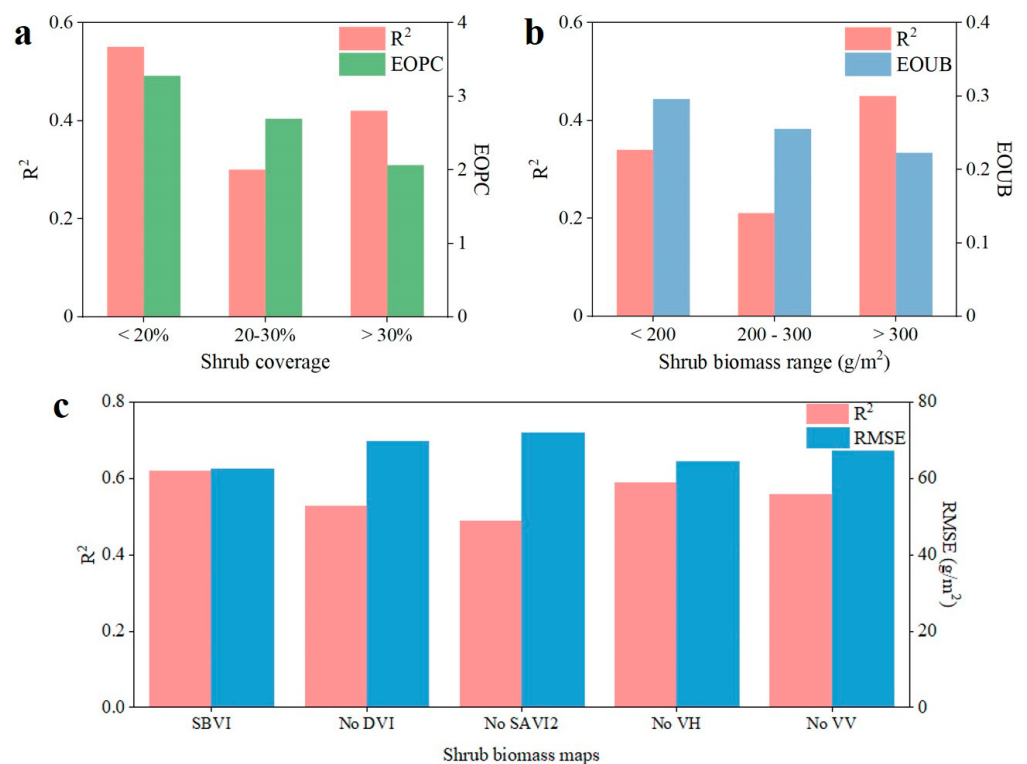


Figure 6. (a) The distribution of R^2 and EOPC within different ranges of shrub coverage. (b) The distribution of R^2 and EOUB within different ranges of shrub biomass. (c) The sensitivity of the biomass model to each variable examined by R^2 and RMSE. These analyses were conducted based on the ground samples. EOPC denotes the error of one percent coverage of shrub, calculated by RMSE/mean shrub coverage. EOUB denotes the error of one unit biomass, calculated by RMSE/mean shrub biomass.

To determine the contributions of four features to the model, a sensitivity analysis was conducted (Figure 6c). It can be observed that SAVI2 has the most significant impact on model accuracy. Removing SAVI2 resulted in a decrease in R^2 by 0.13 and an increase in RMSE by 9.53 g/m^2 . VH had the least impact on the model, as removing VH only led to a decrease of 0.03 in R^2 and an increase of 1.93 g/m^2 in RMSE. The results showed that the four features are ranked from highest to lowest contribution as SAVI2, DVI, VV, and VH.

3.3. Shrub Biomass Mapping Based on Satellite Images in 2023

The 10 m shrub biomass distribution in the Helan Mountains was mapped by the SBVI model (Figure 7). Here, the shrub-covered regions were focused by excluding the non-shrub areas using the 10 m binary map (Section 2.3.5). The results showed the minimum value of shrub biomass was 104.99 g/m^2 , while the maximum value was 564.54 g/m^2 . Despite having more bushes than other vegetation, the biomass is often lower in the southeast. This is because the shrubs in this area are predominantly low-lying. By contrast, the central Helan Mountains have greater elevation and are mostly characterized by tall shrubs, which contribute to the high shrub biomass.

