A 250m annual alpine grassland AGB dataset over the Qinghai-Tibetan Plateau (2000-2019) in China based on in-situ measurements, UAV images, and MODIS Data

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Abstract. The alpine grassland ecosystem accounts for 53% of the Qinghai-Tibet Plateau (QTP) area and is an important ecological protection barrier, but it is fragile and vulnerable to climate change. Therefore, continuous monitoring of grassland aboveground biomass (AGB) is necessary. Although many studies have mapped the spatial distribution of AGB for QTP, the results vary widely due to the limited ground samples and mismatch with satellite pixel scales. This paper proposed a new algorithm using unmanned aerial vehicles (UAVs) as a bridge to re-estimate the grassland AGB on the QTP from 2000 to 2019. The innovations were as follows: 1) In terms of ground data acquisition, the spatial scale matching among the traditional ground samples, UAV photos, and MODIS pixels was considered. During 2015-2019, 906 pairs of quadrat-scale ground-UAV sample data and 2,602 sets of MODIS pixel-scale UAV data were collected (over 37,000 UAV photos). Therefore, the ground validation samples were sufficient and scale-matched. 2) In terms of model construction, the traditional quadrat scale ($0.25m^2$) was successfully upscaled to the MODIS pixel scale (6,2500 m^2) based on the random forest and stepwise upscaling methods. Compared with previous studies, the scale matching of independent and dependent variables was achieved, effectively reducing the impact of spatial scale mismatch. The results showed that the correlation between the AGB values estimated by UAV and the MODIS vegetation indices was higher than that of the traditional sampling method at the pixel scale. The cross-year validation results showed that the constructed pixel scale AGB estimation had good robustness, with an average R^2 of 0.83 and RMSE of 34.13 g/m^2. Our dataset provides an important input parameter for a comprehensive understanding of the role of QTP in global climate change processes. The dataset is available from the National Tibetan Plateau/Third Pole Environment Data Center (https://doi.org/10.11888/Terre.tpdc.272587, Zhang et al., 2022).

1 Introduction

Grasslands, accounting for approximately 37% of the earth's surface, play an essential role in global carbon cycling and food supply (O'mara, 2012). However, most natural grasslands have been degraded to a certain extent due to overgrazing, farmland encroachment, soil erosion, and global climate change (Suttie et al., 2005; Ramankutty et al., 2008; O'mara, 2012). Therefore, timely monitoring of grassland health is crucial for sustainable development and understanding global carbon cycling processing. Aboveground biomass (AGB) is a key indicator of grassland status and an important input parameter for ecological modeling and carbon storage estimation. Thus, accurate and rapid estimation of AGB is valuable for grassland monitoring.

The advent of satellites has made it possible to map the spatiotemporal dynamics of grasslands over large areas. Spectral information from different satellites has been employed for biomass estimation, such as Sentinel-2, Landsat, and MODIS (Wang et al., 2019; Zhang et al., 2016). Although there are differences in spatial and spectral resolution, the core idea of building a biomass model is constructing the linear or nonlinear relationships between the field-measured samples and various satellite spectral indices. Therefore, the estimation accuracy is closely related to the quality and quantity of ground samples (Morais et al., 2021; Yu et al., 2021). However, there are still two deficiencies in ground data acquisition: the large spatial gap between the traditional samples and satellite pixels, and the low efficiency.

How to narrow the spatial gap between traditional samples and satellite pixels is an urgent problem to be solved. Since it is impossible to harvest all grasses within a pixel range, the average of 3-5 quadrats (0.5 m × 0.5 m or 1m × 1m) is usually used as the measurement (Dusseux et al., 2015; Yang et al., 2017), which results in a considerable spatial gap. A lot of studies have been carried out to upscale ground measurements to satellite pixels (Crow et al., 2012; Bian and Walsh, 1993), such as block Kriging geostatistical interpolation, different types of regression models, or machine learning algorithms (Cheng et al., 2007; Wang et al., 2014; Cannavacciuolo et al., 1998; Dancy et al., 1986; Li et al., 2018). However, the accuracy of these methods depends on the density of sampling points. In addition, fine-resolution satellites were used as a bridge to reduce the impact of scale mismatch on AGB estimation (Yu et al., 2021; He et al., 2019). The reason is that the finer the satellite resolution, the smaller the spatial gap with the ground samples (Wang and Sun, 2014; Morais et al., 2021). Therefore, obtaining ground samples that match the pixel scale is the key to improving the accuracy of satellite AGB estimation.

Improving the efficiency of ground sampling is another issue that needs to be addressed. Although the traditional sampling method can yield high-accuracy results, it is time-consuming and labor-intensive. For example, Yang et al. spent five years completing the collection of ground samples to invert the grassland AGB in China (Yang et al., 2010). Moreover, with limited original ground data, some scholars had to use the data published by others to expand the sample size (Xia et al., 2018; Jiao et al., 2017). However, datasets from different sources may affect the overall accuracy due to the differences in sample plot size, sample size, and sampling methods.

The development and popularity of unmanned aerial vehicle (UAV) technology has provided new solutions to the above problems. UAV images have been successfully used to estimate ecological metrics such as FVC, biomass, and canopy height (Chen et al., 2016; Zhang et al., 2018; Bendig et al., 2015). The use of UAVs has the following unparalleled advantages over traditional sampling methods. First, UAVs can effectively obtain two- or three-dimensional vegetation information in a non-destructive way, which is helpful for grassland estimation (Lussem et al., 2019; Zhang et al., 2022a; Zhang et al., 2018). Second, UAVs can rapidly collect key parameters of grassland within satellite pixels (e.g., FVC, Chen et al. 2016). Hence, UAV images can serve as a bridge to reduce the spatial gap between field samples and satellite pixels. However, most current UAV-based grassland biomass estimations are small-scale, with few regional-scale studies. Whether UAVs can be used to reduce the spatial gap between traditional ground sampling and satellite pixels remains an open question. In addition, previous studies lacked cross-year validation to test the robustness of the AGB estimation model over time due to the limited sample size.

This study proposed a new approach that combines traditional ground sampling, UAV photography, and satellite data to produce a new reliable AGB dataset of QTP grassland. The objectives of this study were: 1) to construct a UAV-based grassland AGB estimation model at the quadrat/satellite pixel scales, respectively; 2) to investigate whether UAVs can be used as a bridge to reduce the spatial gap between ground samples and satellite pixels to improve the accuracy of grassland AGB, and 3) to map the AGB of alpine grasslands on the Qinghai-Tibetan Plateau (QTP) from 2000 to 2019.

2 Materials and Methods

2.1 Study Site

QTP is the highest and largest plateau on the earth (26°00′12″~39°46′50″N, 73°18′52″~104°46′59″E), with an average elevation of ~4000 m and an area of approximately 257.24×10^4 km^2 (Figure 1). It is located in western China, with an average annual temperature and precipitation of about 1.6℃ and 413.6 mm, respectively. The main grassland types are alpine meadows, alpine steppe, and sparse grassland, which play a critical role in climate regulation, water conservation, and biodiversity protection (Ding et al., 2013). In this study, the boundary of the QTP of China (Zhang et al., 2014) was downloaded from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn). Grassland type data was derived from the 1:1000000 Chinese digital grassland classification map provided by the China Resource and Environmental Science and Data Center (https://www.resdc.cn/). This data set, generated through field surveys in the 1980s and supplemented by satellite and aerial imagery, is the most detailed grassland-type map available. For comparison with others, we combined the grassland types into three categories: alpine meadow, alpine grassland, and sparse grassland, and resampled to 250 m (Table A1).

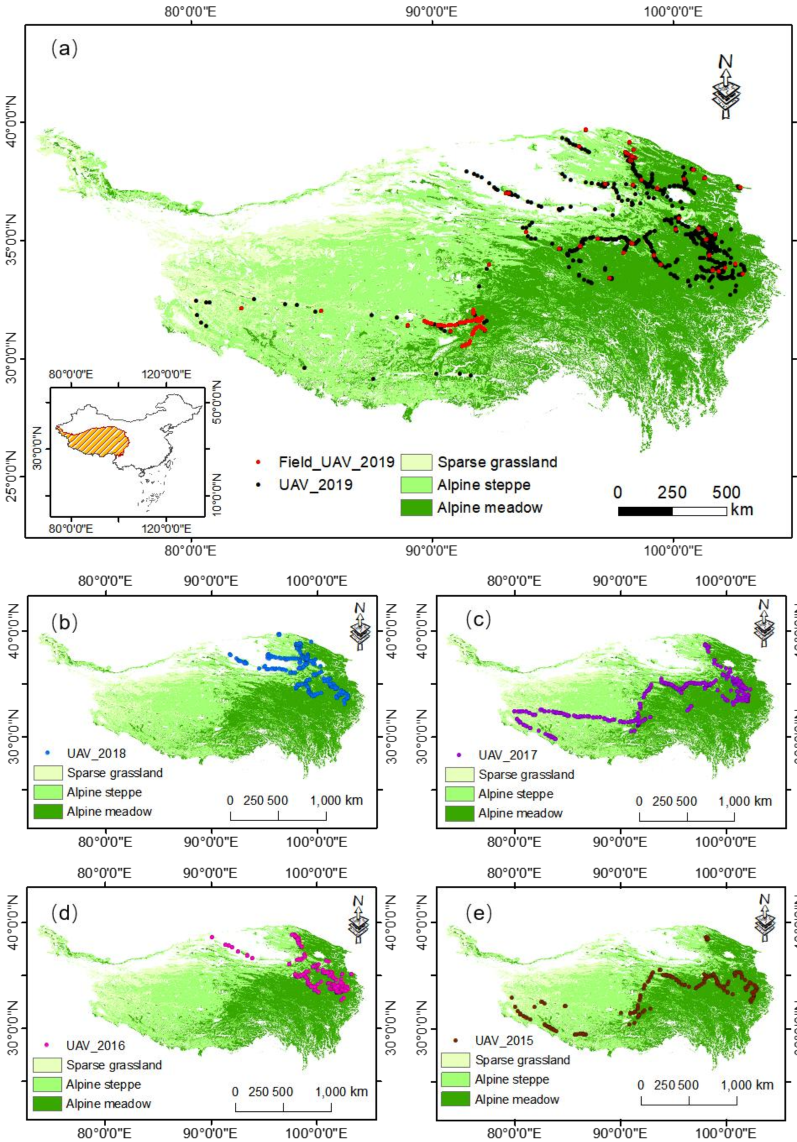

Figure 1. Distribution of field and UAV sampling sites in 2019 (a); UAV sampling sites in alpine grasslands on the QTP from 2015-2018 (b-e). Field_UAV_2019 represents the quadrat-scale sampling sites for the 2019 UAV-Field synchronous grassland biomass experiment. UAV_year represents the UAV sampling point based on the GRID or RECTANGE mode of the corresponding year.

2.2 Overall technology roadmap

Figure 2 was the overall flowchart of this study. It consisted of four main steps: 1) UAV and field investigation; 2) constructing the AGB estimation model at the quadrat scale; 3) upscaling the grassland AGB to the MODIS pixel scale; 4) building the AGB estimation model at the MODIS pixel scale and applying it to the QTP region. More detailed information on each step was described in the following sections.

