Remote Sensing in Ecology and Conservation

Remotely piloted aircraft systems remote sensing can effectively retrieve ecosystem traits of alpine grasslands on the Tibetan Plateau at a landscape scale

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Abstract
Ecosystem trait is a standardized description of biological features of a community, and it bridges individual plants and ecosystem. Conventionally most ecosystem trait data are collected from field survey and the generated data is hard to meet the requirements as set in the concept of ecosystem trait. To a great extent, remotely piloted aircraft systems (RPAS) remote sensing, which is capable of retrieving ecosystem traits across multiple scales, can overcome constraints in field plot survey. In this study, we selected alpine grassland ecosystem on the Tibetan Plateau (TP), which is under-studied due to scarcity of field monitoring data, as the research target. A new data framework was proposed by integrating field plot and RPAS remote sensing data to map spatial patterns of ecosystem traits for the alpine grasslands. Across four landscapes on the TP, ecosystem traits of vegetation coverage (CVC), species number (CSN), individual number (CIN), above ground biomass (AGB), organic carbon content (OC%) and total nitrogen content (TN%) were retrieved. We also calculated Shannon’s Diversity Index and Shannon’s Evenness Index for each plot. The results showed that RPAS-based high spatial resolution RGB image is capable of predicting both physical and chemical ecosystem traits for alpine grasslands on the TP. Remote sensing on physical traits are overall more efficient than on chemical traits, with the highest $R^2$ of 0.86 and 0.48 for physical trait and chemical one, respectively. The bands of Red and Green contributed more to the prediction model than band of Blue did, and the spectral mean value played a greater role than the spectral standard deviation. Based on the retrieved results, a set of spatial patterns on ecosystem traits can be revealed. This study represents an advance on ecosystem trait study and can significantly improve our understanding on ecosystem functions of the alpine ecosystem on the TP.

Introduction
Functional trait is a cornerstone for understanding ecosystem functions (Fry et al., 2014). Previous studies on functional traits have been mostly based on single plants, which are inadequate to understand ecosystem functions in a holistic manner. The recently developed concept of ecosystem traits compensated for the above deficiency to some extents. Ecosystem traits are qualitative or quantitative descriptions of biological factors associated to an ecosystem, and are calculated as the weighted average within a community based on species biomass (He et al., 2019). They inter-relate and also closely associate with indicators obtained from field measurements, remote
sensing monitoring and ecological model simulations. The advent of ecosystem traits provides a new angle to investigate interactions between ecosystems and environments ranging from a site to regional scale (Comas & Eisenstat, 2009; Croft et al., 2020; Halme et al., 2019).

To date, most studies on functional traits rely on traditional field measurements and related products are primarily centered around one single site (Knyazikhin et al., 2013; Piao et al., 2011; Tao et al., 2018). Normally, several quadrats are set within a site and functional traits of each quadrat are calculated through the community survey data. Most studies just took the average over the multiple quadrats as the site value and then correlated this simple average with raster indexes of remote sensing images. This leads to a failed recognition of local variations in functional traits and scaling-up to ecosystem level. The current researches on plant functional traits are mainly centered around three categories, physical properties of plant leaves (Tian et al., 2016; Wang et al., 2016; Yan et al., 2016), chemical characteristics of plant leaves (Han et al., 2005; Han et al., 2011; He et al., 2006; Ordoñez et al., 2009) and below ground root traits (Comas & Eisenstat, 2009; Guo et al., 2008; Kong et al., 2014). As a scale beyond individual plants, studies on ecosystem traits can be also grouped into three categories as above ground physical traits, above ground chemical traits and below ground root traits. The specific indicators for ecosystem traits are not limited to those for individual plants. Indicators obtained from the community scale, such as species number, individual number and community height are conventionally excluded from ecosystem traits (Batistoti et al., 2019; Halme et al., 2019).

To improve its capability in predicting ecosystem functions, mounting efforts should be dedicated to mapping the spatial and temporal patterns of ecosystem traits beyond a site scale. The conventional field sampling inherits the features of high accuracies, but it is not devoid of constraints. Shaped by a variety of environmental and biological factors (Chen et al., 2020; Cox et al., 2000; Huang et al., 2016), ecosystem traits exhibit high spatial heterogeneity. However, the limited spatial coverage of field quadrats constrains their representative of ecosystem traits at a landscape or regional scale (Diaz et al., 2007; Tang et al., 2019). Moreover functional traits obtained from field measurements are mostly species-based, restricting their scaling up to larger scales. By taking weighted average within a certain grid, remote sensing results can effectively circumvent these constraints and provide an actual value reaching the requirements set by ecosystem traits. The developing remote sensing technology also provides accruing products and surrogates to retrieve ecosystem trait information at scales beyond a site (Halme et al., 2019; Wang et al., 2013; Zhang et al., 2020). For example, global GIMMS LAI Datasets and TanSat Global Chlorophyll Fluorescence Dataset are all mature and reliable ecosystem traits products at a global scale (Croft et al., 2020; Li et al., 2020).