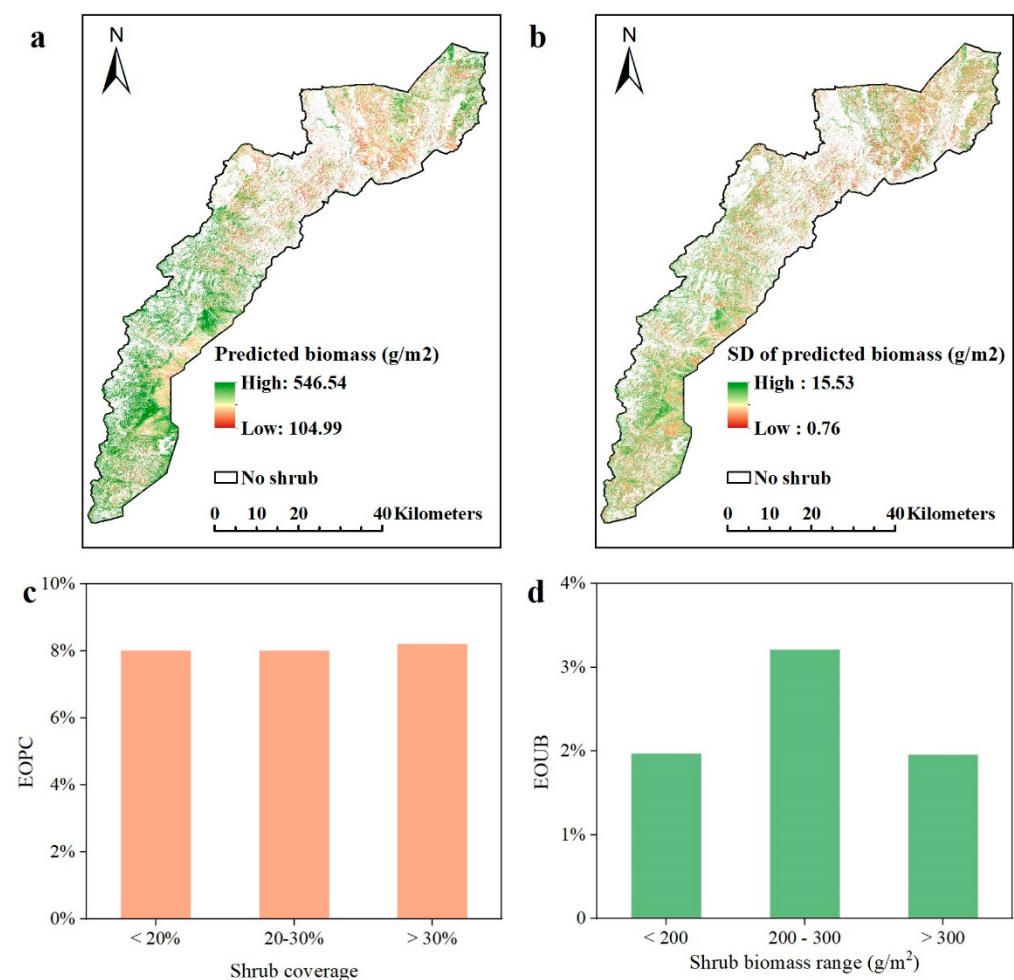


Figure 7. (a) The estimated distribution map of shrub biomass in the Helan Mountains. (b) The corresponding map of standard deviation (SD). (c) The distribution of EOPC within different ranges of shrub coverage. (d) The distribution of EOUB within different ranges of shrub biomass. These analyses were conducted based on the estimated distribution map of shrub biomass and the corresponding map of standard deviation. EOPC denotes the error of one percent coverage of shrub, calculated by $SD/\text{mean shrub coverage}$. EOUB denotes the error of one unit biomass, calculated by $SD/\text{mean shrub biomass}$.