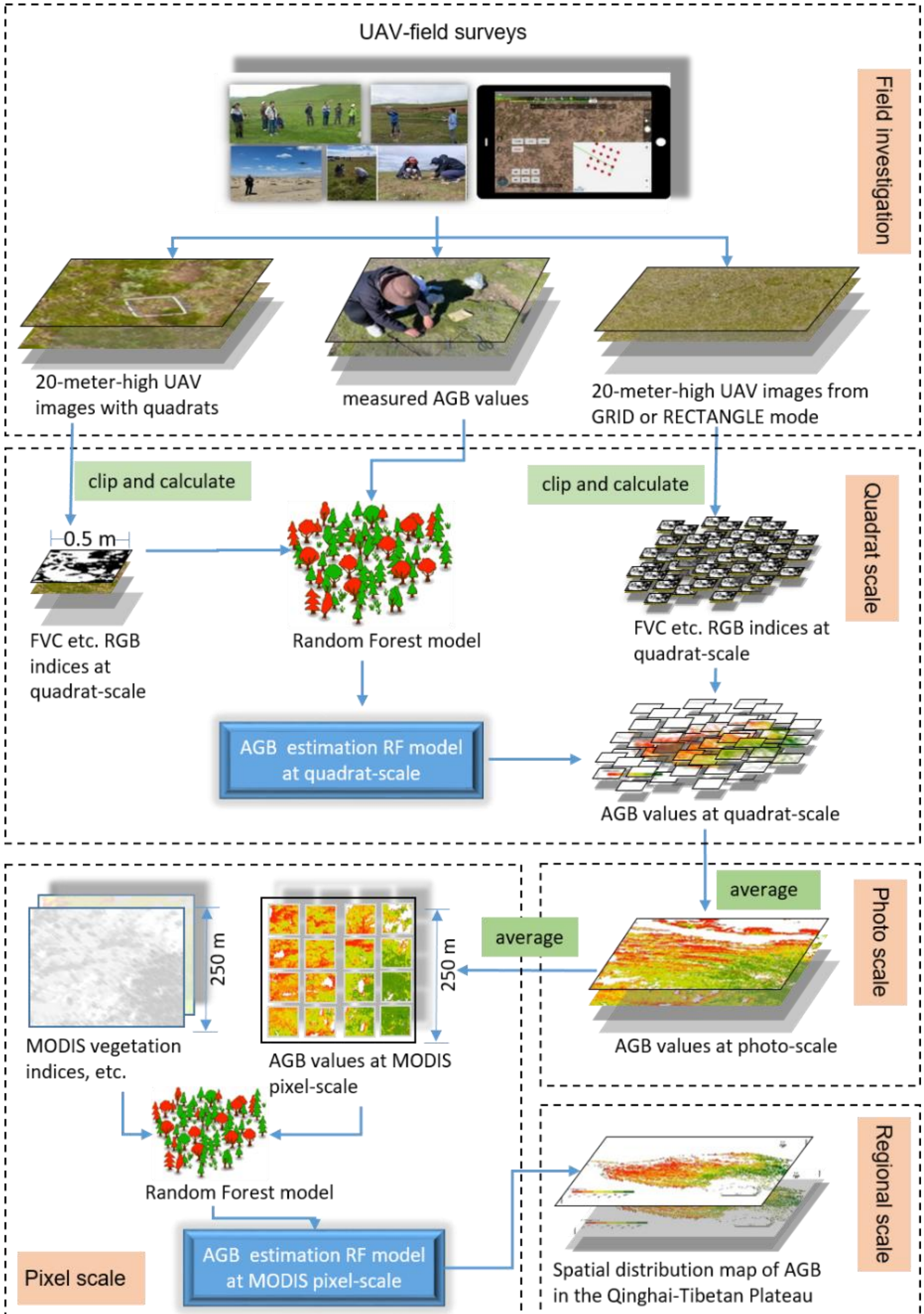

Figure 2. The overall flowchart of UAV field survey and the construction of grassland AGB estimation models at different spatial scales.

2.3 Field investigation

2.3.1 UAV and route planning

DJI Phantom 3 Professional (DJI Company, Shenzhen, China), a popular consumer quadrotor UAV with a high-resolution RGB camera, was used to collect UAV images of the QTP from 2015 to 2019. It has a 1/23-inch CMOS sensor and is capable of taking 12-megapixel photos. In addition, it uses a 3-axis stable gimbal to take photos vertically downward to eliminate the distortion of UAV images. It has good environmental adaptability, with an operating temperature range from 0° to 40°, and a maximum take-off altitude of 6000 meters. Therefore, it is well adapted to the low temperature and high altitude of the QTP. More detailed information about the UAV system was listed in Table A2.

Fragmentation Monitoring and Analysis with aerial Photography (FragMap) system, capable of long-term collaborative observation, was used for UAV route planning (Yi, 2017). During 2015-2019, we conducted UAV monitoring of the QTP grasslands using FragMap (Figure 1). Over 2,000 fixed flight routes were set up during this period, and more than 37,000 UAV images were collected, providing a reliable UAV dataset for this study (Table 1).

Table 1. UAV sampling information from 2015 to 2019

Year	Flight Mode	Number of routes	Photo number	Acquisition time
2015	RECTANGLE	214	2568	7.05 ~8.24
2016	RECTANGLE	334	4008	6.20~9.29
	GRID	150	2400	6.20~9.23
2017	RECTANGLE	315	3780	5.10~10.24
	GRID	322	5152	7.15~8.22
2018	RECTANGLE	79	948	7.22~8.03
	GRID	303	4848	7.04~8.29
2019	GRID	885	14160	7.12~9.21
	Total	**2602**	**37864**	

GRID, RECTANGLE, and BELT are the most commonly used flight modes in the FragMap software. GRID and RECTANGLE modes have 16 and 12 waypoints for capturing UAV images within a MODIS pixel range (Figure A1). Their flying height and speed are set to 20 m and 3m/s, respectively. The spatial coverage of a 20-meter-high UAV photo is about 26 m × 35 m. The BELT mode is similar to GRID, but is designed to obtain near-ground UAV image data with higher resolution (Figure 3b). It can be combined with the traditional sampling method to ensure the consistency of UAV images with the ground samples (Figure 3d). Typically, the BELT size is set to 40 m × 40 m, and the flying height and speed are set to 2 m and 1 m/s to ensure that field crews have enough time to place sampling frames under the UAV waypoints. As with the GRID mode, 16 UAV images can be captured in a single flight. Compared with the MOSAIC flight mode (which requires a guaranteed overlap rate between photos to obtain a full view of an area), our design is more in line with the traditional ecological sampling concept. It allows for a better balance of spatial representation and accessibility of samples, resulting in efficient sample collection.

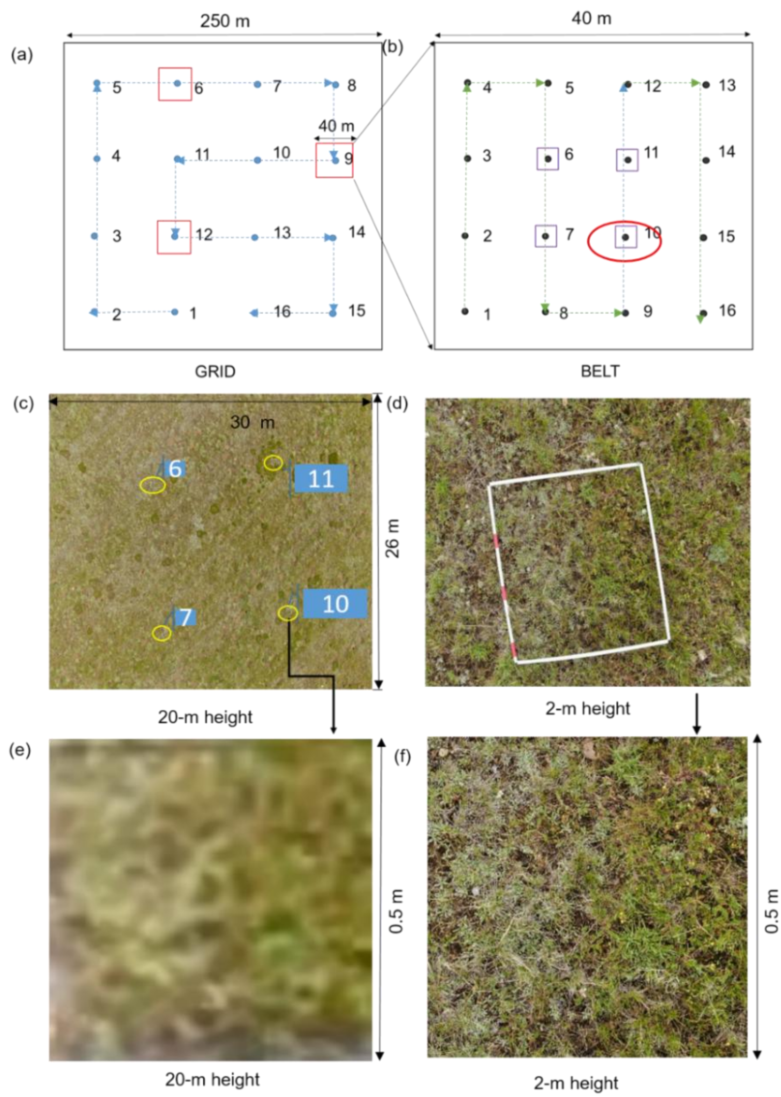

Figure 3. Schematic diagram of the UAV-field synchronization experiment in 2019: a combination design of GRID (a) and BELT (b) flight modes; a UAV image with a quadrat from the BELT mode at the height of 2 m (d); a 20-meter-high UAV image including four sample quadrats (c); and the cropped UAV images at quadrat scale from 20 m (e) and 2 m (f) height, respectively.

2.3.2 Synchronization experiment of UAV and field sampling

A UAV-field biomass synchronization experiment was designed in 2019 to ensure spatial matching among satellites, UAVs, and ground sampling (Figure 3). The specific implementation steps were as follows. First, we set a GRID flight mode with a MODIS pixel size (250 m × 250 m) (Figure 3a). Then, three waypoints were randomly selected from the GRID mode to set the BELT flight modes (40 m × 40 m). For each BELT, a sampling frame (0.5 m × 0.5 m) was placed at its 6, 7, 10, and 11 waypoints to ensure that the GRID image could contain the four frames mentioned above (Figure 3b-c). Then, at the end of all flights, the grassland AGB samples were cut, bagged, and numbered. Finally, these samples were oven-dried at 65℃ to constant weight to obtain the field-measured AGB values.

2.4 Data processing

2.4.1 UAV photo pre-processing and indices calculation

Pre-processing of UAV photos included image quality inspection, cropping, and calculation of different indices. First, we eliminated overexposed or blurred 20-meter-high UAV images. Second, the pixels in the sampling frames were cropped and saved (Figure 3e). Third, the RGB indices for the cropped UAV images were calculated. Similar to our previous study, indices included color space, histogram, and vegetation indices, the details of which can be found in Zhang et al. (2022a). In addition, 30 other RGB vegetation indices were added as candidate independent variables. The names, formulas, and references of the above indices were shown in Table A3.

2.4.2 MODIS vegetation index and other spatial data

The MOD13Q1(v006) product was downloaded from the NASA earth explorer website (https://earthexplorer.usgs.gov/) for inversion of the alpine grassland AGB on the QTP. The data contained two commonly used vegetation indices, the Normalized Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), with spatial and temporal resolutions of 250 m and 16 days, respectively. A total of 2,842 scenes from 2000 to 2019 were downloaded. Then, the MODIS images were reprojected and stitched using the MODIS Projection Tool (MRT). After that, the corresponding vegetation indices closest to the time of the UAV sampling were extracted to construct/validate a pixel-scale AGB estimation model. In addition, the kNDVI index was calculated to overcome the NDVI saturation issue based on the equation kNDVI= TANH ($NDVI^2$) (Camps-Valls et al., 2021). The annual maximum vegetation indices were calculated by the maximum value composition (MVC) algorithm to estimate the spatial AGB distribution of QTP from 2000 to 2019 (Holben, 1986; Wang et al., 2021; Gao et al., 2020).

Furthermore, meteorological, soil texture and topographic data were also included as candidate independent variables for constructing the pixel-scale AGB estimation model. Meteorological factors, including annual mean temperature (TA), annual mean precipitation (PREC), and annual total solar radiation (RAD), were calculated based on the daily meteorological dataset from the National Meteorological Information Center of China. The data processing steps mainly included interpolation, cumulative summation, and annual averaging to obtain a meteorological raster dataset with a spatial resolution of 1000 meters (Li et al., 2021). Moreover, soil texture data at 1 km spatial resolution, including the ratio of soil organic matter (SOM), clay, sand, and silt, were downloaded from the Resource and Science and Data Center of China (https://www.resdc.cn/). All the meteorological and soil datasets were resampled into 250 m by ArcGIS software to match the MODIS data.

Terrain factors included the digital elevation model (DEM), slope, and aspect. The DEM was derived from Shuttle Radar Topography Mission (SRTM) imagery (version 004, 90 m) and resampled to 250 m. The slope and aspect data were derived from DEM data using the terrain analysis tool of ArcGIS software.

2.5 AGB modeling and computation at different scales

We estimated the grassland AGB at three scales: the quadrat scale, the photo scale, and the satellite pixel scale (Figure 4). More detailed information was described as follows.

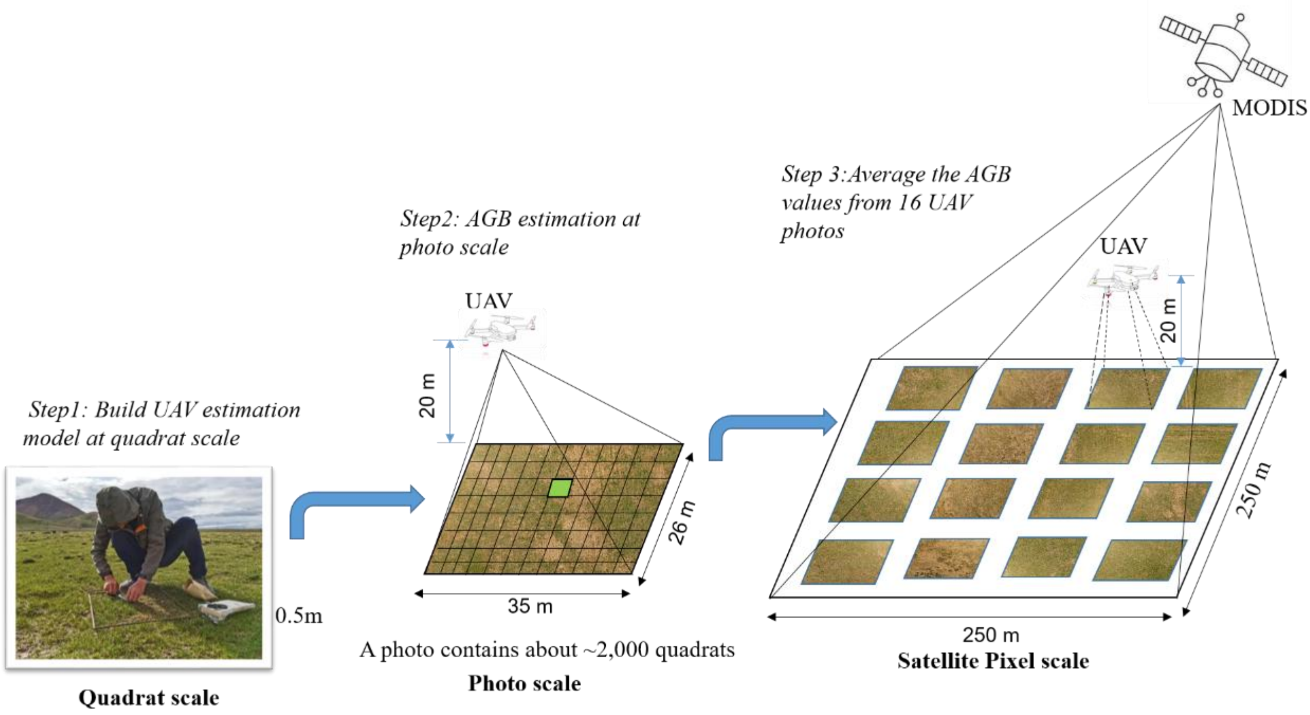

Figure 4. Upscaling steps to estimate grassland AGB matching the MODIS pixel scale.

2.5.1 Modeling method

Random Forest (RF) (Breiman, 2001) is an ensemble-learning algorithm that has been widely used to estimate AGB due to its excellent performance (Ghosh and Behera, 2018; Mutanga et al., 2012; Wang et al., 2016). The two main parameters, namely the number of regression trees in the forest *(ntree*) and the number of feature variables required to create branches (*mtry*), were first optimized based on the root mean square error (RMSE) of training data. Here, the value of *ntree* was set from 100 to 5000 with an interval of 100, while *mtry* was set as the square root of the number of training sample features. In addition, the importance of each predictor was ranked by calculating the percentage increase in mean square error (%IncMSE).

The backward feature elimination method (BFE) was used to reduce the number of input variables to simplify the RF model (Vergara and Estévez, 2014). The main steps were as follows: 1) constructing an AGB RF model by including all predictor variables in the initial stages and calculating the %IncMSE index for each variable; 2) eliminating the least promising variable and then rerunning the RF model until only one independent variable was left. Moreover, the corresponding coefficient of determination (R^2) and the corresponding RMSE were calculated in each iteration； 3) the smallest subset of variables with the highest R^2 was selected as the final optimized indices.

In addition, different training and validation strategies were used at different scales. At the quadrat scale, a 10-fold cross-validation method was used due to the limited ground samples (Kohavi, 1995). At the pixel scale, 30% of the UAV-estimated AGB samples in 2019 were randomly selected as an independent validation dataset due to the large sample size. Meanwhile, the UAV_AGB values from 2015 to 2018 were used for cross-year validation to test the robustness of the model over time. Statistical metrics R^2 (Eq.1) and RMSE (Eq.2) were used to evaluate the performance of the model.

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

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

where n is the number of samples, y_i and $\hat{y}_i$ represent the measured and the predicted AGB value, respectively, $\bar{y}_i$ is the mean value of measured AGB samples.

2.5.2 AGB RF estimation model at the quadrat scale (0.25 m^2)

Since the spatial coverage of a 20m-high UAV photo (26 m×35 m) is much wider than a single 2m-high UAV photo, making it easier to match to the MODIS pixel scale. Hence, the 20m-high UAV photos containing the sample frames were chosen for constructing the quadrat-scale AGB estimation model. A total of 906 pairs of quadrat-scale UAV-field AGB observation data were collected, with good spatial representativeness (Figure 1 a, red dots). The observed AGB values ranged from 0 to 450 g/m^2, with mean and median values of 59.75 g/m^2 and 33.04 g/m^2, respectively, most of which were less than 100 g/m^2

(Figure 5a). The cropped 20-meter-high UAV image indices and the measured AGB values were used as the independent and dependent variables to build the RF model (Figure 2).

2.5.3 AGB calculation at the photo scale (~900 m^2)

The steps for AGB estimation of the whole 20-meter-high UAV photo were as follows: 1) First, each UAV photo was divided into ~2,000 quadrat-sized small patches. 2) Second, the AGB of each small patch was calculated based on the quadrat-scale AGB estimation model. 3) Finally, the average of all small patches was calculated as the AGB of the whole photo. Based on the above steps, the AGB values of 37,487 images in GRID or RECTANGLE mode were calculated using more than 74 million AGB values of the quadrat scale (Table 1).

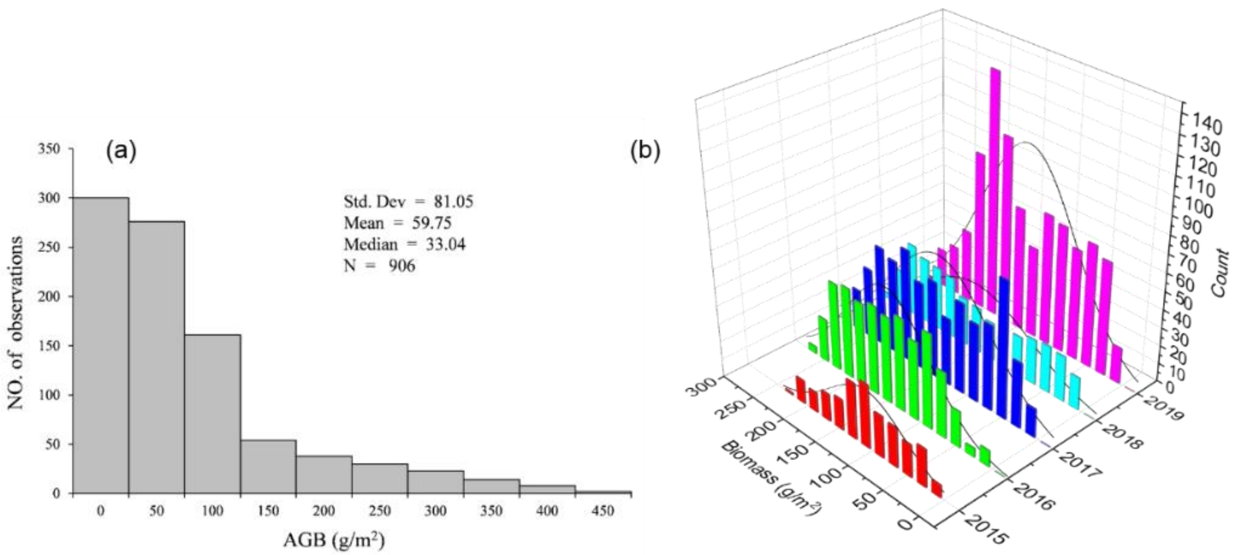

Figure 5. Histograms of field-measured AGB values at quadrat scale (a) and UAV-estimated AGB values of different years at the photo scale (b).

2.5.4 AGB RF model construction at MODIS pixel-scale (6,2500 m^2)

The following steps were involved in constructing the AGB estimation model at the pixel scale. 1) Since the coverage of a GRID or RECTANGLE mode was similar to that of a MODIS pixel, the average of its 16 or 12 photos was taken as the AGB value of the corresponding pixel. From 2015-2019, a total of 2,602 UAV-estimated AGB samples were obtained at the pixel scale (Table 1). 2) The MODIS vegetation indices and other spatial metrics corresponding to each GRID or RECTANGLE mode were then extracted using the ArcGIS software. Here, the MODIS NDVI, EVI, and kNDVI indices closest to the sampling time were chosen to minimize the time difference between sampling and satellite overpass.3)

Subsequently, the UAV-estimated AGB values and the extracted spatial indices were used as dependent and independent variables to build the AGB estimated model at the pixel scale using the RF algorithm.

2.6 Uncertainty analysis

Since the actual AGB values of MODIS pixels cannot be directly obtained, vegetation indices were used to quantify the uncertainty of different AGB estimation methods. In other words, the higher the correlation between the estimated AGB and MODIS vegetation indices, the more accurate the estimation model was. The performance of the estimation model was evaluated through three aspects. In this study, we first compared the correlation between the MODIS vegetation indices and AGB values obtained by traditional sampling and UAV estimation methods. We also explored the uncertainties of UAV sampling coverage by randomly combining the number of photos in a MODIS pixel, and tested whether the estimated AGB was closer to the true value as the number increased. Furthermore, the AGB validation results from GRID or RECTANGLE at the pixel scale were compared to understand the uncertainties caused by different flight modes.

2.7 Trend analysis of grassland AGB

This study combined the Theil-Sen median trend analysis and Mann-Kendall test to analyze the temporal variation characteristics of grassland AGB of QTP (Jiang et al., 2015). Theil-Sen median trend analysis is a robust trend statistical method with high computational efficiency, insensitive to outliers (Hoaglin et al., 1983). The Mann-Kendall test is a nonparametric test for time series trends, which does not require the measurements to follow a normal distribution and is not affected by missing values and outliers. The Theil-Sen Median trend analysis and Mann-Kendall trend test have been widely used to analyze vegetation index, cover, and biomass (Gao et al., 2020; Jiang et al., 2015; Fensholt et al., 2009). The formulas for the Theil-Sen median trend analysis and the Mann-Kendall method are detailed in Jiang et al. (2015).