Figure 7b depicts the spatial distribution of the standard deviation associated with the biomass predictions from the 89 models based on the LOOCV method. The result shows that higher standard deviations generally happened in the areas with higher shrub biomass, while the lower standard deviations were in the regions with lower shrub biomass. Figure 7c,d illustrate the distributions of the estimation errors under different shrub cover and biomass gradients, respectively. EOPC shows that the estimation errors vary, with the shrub cover with a mean value of around 8%. The EOUB indicates that the overall estimation error is less than 4%, and the estimation errors are even lower than 2% in both the high and low shrub biomass ranges.

3.4. Distribution of Shrub Biomass along with Different Environmental Factors

The distribution characteristics of shrub biomass were observed by temperature, precipitation, aridity index, and elevation. Figure 8a shows the shrub biomass mainly distributed in the regions with annual mean precipitation of 200–250 mm. Figure 8b displays the distribution of shrub biomass across different ranges of mean annual temperature. The shrub biomass mainly occurred in the regions with a mean annual temperature of 7–9 °C. As shown in Figure 8c, the shrub biomass is predominantly distributed within the aridity index range of 0.1–0.15, suggesting that shrubs may prefer to grow in more arid environments. Additionally, Figure 8d indicates that the shrub biomass is primarily distributed in areas with an elevation below 2500 m, implying that higher elevation regions may not be as suitable for shrub growth.

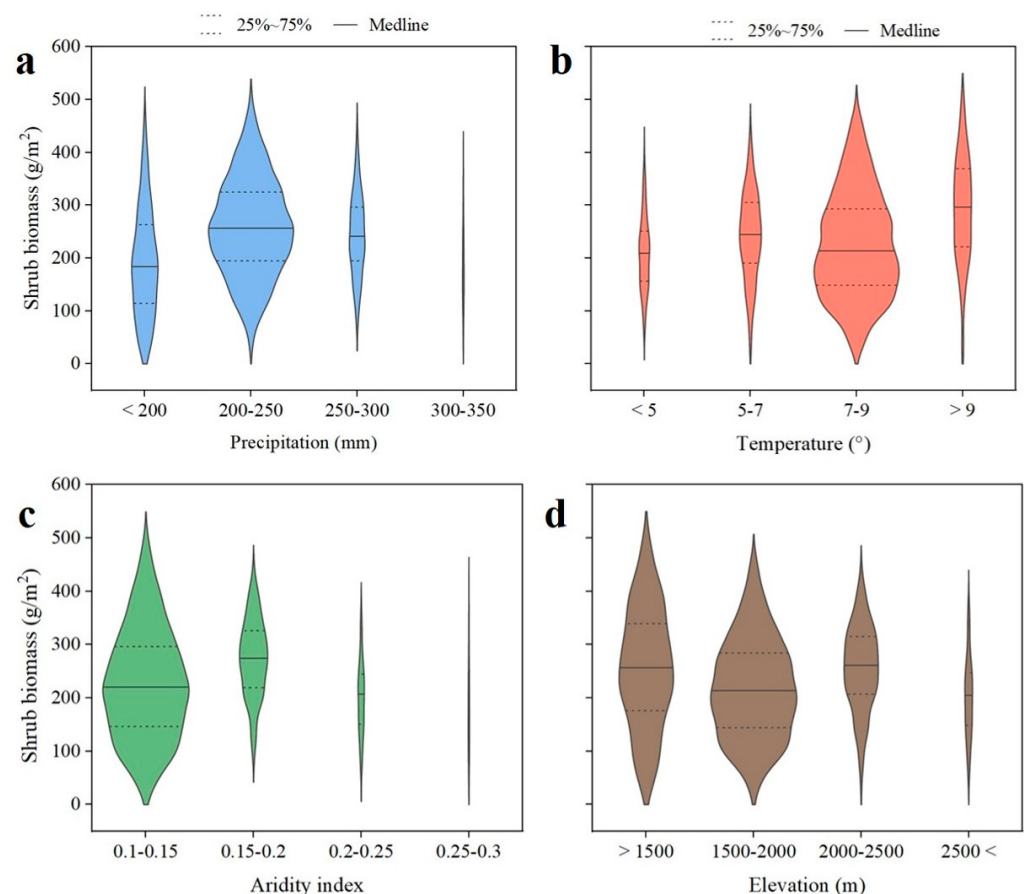


Figure 8. (a) The distribution of shrub biomass under precipitation gradients. (b) The distribution of shrub biomass under temperature gradients. (c) The distribution of shrub biomass within different ranges of aridity index. (d) The distribution of shrub biomass along elevation gradients.

4. Discussion

4.1. Advantages of Integrating UAV and Satellite Data for Shrub Biomass Estimations

The shrub biomass estimated based on the integration of UAVs and satellite imagery has significant implications for ecological research and environmental monitoring. Previous studies just relying on field-sampled shrub biomass and satellite imagery often have limited estimate accuracy ($R^2 < 0.6$) [91,92]. The accuracy is reported to be affected by the following factors, including (1) the scale mismatch between the limited ground measurement area and the resolution of satellite images [27] and (2) the number of field samples [28]. The UAVs can provide images to capture the canopy structure and coverage of shrubs at centimeter spatial resolution, which makes it possible to match the spatial scales of the ground measurements. The shrub, low stature, and patchiness of vegetation make UAVs well-suited for assisting in large-scale ground community surveys. Meanwhile, it is also possible to aggregate the UAV observations to match different satellite spatial resolutions. Thus, the scale effects on the shrub biomass estimations between ground measurements and satellite observations could be reduced by the utilization of UAVs. In this study, a grid was established with a consistent spatial resolution of the satellite images, which makes it possible to estimate shrub biomass within each grid cell. This approach provided an improved satellite-based shrub biomass estimation ($R^2 = 0.62$) with the integrated samples from ground measurements and UAV-based estimations (Figure 5). Furthermore, the utilization of UAV imagery provided a cost-effective and efficient method for estimating shrub biomass, which resulted in obtaining sufficient shrub biomass samples for developing robust models. However, the integration of UAV and satellite data also has limitations. For example, the temporal differences between the UAV and satellite imagery acquisitions may introduce uncertainties in capturing the shrub biomass. Therefore, further research should focus on exploring the potential of integrating multi-scale remote sensing data to achieve more comprehensive and accurate estimations of shrub biomass.

4.2. Uncertainties of Shrub Biomass Estimation

In this study, EOPC and EOUB were used to determine the estimation accuracy of the models in different shrub coverage or shrub biomass ranges. The spatial distribution maps generated using the leave-one-out cross-validation (LOOCV) and random forest regression (RFR) methods can also clearly characterize the accuracy of shrubland biomass estimation in different regions. The results show that in areas with shrub coverage exceeding 30% and biomass greater than 300 g/m^2 , the estimation uncertainty is the lowest, with an average uncertainty below 4% and the lowest values even below 2%. These results suggested that the estimation accuracy of the models improved with the increases in shrub coverage or shrub biomass. Previous studies also found that the spectral signals of shrubs are weak in pixels with low shrub coverage, which makes it more difficult to identify the shrubs in these regions [93–96]. In the high biomass areas, the spectral signals of the shrubs are strong, which may allow the satellite-based models to better identify the distributions of shrub biomass [93–96]. This indicates that the integration approach of the multi-source data works well over most of the areas, especially for those with moderate or high shrub covers. For the regions with low shrub coverage, using more shrub biomass samples should be a possible way to improve the model's performance. This will be tested in our near future studies. The uncertainty analysis not only provided an assessment of the resultant biomass map but also directed our future improvements.