3 Results

3.1 Independent variables selected for AGB modeling

The independent variables for AGB estimation at the quadrat and pixel scales were presented in Table 2. A total of 36 independent variables were selected at the quadrat scale, including 26 vegetation RGB indices, 6 histogram indices, and 4 color space indices (Figure A2). At the pixel scale, five variables were selected, including NDVI, kNDVI, EVI, PREC, and DEM (Figure A3).

Table 2: Selected independent variables for the AGB modeling at quadrat and pixel scales. The full names of each variable at the quadrat scale were listed in Table A3.

Scale	Model	Number	Independent variables
Quadrat	RF_Q	36	FVC, WI, GI, EXG, TGI, EXGR,VEG, GRATIO, COM, CIVE, RGBVI, EXR, GLA, GRRI, MVARI, MGRVI, GRVI, RGRI, GBRI, VARI, NDI, RRATIO, EXB, V, IPCA, INT, HOC_R_CORR, HOC_B_CHIS, HOC_R_CHIS, HOC_G_CHIS, HOC_G_CORR, HOC_B_CORR B, H, G, R,
Pixel	RF_P	5	NDVI, kNDVI, EVI, DEM, PREC

3.2 Modeling and accuracy assessment

For the AGB estimation model at the quadrat scale, the results of 10-cross validations showed that there was a significant linear relationship between the estimated and the measured values (R^2=0.73, p<0.001, Table 3, Table A4). The student's t-test was also used to assess whether there was a significant difference between the predicted AGB values and the measured values at a confidence level of 95%. As shown in Table 4, there was no significant difference (p=0.51>0.05) with an RMSE of 32.94 g/m^2. The scatter plot showed that the model predicted well when the measured biomass was less than 150g/m^2, but showed some underestimation when it was more than 200g/m^2 (Figure 6a). It may be because the number of samples more than 200g/m^2 is relatively small, accounting for only 8.50% of all samples (Figure 5a). Although the sample size of UAVs varied from year to year, most of the AGB values estimated from photos ranged from 0 to 300 g/m^2 (Figure 5b).

For the pixel-scale AGB estimation model, there was a strong linear relationship between the predicted AGB and UAV estimates for 2015-2019 (Table A4). The fitting coefficient R^2 was 0.85 for 2017-2019, and slightly lower for 2015-2016 at 0.63 and 0.77, respectively (Table 3, Figure 6b-f). The RMSE of the pixel-scale model ranged from 23.36 to 34.07 g/m^2 (Table 3). In addition, we found no significant differences between the predicted and measured average AGB values except for 2017 and 2018 (Table 4). While the average model projections for 2017 and 2018 were 14.72% and 13.78% lower than the UAV estimates, they were within acceptable ranges. Therefore, the constructed pixel-scale AGB estimation model had good performance and robustness in different years (Figure 6b~f).

Table 3: Validation results of AGB models at quadrat and pixel scales

Scale	Year	Training set		Validation set	
		R^2	RMSE(g/m^2)	R^2	RMSE(g/m^2)
Quadrat-scale	2019	0.94	20.18	0.73 ***	32.94
Pixel-scale	2019	0.96	10.68	0.85 ***	23.36
	2018	__	__	0.85 ***	24.83
	2017	__	__	0.85 ***	23.83
	2016	__	__	0.77 ***	31.28
	2015	__	__	0.63 ***	34.07

'***' significant at p<0.001

Table 4: T-test results between the predicted and measured AGB values for the modes at the quadrat and pixel scales

Validation model	Measured mean	Predicted mean	t	df	p-value
2019_Quadrat-scale	51.57	54.35	-0.66	939.35	0.51
2019_Pixel_scale	136.68	137.7461	-0.15	340.78	0.88
2018_Pixel_scale	152.49	131.48	4.01	723.81	6.63e-05
2017_Pixel_scale	141.42	120.60	5.48	1225.2	5.26e-08
2016_Pixel_scale	149.56	142.70	1.68	961.99	0.09413
2015_Pixel_scale	108.65	98.23	1.96	1225.2	0.05

3.3 Correlation analysis between AGB values and MODIS indices

The correlations between the UAV-estimated AGB values and MODIS vegetation indices were much better than the traditional sampling method (Figure 7a). For example, the correlation between NDVI and traditionally measured AGB was only 0.53, much lower than that obtained from a single UAV image (r=0.74). Moreover, the correlation between NDVI and UAV-estimated AGB increased with the number of UAV photos. It increased rapidly as the number increased from 1 to 4 (from 0.74 to 0.86), then slowed down and stabilized (from 0.87 to 0.88). In addition, we compared the scatter plots and fitting lines between NDVI and different AGB estimation methods (Figure 7b-f). The results showed a weak linear relationship between the traditionally measured AGB and NDVI, with an R^2 of 0.29. With the UAV sampling method, the linear relationship was greatly improved and increased with the number of photographs. The fit coefficient R^2 increased from 0.54 to 0.78, much higher than the traditional sampling method (Figure 7).

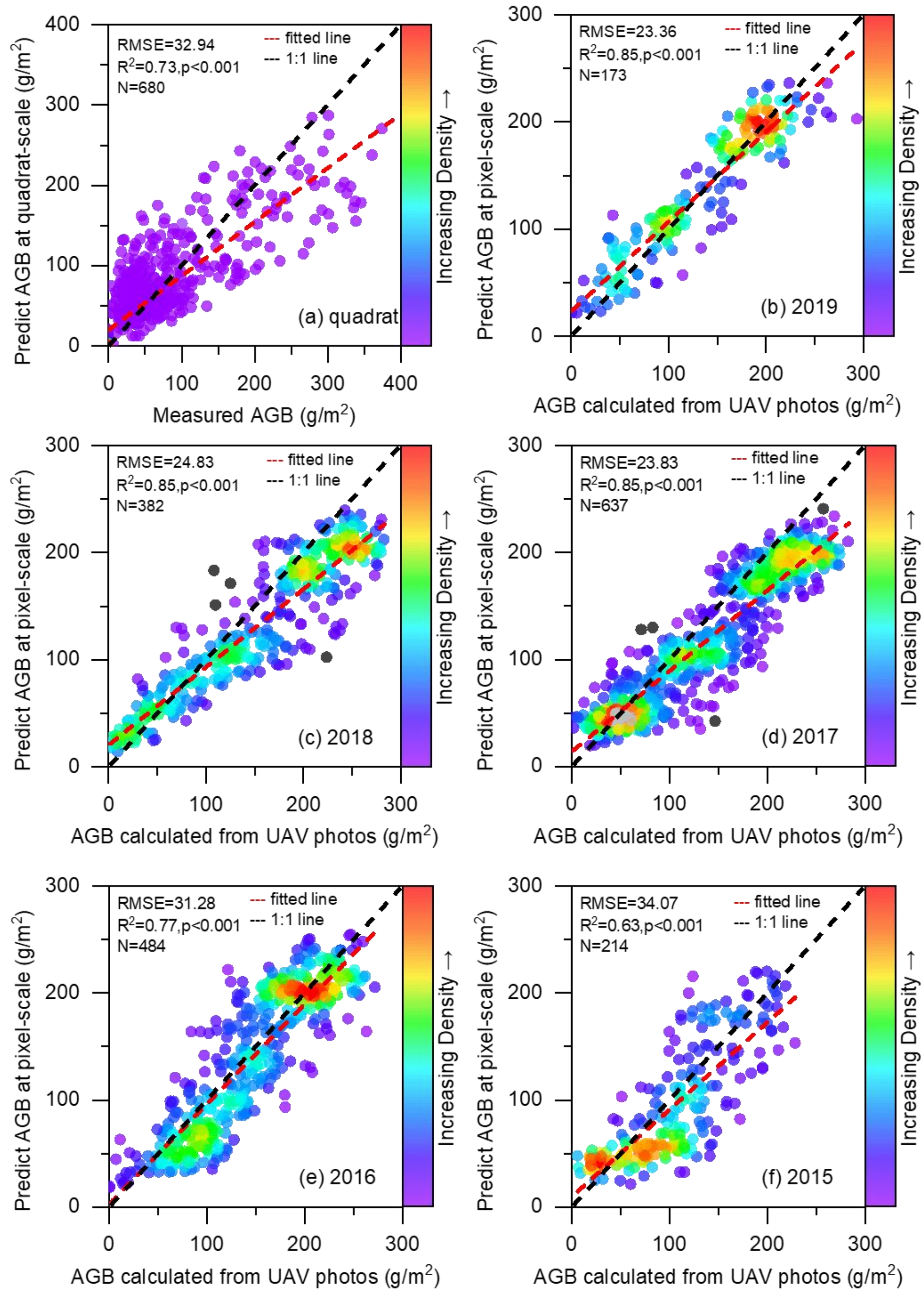

Figure 6. Validation results of the AGB estimation models at the quadrat (a) and MODIS pixel scale for 2015-2019 (b~f).

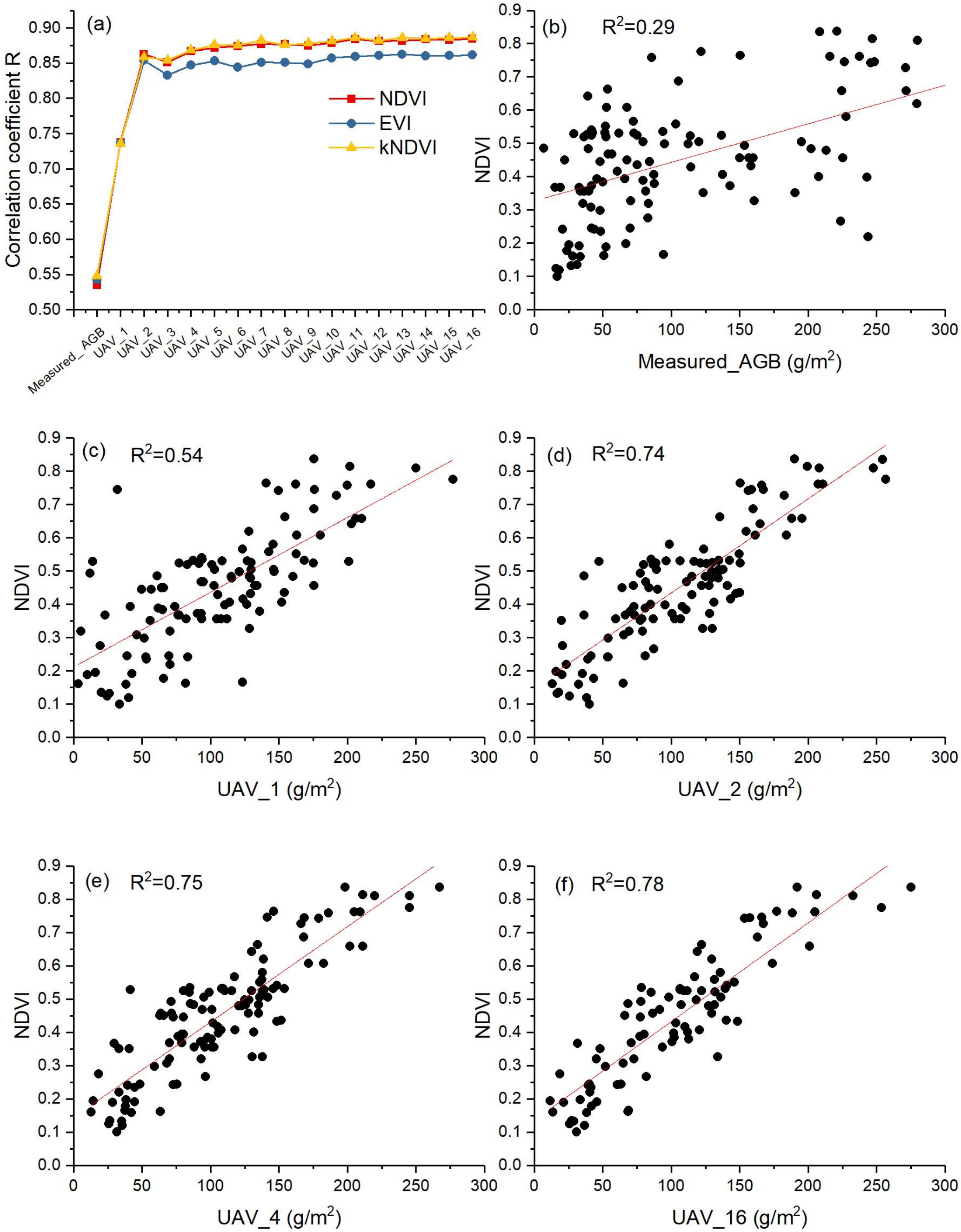

Figure 7. Correlation between MODIS vegetation indices and different AGB estimation methods (a); scatter plots of NDVI with different AGB estimation methods (b-f). UAV_x, x represents the number of UAV photos used to estimate the average AGB at the MODIS pixel scale. Here, x ranges from 1 to 16.

3.4 Spatial distribution of grassland AGB

The spatial distribution of the average grassland AGB on the QTP from 2000 to 2019 was calculated (Figure 8). The AGB gradually increased from west to east. As shown in Figure 8b, the average biomass of eastern OA1, IIAB, IB1, and IIC2 eco-geographical regions ranged from 150 to 190 g/m^2, and the average AGB of IC1 and IIC1 ranged from 80 to 110 g/m^2. The average AGB of IID2, IID3, IC2, and IID1 in the west was relatively low, ranging from 35 to 75 g/m^2. The ID1 region was dominated by sparse grassland with the lowest average interannual AGB values, which fluctuated around 20 g/m^2 (Figure 8b). The average AGB of QTP showed an insignificant increasing trend between 2000 and 2019, with an average growth rate of 0.22 $gm^{-2}a^{-1}$ (Figure 9a). The overall mean AGB of the QTP was 103.6 g/m^2, with 151.85 g/m^2, 60.85 g/m^2, and 28.91 g/m^2 for alpine meadow, alpine steppe, and sparse grassland, respectively (Figure 9b). In addition, the temporal trend of grassland AGB in each pixel was analyzed. As shown in Figure 10, the IID3, ID1, IID2, and IIC2 eco-geographical regions of the northern QTP showed an increasing trend from 2000 to 2019, while the IC2, IB1, and IIC1 regions showed some degradation. Therefore, there was spatial heterogeneity in the temporal variation.

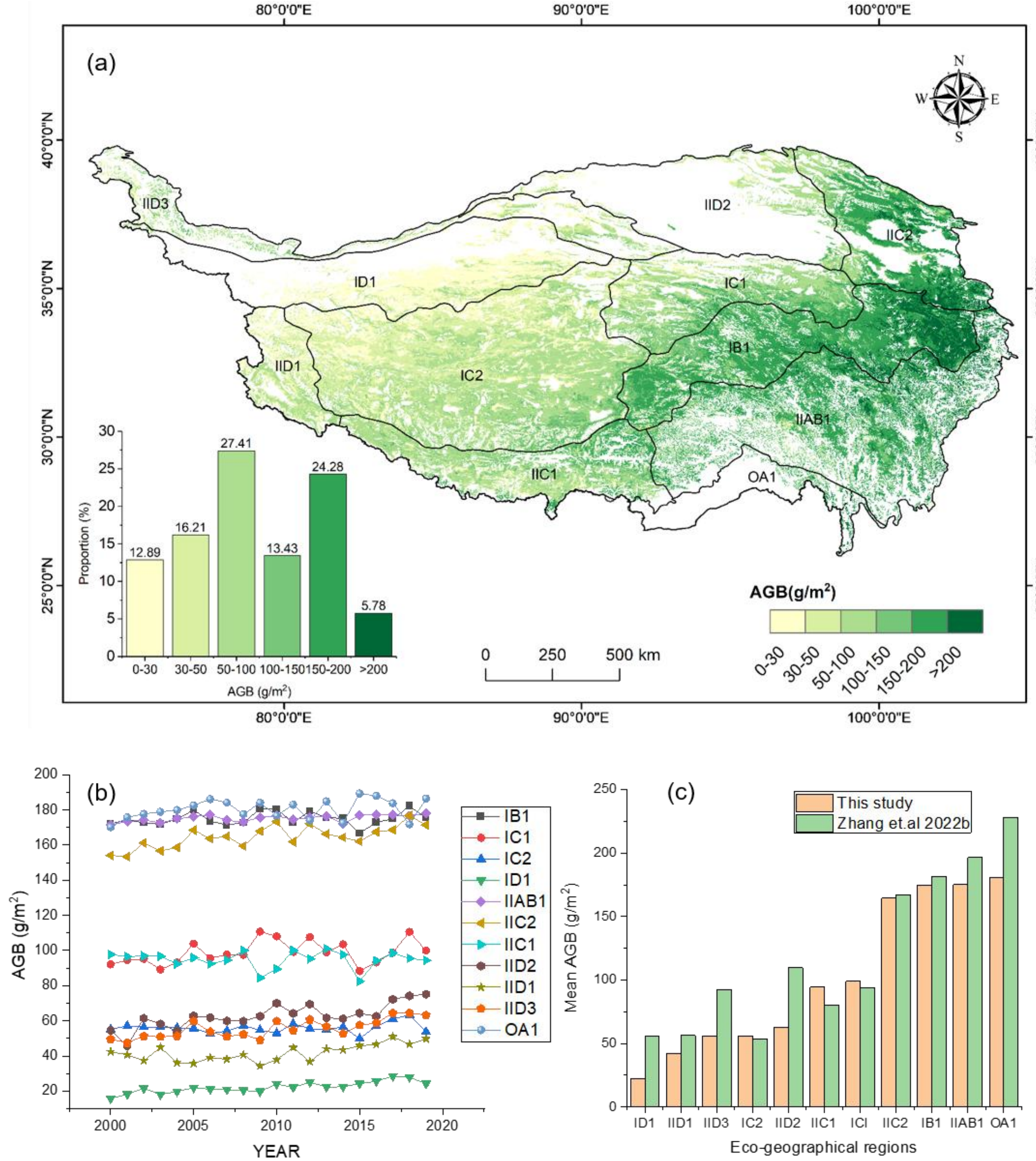

Figure 8. (a) The spatial distribution of average grassland AGB on the QTP from 2000 to 2019. IID1, IID2, IID3, ID, IIC1, IIC2, IC1, IB1 IIAB1, and OA1 are the eco-geographical regions of the QTP(Zheng, 1996). The full names of each eco-geographical region were listed in Table A5. (b) AGB values of each eco-geographical region from 2000 to 2019. (c) Comparison of multi-year AGB averages in the different eco-geographical regions.

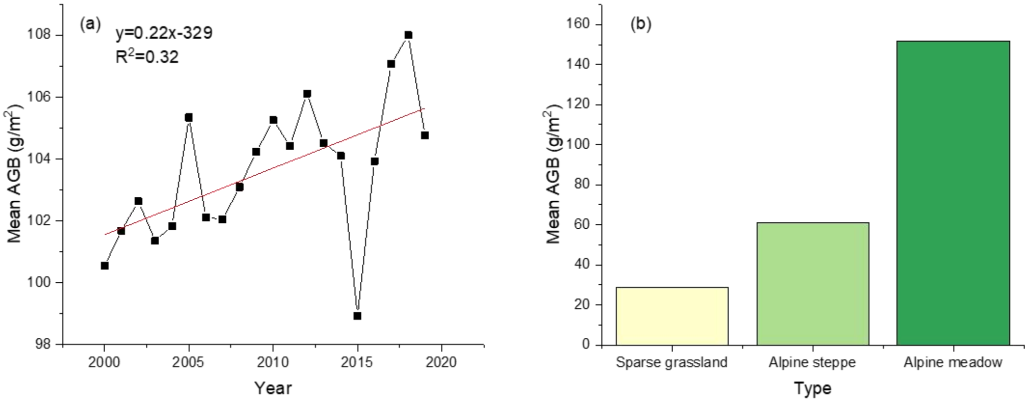

Figure 9. Variation trend of average grassland AGB on the QTP from 2000 to 2019 (a) and average AGB of different grassland types (b).

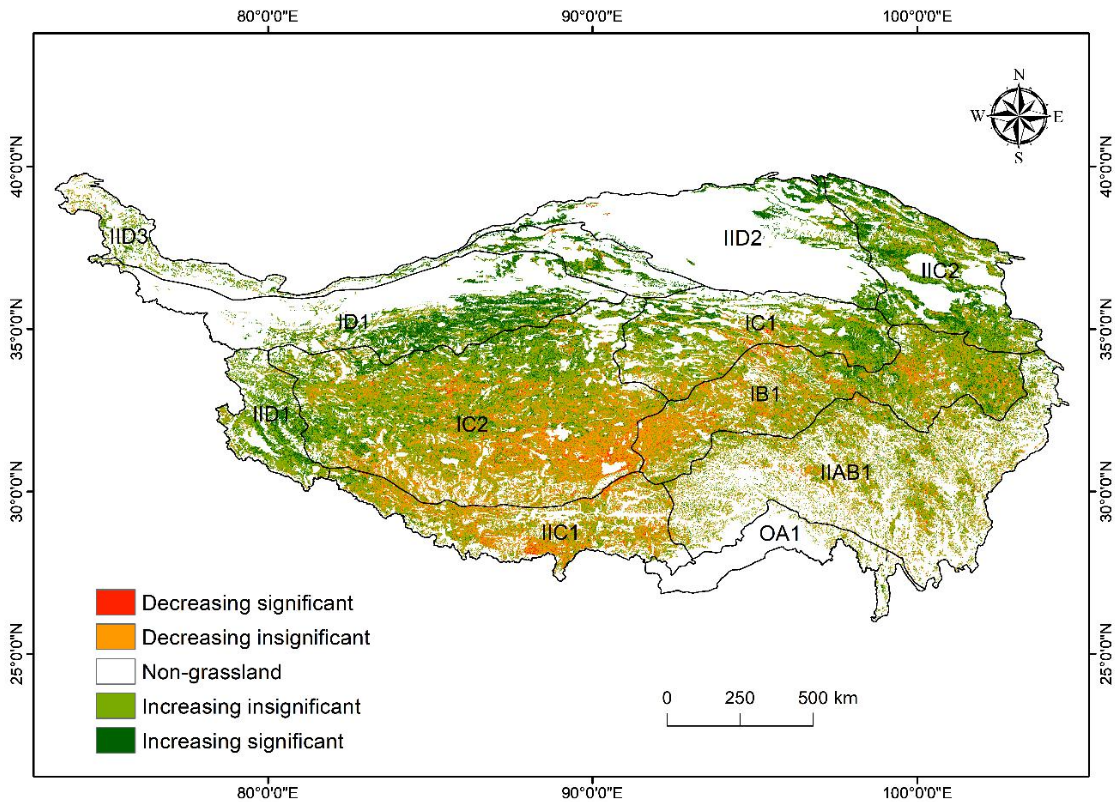

Figure 10. Spatial trends of grassland AGB on the QTP from 2000 to 2019. IID1, IID2, IID3, ID, IIC1, IIC2, IC1, IB1 IIAB1, and OA1 are the eco-geographical regions of the QTP (Zheng, 1996). The full names of each eco-geographical region were listed in Table A5.