4.3. Spatial Characteristics of Biomass in Shrubland

The study found that shrub biomass was more extensively distributed within the precipitation range of 200–250 mm. As precipitation continued to increase beyond 250 mm, the distribution of shrub biomass correspondingly decreased. It is shown that precipitation below 250 mm may be an optimal range for shrub growth in the area. Excessive precipitation may impact the growth environment of shrubs, leading to a shift in dominant species from shrubs to other plant types in the Helan Mountains and resulting in a reduction in

shrub biomass [97–99]. The phenomenon may be attributed to the fact that the increased availability of water under high precipitation regimes appears to favor the proliferation and competitive dominance of grass-like vegetation, thereby potentially suppressing the development and abundance of shrub communities [100]. Regarding temperature, the majority of shrub biomass is found in areas with an average annual temperature range of 7–9 °C. This suggests that shrubs are most suitable for growth within specific thermal conditions. Temperatures that are either too high or too low may exceed the adaptive range of the shrubs, affecting their physiological activities and growth rates [101]. The optimal temperature range facilitates the shrubs' ability to carry out photosynthesis and respiration, thereby sustaining their growth and biomass accumulation. Furthermore, the shrub biomass was mostly distributed within the aridity index range of 0.1–0.15. Aridity helps maintain the richness and diversity of species with different morpho-functional and life history traits in shrub canopies [99,102]. Regarding elevation, the distribution of shrub biomass did not exhibit a clear trend with changes in altitude. The study found that the majority of shrub biomass was concentrated in areas below 2500 m in elevation. At higher elevations, the lower air temperatures and harsher climate conditions may limit the growth cycles and rates of the shrub communities [103,104]. Additionally, the soil conditions and nutrient availability in the high-elevation areas may be less favorable compared to lower-elevation regions, further impacting the development of the shrub vegetation. Previous studies have suggested a correlation between shrub biomass distribution and the four environmental factors selected in this study in the southwestern region of China. Therefore, future research will be conducted to unravel the complex relationships between shrub biomass dynamics and environmental factors in further studies.

4.4. Limitations and Improvements

Although this research yielded some progress, certain limitations must be acknowledged. Firstly, shrub biomass may be impacted by factors such as soil moisture, topographical variances, and understory vegetation [8,105]. Future research could incorporate additional environmental factors to improve model accuracy. Second, applying our best model to other regions may result in additional errors. Due to spatial heterogeneity and differences in shrub species, the relationships between vegetation indices and shrub biomass may vary, leading to different optimal feature combinations. In the future, this research will be expanded to other regions to enhance the transferability of our model and apply it to regions with more diverse climatic environments. Additionally, a greater variety of data is aimed to be utilized, such as hyperspectral data, to develop more accurate shrub biomass estimation models. Finally, the results indicate that our model's precision is lower in areas with low shrub cover and biomass than in other regions; acquiring more shrub biomass data in these regions could be an improvement approach.

5. Conclusions

This study proposed a novel approach to improve the estimation of shrub biomass at a regional scale by increasing the shrub biomass samples and reducing the spatial scale mismatch between ground measurements and satellite observations by UAV. The workflow included the following parts: First, a shrubland distribution map was generated for the Helan Mountains, China. Subsequently, the shrub biomass was obtained at the UAV level based on the UAV images and the allometric growth equation for the shrub biomass fitted using field measurements. Then, the best shrub biomass estimation model at the satellite level was obtained by comparing three RFR models driven by different remote sensing features. This model was used to generate the distribution map of shrub biomass in the Helan Mountains in 2023. Based on the resultant map, the distribution of shrub biomass along with different environmental factors was assessed. The results indicate that using UAV imagery to calculate shrub biomass provides a more convenient and effective method to supplement shrub biomass samples, significantly reducing the workload and costs of fieldwork. Combining remote sensing imagery from different sensors will likely provide

more assistance for future research on large-scale shrub biomass estimation. Although this study made some progress in the method, there are still limitations in sample size, data resolution, and incomplete environmental factors considered. In the following works, this work will be expanded to other regions to validate and improve the proposed methodology.

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