4. Discussion

4.1 Scale matching and its influence factor

In previous studies, the AGB value of a satellite pixel was represented by the average value of 3-5 quadrat-scale samples, so there is a large spatial gap between the ground samples and the satellite pixels (Yang et al., 2017; Yang et al., 2009; Meng et al., 2020). The spatial gap between ground samples and satellite indices affects the accuracy of grassland AGB models. The smaller the spatial gap between the two, the higher the accuracy of the model (Morais et al., 2021). We addressed this issue using the UAVs as a bridge to reduce the spatial gap. Spatial scale matching of dependent and independent variables was achieved in estimating AGB values at different scales. First, at the quadrat scale, the independent variables were all derived from cropped 20-meter-high UAV images corresponding to the ground samples (Figure 3e). Then, the 20-meter-high UAV image was cropped into ~2000 quadrat-sized patches to ensure consistency with the quadrat-scale model, and the average of these patches was used as the final AGB at the photo scale. Finally, by averaging the AGB of 16 or 12 UAV photos within the MODIS pixel, the AGB value matching the MODIS pixel scale was calculated (Figure A1). With these three steps, we successfully upscaled the measured AGB from the traditional quadrat scale (0.5 m×0.5 m) to the photo scale (26 m×35 m) and MODIS pixel scale (250 m×250 m). Our results showed that the correlations between the UAV-estimated AGB values and the MODIS vegetation indices were higher than that of the traditional sampling method (Figure 7).

Furthermore, we found that the spatial coverage of the UAV sampling had an impact on the scale matching. Our results showed that the closer the spatial coverage of the UAV sampling was to the satellite pixel, the higher its correlation with MODIS spectral indices (Figure 7a). It was also confirmed by comparing the validation results of different flight modes. At the pixel scale, we found that the R^2 between the model predictions and the AGB values estimated based on the GRID mode was better than that of RECTANGLE (Figure 11). The reason is that GIRD mode can take 16 pictures within a MODIS pixel, while RECTANGLE mode only takes 12 pictures (Figure A1).

The above results confirmed that UAVs could serve as a bridge to effectively reduce the spatial gap between traditional samples and satellite data.

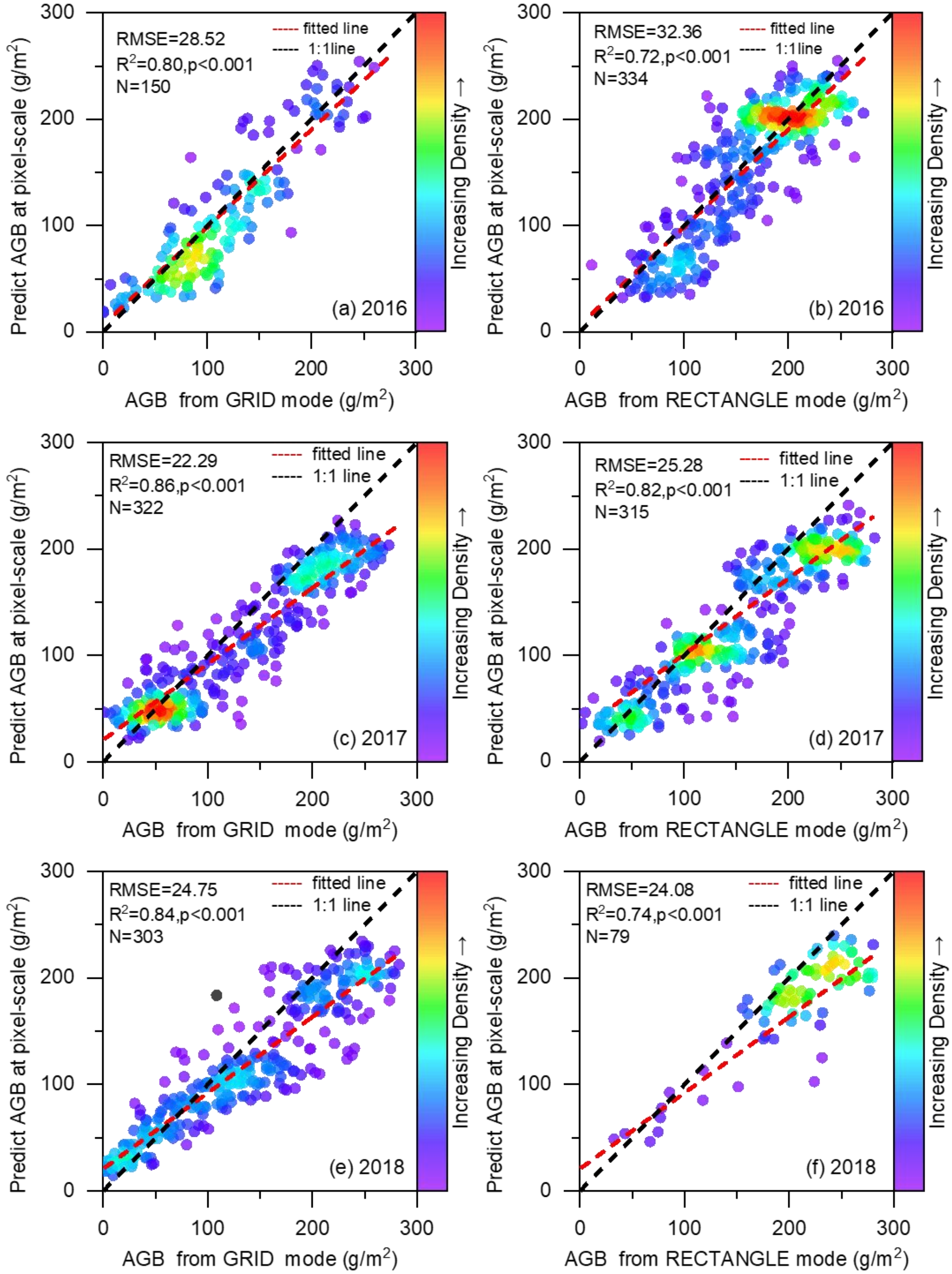

Figure 11. Comparison of validation results for the GRID (a,c,e) and RECTANGLE (b,d,f) modes in 2016-2018.

4.2 Importance of the addition of non-vegetation samples

Compared with traditional sampling, UAV sampling has the advantage of wide spatial coverage (0.5 m×0.5 m vs. 35 m×26 m). Thus, the UAV image could capture vegetation and non-vegetation background information, such as roads, water, soil, gravel, riverbed, etc. (Figure A4). Adding non-vegetation samples could improve the accuracy of AGB estimation at the photo scale, especially for low-cover areas, to avoid overestimation. It was also true for the pixel-scale AGB estimation model. However, the traditional sampling method gave less consideration to the non-vegetation areas. The sample plots were mainly set in areas with homogeneous spatial distribution, and rarely in areas with spatial heterogeneity. This shortcoming may limit the accuracy of AGB estimation due to the high spatial heterogeneity of the QTP. Fortunately, the UAV sampling method can avoid this drawback. It can objectively record surface information and reduce the influence of manual plot selection on AGB estimation.

4.3 Comparison of the estimated AGB with previous studies

We compared our results with previous studies at the quadrat, pixel, and regional scales.

At the quadrat scale, consistent with our previous study, we further confirmed that the UAV RGB images could be used to estimate grassland AGB (Zhang et al., 2022a; Zhang et al., 2018). Similar to the 2-meter-high UAV image, the indices from the 20-meter-high UAV image could be used to estimate the grassland AGB at the quadrat scale (R^2=0.73, RMSE=44.23 g/m^2, Figure 6a). Compared with the 2-meter-high UAV image, the 20-meter-high UAV image is more suitable for matching the MODIS pixel due to its wider spatial coverage (26 m ×35 m).

At the pixel scale, compared with other studies, this paper achieved the spatial scale matching of independent and dependent variables during the modeling. In previous studies (Yang et al., 2009; Yang et al., 2017; Meng et al., 2020), they constructed the models from the measured AGB values at the quadrat-scale and the spectral indices of the satellites without considering the spatial scale difference. It partly explained why the R^2 of the AGB linear model constructed by Yang et al. was only 0.4 (Yang et al., 2009). Our results confirmed that the R^2 of the linear model could be increased from 0.29 to 0.78 after reducing the spatial gap between measured AGB and NDVI (Figure 7). In addition, thanks to the rapid sampling of UAV AGB, a total of 2,602 samples matching the pixel scale were collected during 2015-2019. It allowed us to perform cross-year validation to assess the robustness of the model over time, which has rarely been performed in previous studies. Our results showed similar validation results for 2017-2019 (R^2=0.85, p<0.001) despite different sample sizes and spatial distributions (Figure 1, Table 1). But in 2015-2016, R^2 was relatively low, at 0.63 and 0.77, respectively (Table 3, Figure 6). The reason was that during 2015-2016, some photos with abnormal white balance were obtained due to improper settings, which reduced the estimation accuracy (Figure A5). The validation results showed that the pixel-scale AGB estimation model had good robustness in different regions and times when the photo quality was acceptable.

Table 5: Comparison of AGB estimation results of different studies on the QTP

Mean AGB (g/m²)	Alpine steppe (g/m²)	Alpine meadow (g/m²)	Study period	Approach	Input parameter	References
68.8	50.1	90.8	2001-2004	Linear regression	EVI	(Yang et al., 2009)
__	22.4	42.37	2000-2012	Linear regression	NDVI	(Liu et al., 2017)
120.73	__	__	1980–2014	Exponential regression	NDVI	(Jiao et al., 2017)
78.4	__	__	1982-2010	RF	NDVI, climate	(Xia et al., 2018)
77.12	76.43	154.72	2000-2014	RF	NDVI, EVI, climate, terrain	(Zeng et al., 2019)
59.63	42.75	77.56	2000-2017	RF	NDVI, climate	(Gao et al., 2020)
102.4	__	__	2000-2020	RF	climate, soil, and terrain	(Zhang et al., 2022b)
70.00	__	__	1960–2002	Century	climate and soil data	(Zhang et al., 2007)
119.78	__	__	2002–2004	Orchidee	climate, soil and LAI data	(Tan et al., 2010)
103.6	60.85	151.85	2000-2019	RF	MODIS	this study

At the regional scale, consistent with previous results, we found an overall increase in AGB over the QTP from 2001 to 2019, albeit with fluctuations (Zeng et al., 2019; Gao et al., 2020). The annual average AGB of grassland was 103.6 g/m^2, which was closest to Zhang et al.(Zhang et al., 2022b) and within the range of the previous estimates (59.63-120.73 g/m^2) (Table 5). The mean AGB varied among different grassland types, with 151.85 g/m^2 for the alpine meadow and 60.85 g/m^2 for the alpine steppe. Our estimation results were similar to those of Zeng et al. (Zeng et al., 2019), but the overall average AGB was higher than their estimate of 77.12 g/m^2. The spatial distribution of AGB was consistent with previous studies, showing a west-to-east increasing trend (Zhang et al., 2022b; Xia et al., 2018). Specifically, the average AGB of OA1, IIAB, IB1, and IIC2 eco-geographical regions in the east was significantly higher than that of IID2, IID3, IC2, IID1, and ID1 regions in the west (Figure 8). In general, the average AGB estimates for each eco-geographical region in this paper were not much different from those of Zhang et al. (2022b). Among them, our average AGB estimates for ID1, IID1, IID3, and IID2 regions were slightly lower, but our values were closer to the measured values of these regions (Figure 8c). The reason may be that they calculated the potential AGB, while we calculated the actual AGB, so our estimate was relatively low. In terms of spatial and temporal trends, the data results showed that the eco-geographical regions in the northern part of the QTP demonstrated an increasing trend (IID3, ID1, IID2, and IIC2), while the IC2, IIC1, and IB1 regions exhibited significant or non-significant decrease, which was consistent with the results of others (Gao et al., 2020; Liu et al., 2017).

The difference between our estimated grassland AGB and previous studies might be due to differences in data sources and modeling methods. Firstly, the sample size and spatial distribution of ground samples were different. The number of ground samples is the most important variable affecting the accuracy of the grassland AGB estimation model (Morais et al., 2021).

Unlike previous studies, we collected ground validation data by combining the traditional sampling method and UAVs. The newly proposed method could overcome the shortcomings of traditional samplings (time-consuming and labor-intensive). It no longer takes years to obtain spatially representative, large-scale ground validation data (Yang et al., 2017). With UAV sampling, ground observations matching the satellite pixel scale can be obtained in only 15-20 minutes, which is difficult to achieve in traditional surveys. Our new sampling method not only accelerates the sampling speed and increases the sample size, but also improves the spatial match between ground samples and satellite pixels. As a result, our ground validation data is superior to previous studies in terms of quantity and spatial match to the satellite data. Secondly, the input parameters of AGB estimation models were different. Some scholars used only a single vegetation index (NDVI or EVI), while others combined the vegetation index with meteorological, soil, and terrain indices to construct the AGB estimation models (Table 5). In this study, NDVI, kNDVI, EVI, DEM, and PREC were used as the final predictor variables to construct the AGB estimation model at the pixel scale (Table 2). Thirdly, modeling methods might also affect the simulation results. As shown in Table 5, the overall AGB averages of the QTP estimated based on different methods (such as linear or nonlinear regression, machine learning, and ecological process model methods) varied considerably. Yang et al.(2017) found that the model performance of ANN was much better than the linear regression model when using the same dataset to estimate grassland AGB in the Three-River Headwaters Region of China. Jia et al.(2016) reported that the model forms could bring 13% uncertainty to the AGB estimation. Wang et al. compared the RF with the support vector regression (SVR) machine learning algorithm and found that the RF yielded the best performance in grassland biomass estimation (Wang et al., 2017).

4.4 Limitations and further work

We acknowledge that there are some shortcomings in this study. 1) The predicted values of the quadrat-scale model were underestimated when the measured biomass values were greater than 250 g/m^2 (Figure 6). One reason may be that the number of samples greater than 250 g/m^2 was relatively small, accounting for only 5.18 % of all samples. Another reason may be that for high biomass grasslands, a single UAV RGB photo can only reflect information such as vegetation cover and greenness, but not height information. This feature is very unfavorable for estimating AGB in grassland areas with high vegetation coverage and height. Studies have shown that adding vegetation height information can help improve the estimation accuracy of grassland AGB (Zhang et al., 2022a; Lussem et al., 2019; Viljanen et al., 2018). In future work, an affordable DJI Zensil L1 Lidar UAV will be introduced to invert the height of the grassland. 2) At the pixel scale, limited by the estimation accuracy of AGB from UAV, there was also some underestimation in the high biomass area. Although the MODIS index closest to the sampling time was chosen for the construction/validation of the AGB estimation model, there was still a time difference between the measured samples and the MODIS indices, which might lead to estimation errors. In addition, the NDVI saturation problem was not considered in this study, which might affect the AGB estimation accuracy of QTP (Tucker, 1979a; Gao et al., 2000; Mutanga and Skidmore, 2004; Tucker, 1979b). In the next step, we will continue to collect samples with high biomass and try to correct the NDVI saturation problem to optimize the simulation accuracy of the data set. 3) During 2015-2016, our study had just started, and the appropriate camera parameters were still being explored. As a result, some photos with abnormal white balance were obtained, reducing the accuracy of AGB estimation at the photo scale (Figure A5). 4) We collected grassland AGB only during the peak growing season, and the applicability of the proposed method to other growing seasons needs further study. 5) During the modeling process, due to the limited positioning accuracy, only the center points of the flight path were used to find the corresponding MODIS pixels. Moreover, although the UAV images in GRID or RECTANGLE mode could cover most areas of a MODIS pixel, full pixel coverage was still not achieved. Therefore, we will gradually upscale to MODIS pixels by combining UAVs with Sentinel-2 or Landsat images.

5. Data availability

The dataset is available from the National Tibetan Plateau/Third Pole Environment Data Center (https://doi.org/10.11888/Terre.tpdc.272587). The dataset contains 20 years of AGB spatial data of the QTP with a resolution of 250 m and is stored in TIFF format. The name of the file is "AGB_yyyy.tif", where yyyy represents the year. For example, AGB_2000.tif represents this TIFF file describing the alpine grassland AGB condition of QTP in 2000. The data can be readily imported into standard geographical information system software (e.g., ArcGIS) or accessed programmatically (e.g., MATLAB, Python).

6. Conclusion

In this study, a new AGB dataset for alpine grasslands on the QTP was calculated based on traditional ground sampling, UAV photography, and MODIS imagery. The uniqueness of this dataset is the use of UAVs as a spatial scale-matching bridge between traditional samples and satellite pixels. The study confirmed that the UAV images could be used for AGB estimation at the quadrat /pixel scale, with R^2 of 0.73/0.83 and RMSE of 44.23/34.13 g/m^2, respectively. At the pixel scale, the correlation between AGB estimated by UAV and MODIS vegetation index was higher than that of the traditional sampling method (0.88 vs. 0.53). Moreover, the spatial scale matching of the dependent and the independent variables was achieved during the modeling. In addition, we performed a cross-year validation of the pixel-scale AGB estimation model to confirm the robustness of the model and the accuracy of this dataset. The availability of the new dataset is helpful in many applications. First, this dataset provides reliable regional data for estimating grassland productivity, carbon storage, ecological carrying capacity, and ecological service functions (such as feed for grazing livestock) of the QTP. Second, the dataset can be used to understand the mechanisms of environmental processes, such as hydrological cycle processes, soil erosion and degradation, and carbon cycle processes in the QTP. In addition, this dataset can be used as input or validation parameters for various ecological models to understand the response mechanism of the QTP to global climate change.

7. Author contributions

HZ contributed to the study conceptualization, methodology, funding acquisition, and the original draft of the manuscript. ZT, BW, and HK contributed to resources and formal analysis. QY and YS contributed to data collection and manuscript review. BM, ML, and JC contributed to the methodology and reviewed the manuscript. YL and JZ participated in reviewing and editing the manuscript. SN contributed to the data collection and review of the manuscript. SY contributed to the study conceptualization, funding acquisition, and manuscript review. All authors have read and approved the manuscript.

8. Competing interests

The authors declare that they have no conflict of interest.

9. Acknowledgements

We would like to express our gratitude to the other students and staff who participated in the field investigation.

10. Financial support

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Appendix

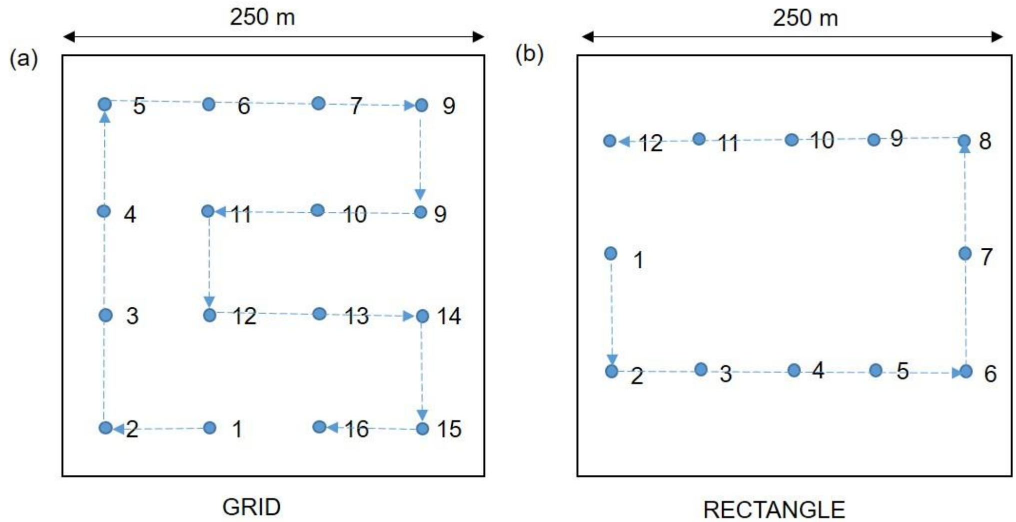

Figure A1. Waypoints for GRID (a) and RECTANGLE (b) flight modes.

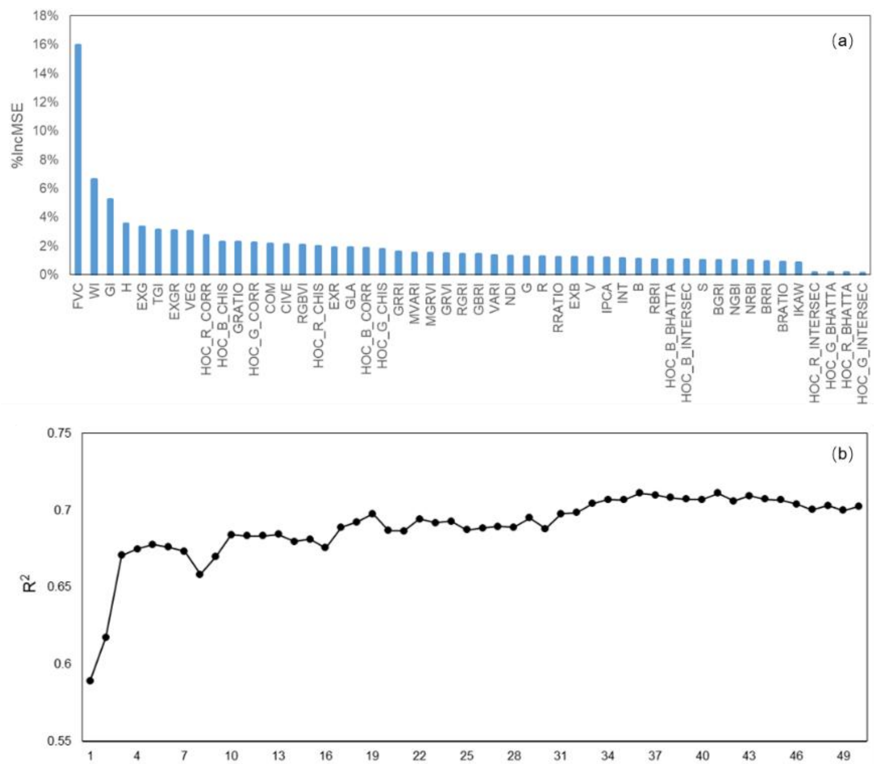

Figure A2. The importance values for each independent variable (a) and the R^2 results of the different number of input variables at the quadrat scale.

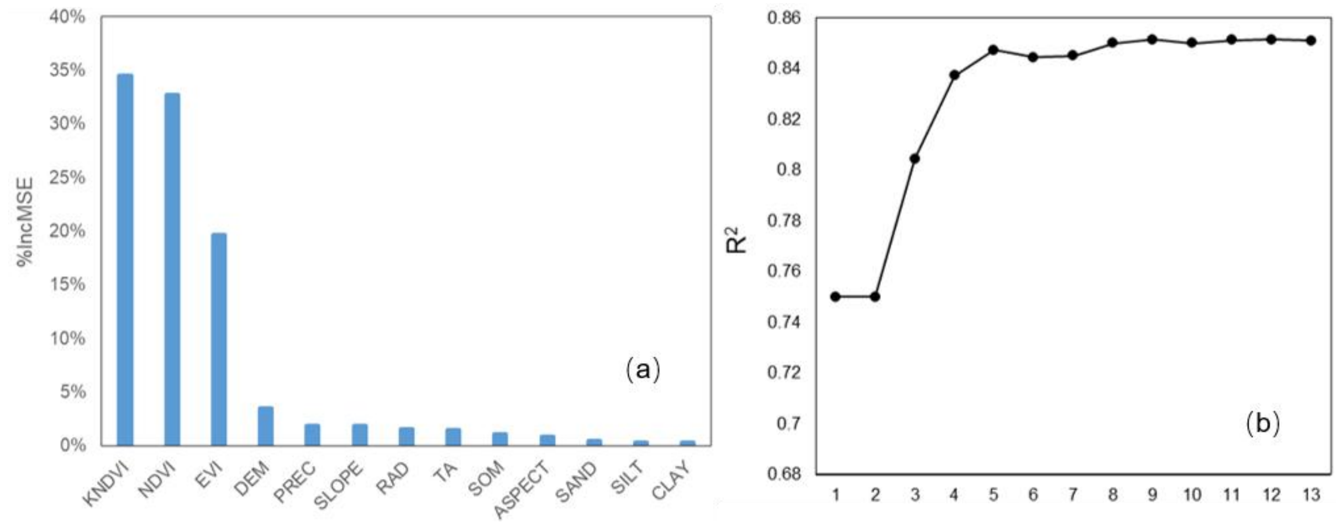

Figure A3. The importance values for each independent variable (a) and the R^2 results of the different number of input variables at the pixel scale.

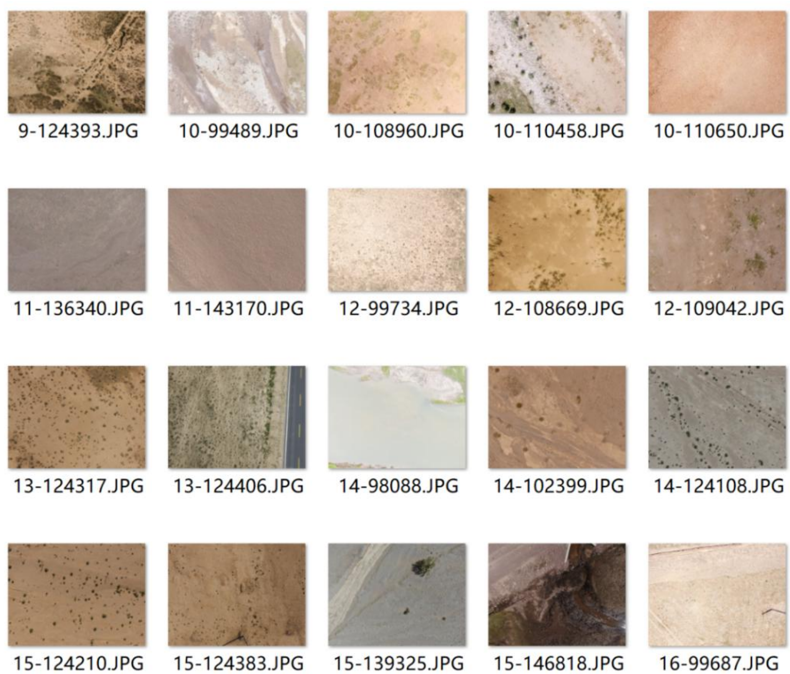

Figure A4. Examples of 20-meter-high UAV images with different non-vegetation background information.

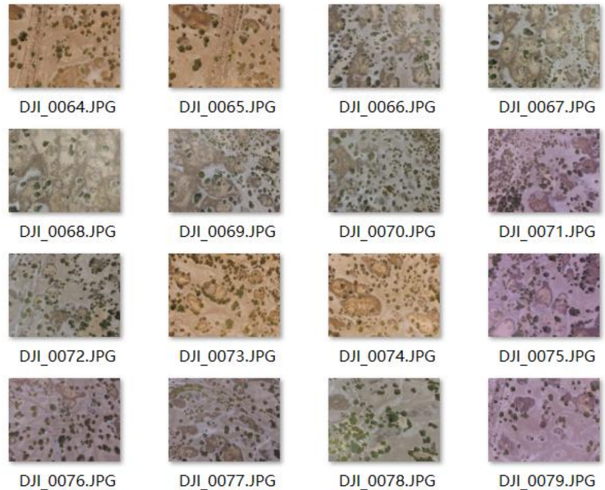

Figure A5. An example of a set of GIRD photos with abnormal white balance in 2015.

Table A1. Combined grassland types

New grassland type	Original grassland type
Alpine meadow	Alpine meadow, Lowland meadow, Montane meadow，
Alpine steppe	Temperate steppe, Alpine steppe, Alpine meadow steppe
Spare grassland	Temperate steppe desert, Alpine desert

Table A2. Features of DJI Phantom 3 Pro

	Features	Description
	Sensor	1/23-inch; Effective-pixel: 12-megapixel
	Filed of view	FOV 94° 20 mm
	Aperture	f/2.8
	Shooting speed	Electronic shutter: 8-1/8000 s
	Photo size	4000×3000
DJI Phantom 3 Pro	Flight time	~25 min
	Image format	JPEG
	Hovering accuracy	±0.5 m vertically; ±1.5 m horizontally
	Weight	1280 g

Table A3: Details of the independent variables for quadrat-scale AGB estimation

Acronym	Index name	Formula	Reference
GRVI	Green Red Vegetation Index	(G-R)/(G+R)	(Tucker, 1979a)
EXG	Excess Green Vegetation Index	2G-R-B	(Woebbecke et al., 1995)
GLA	Green leaf area	(2G-R-B)/(2G+R+B)	(Louhaichi et al.)
MGRVI	Modified Green Blue Vegetation Index	(G2-R2)/(G2+R2)	(Bendig et al., 2015)
RGBVI	Red Green Blue Vegetation Index	(G2-B*R)/(G2+B*R)	(Bendig et al., 2015)
EXB	Excess Blue Vegetation Index	(1.4*B-G)/(G+R+B)	(Maimaitijiang et al., 2019)
NDI	Normalized difference index	(R-G)/(R+G)	(Woebbecke et al., 1993)
EXR	Excess Red Vegetation Index	1.4*R-B	(Meyer and Neto, 2008)
EXGR	Excess Green minus Excess Red index	ExG−ExR	(Meyer and Neto, 2008)
RRATIO	Red Ratio	R/(R+B+G)	(Woebbecke et al., 1995)
BRATIO	Blue Ratio	B/(R+B+G)	(Woebbecke et al., 1995)
GRATIO	Green Ratio	G/(R+B+G)	(Woebbecke et al., 1995)
VARI	Visible Atmospherically Resistance Index	(G -R)/(G + R - B)	(Gitelson et al., 2002)
NRBI	Normalized Red Blue Index	(R-B)/(R+B)	(Michez et al., 2016)
NGBI	Normalized Green Blue Index	(G-B)/(G+B)	(Michez et al., 2016)
VEG	Vegetative index	G/(RaB(1-a)),where a=0.667	(Hague et al., 2006)
WI	Woebbecke Index	(G−B)/(R−G)	(Woebbecke et al., 1995)
CIVE	Color Index of Vegetation	0.441R – 0.881G+0.385B+18.78745	(Kataoka et al., 2003)
COM	Combination Vegetative index	0.25ExG+0.3ExGR+0.33CIVE +0.12VEG	(Guijarro et al., 2011)
TGI	Triangular Greenness Index	G-0.39R-0.61B	(Hunt et al., 2014; Michez et al., 2018)
RGBVI	Red Green Blue Vegetation Index	(G2-B*R)/(G2+B*R)	(Bendig et al., 2015)
GRRI	Green Red Ratio Index	G/R	(Maimaitijiang et al., 2019)
GBRI	Green Blue Ratio Index	G/B	(Maimaitijiang et al., 2019)
RBRI	Red Blue Ratio Index	R/B	(Maimaitijiang et al., 2019)
BRRI	Blue Red Ratio Index	B/R	(Jibo et al., 2018)
BGRI	Blue Green Ratio Index	B/G	(Jibo et al., 2018)
RGRI	Red Green Ratio Index	R/G	(Jibo et al., 2018)
INT	Color Intensity Index	(R+B+G)/3	(Ahmad and Reid, 1996)
MVARI	Modified VARI	(G-B)/(G+R-B)	(Cen et al., 2019)
IPCA	Principal Component Analysis Index	$0.994\times\lvert R-B\rvert+ 0.961\times\lvert G-B\rvert+ 0.914\times\lvert G-R\rvert$	(Saberioon et al., 2014)

Table A3: Details of the independent variables for quadrat-scale AGB estimation (continued)

Acronym	Index name	Formula	Reference
R	An average value of R channel of the quadrat-scale UAV image		
G	An average value of G channel of the quadrat-scale UAV image		
B	An average value of B channel of the quadrat-scale UAV image		
H	An average value of H channel of the quadrat-scale image in HSV color space		
S	An average value of S channel of the quadrat-scale image in HSV color space		
V	An average value of V channel of the quadrat-scale image in HSV color space		
FVC	Fractional Vegetion Cover		
EGI	Extra Geen Index	EGI=2G-R-B	(Zhang et al., 2022a)
GI	Green Index	GI=9×(H×3.14159/180) +3×S+V	
HOC_*i*_CORR	The histogram correlation coefficient between the *i* band and the black reference histogram, where the *i* represents the three bands of RGB	$corr\frac{\sum_I (H_1(I)-\bar{H}_1)(H_2(I)-\bar{H}_2)}{\sqrt{\sum_I (H_1(I)-\bar{H}_1)^2 \sum_I (H_2(I)-\bar{H}_2)^2}}$	
HOC_*i*_INTERSEC	The histogram intersection coefficient between the *i* band and the black reference histogram, where the *i* represents the three bands of RGB	$intersec = \sum_I \min(H_1(I), H_2(I))$	
HOC_*i*_BHATTA	The histogram Bhattacharyya distance coefficient between the *i* band and the black reference histogram, where the *i* represents the three bands of RGB	$bhatta = \sum_I \min(H_1(I), H_2(I))$	
HOC_*i*_CHIS	The histogram correlation coefficient between the *i* band and the black reference histogram, where the *i* represents the three bands of RGB.	$chis = \sum_I \frac{\left(H_1(I)-H_2(I)\right)^2}{H_1(I)}$	

Table A4：Regression analysis for AGB estimation models at quadrat and pixel scales

Model name	Coefficient	Value	Standard Error	t-Value	p-value
2019_Quadrat-scale	Slope	0.67	0.016	42.58	9.05e-194
	Intercept	20.10	1.49	13.59	5.96e-37
2019_Pixel_scale	Slope	0.84	0.03	31.59	2.75e-73
	Intercept	23.20	4.04	5.74	4.24e-8
2018_Pixel_scale	Slope	0.73	0.02	45.81	8.28e-157
	Intercept	20.43	2.74	7.46	6.01e-13
2017_Pixel_scale	Slope	0.75	0.01	59.13	1.98e-260
	Intercept	13.89	2.04	6.82	2.19e-11
2016_Pixel_scale	Slope	0.94	0.02	40.45	4.69e-157
	Intercept	2.48	3.75	0.66	0.03
2015_Pixel_scale	Slope	0.82	0.04	18.88	2.59e-47
	Intercept	9.50	5.25	1.81	0.04

Table A5: List of abbreviations of eco-geographical regions and the mean AGB of the QTP

Abbreviation	Full name
IB1	Golog-Nagqu high-cold shrub-meadow zone
IIAB1	Western Sichuan-eastern Tibet montane coniferous forest zone
IC1	Southern Qinghai high-cold meadow steppe zone
IC2	Qiangtang high-cold steppe zone
ID1	Kunlun high-cold desert zone
IIC1	Southern Tibet montane shrub-steppe zone
IIC2	Eastern Qinghai-Qilian montane steppe zone
IID1	Nagri montane desert-steppe and desert zone
IID2	Qaidam montane desert zone
IID3	Northern slopes of Kunlun montane desert zone
OA1	Southern slopes of Himalaya montane evergreen broad-leaved forest zone

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