Although satellite remote sensing has achieved high performances on reflecting ecosystem traits, current efforts have been biased largely to forest ecosystems and agroecosystems. Grassland ecosystems have been paid insufficient attentions due to their low height and small entity. Even for high spatial resolution data of Sentinel-2, it is still too coarse to retrieve functional traits of individual grass and even their composited community. Present mapping on ecosystem traits has been focused on either a small region with high spatial resolution or on an extended region with coarse resolution (Ledgard & Steele, 1992; Zu et al., 2018). Then a data gap exists for ecosystem trait study at the scale between in-suit measurement of a site and satellite remote sensing monitoring of a region, which significantly inhibits our coherent understanding of ecosystem functions from local to regional scale.

The development of aerial remote sensing in recent years has brought about new opportunities to fill in this gap, especially for the development of remotely piloted aircraft systems (RPAS) remote sensing (Jay et al., 2019; Jenal et al., 2019). RPAS is favored due to their capability carrying a variety of spectral sensors and convenient accessibility to local targeted sites (Tang et al., 2019). Considering economic cost and equipment safety, RPAS is commonly loaded with lens comprising bands of red (R), green (G) and blue (B), especially for the extreme environments such as windy and high-altitude regions. Although these limited number of bands are concentrated in the visible range, their efficiencies in capturing species identity, nutrition content and morphological structure have been proved (Batistoti et al., 2019; Han et al., 2019; Lopezgranados et al., 2019; Lu et al., 2020; Santini et al., 2019; Su et al., 2019), especially for forest ecosystems and agroecosystem (Batistoti et al., 2019; Jay et al., 2019; Lopezgranados et al., 2019; Lussem et al., 2019). Among the ensemble, more sophisticated technique has been developed in retrieving chemical traits (e.g. nutrient elements of C, N, P, chlorophyll, lignin) over physical ones (e.g. vegetation coverage, species number, individual number, community height, etc.) (Anderson & Gaston, 2013; Feng et al., 2020; Fernandezgallego et al., 2019). RPAS images can provide centimeter spatial resolution products and open up windows for monitoring low-statured grasses. New opportunities arise in obtaining ecosystem traits at a scale beyond landscape and exploring their relationships with environmental factors.

The Tibetan Plateau (TP) represents an ecosystem highly sensitive to climate change (Chen et al., 2020;
Zhang et al., 2019c). Due to the low temperature and high altitude, plants are characterized by functional traits of low community height and productivity, which are normally a bottleneck for remote sensing retrieval. The harshness of physical environments also restricts the accessibility of conventional measurement venues to many sites on the TP. These conditions set the stage for extreme functional trait data scarcity on the TP. A limited pool of ecosystem trait data is mostly accumulated from in-situ plot measurements, while data beyond the site scale are highly inadequate. The data shortage significantly constrains our understanding on ecosystem traits and functions on the TP.

In this study, we selected four landscapes along elevation and precipitation gradients which define the conditions for four typical alpine grassland communities; also, we incorporated the main land use type of grazing on the TP. For the four landscapes, we used RPAS visible spectral remote sensing to obtain high spatial resolution images, and established their linkages with in-situ measurements. Specifically, we aimed to: (1) propose a framework for monitoring ecosystem traits by RPAS visible remote sensing; (2) verify the feasibility of RPAS digital images in monitoring ecosystem traits and quantify the contribution of each band in prediction; (3) validate the prediction model and generate high spatial resolution maps of ecosystem traits.

Materials and Methods

Alpine meadow grassland plot network

Among the four types of alpine grasslands along an environmental and land use gradient, we set up a plot network of 77 0.5 × 0.5 m plots (Fig. 1; Table 1). The covered types of grasslands include typical meadow steppe (Nagqu County, NQ; 34 plots), a transitory type from meadow steppe to steppe (Damxung County, DX; 10 plots), a transitory type from meadow steppe to desert steppe (Baingoin County, BG; 12 plots), and degraded grassland type (hereafter called Degraded Area, DA; 21 plots). Detailed information about all the plots, such as coordinates and in-situ measurement time is provided in Table S1. Within each landscape, plots were spaced uniformly to increase their representative of the local species distribution.

In situ trait measurement

In each plot, all grasses were identified to species level and measured through a sampling frame inset by 5-by-5 cm grids (Fig. S1). The sampling frame was faced northward to match the grid edges of the remote sensing image. The latitude, longitude and elevation from mean sea level of the central location of each plot were recorded by the GPS of Trimble Geo 7X (Horizontal accuracy 1 cm ± 1 ppm HRMS; Trimble Inc., Sunnyvale, CA, USA).

Parameters characterizing community traits, including coverage, individual number, frequency and height (Cornelissen et al., 2003; Díaz et al., 2015) were measured. Here, frequency represents the proportion of the grids occupied by a certain species to the total number of grids. If there are more than three individuals of a species, we randomly selected three and took their average as the species height of the plot. Soil temperature and moisture were measured three times within each plot using detector of HT-TSW, which can provide a temperature accuracy of 0.5°C and moisture accuracy of 1%. The above-ground biomass was mowed by species. A total of 623 samples were collected. All field measurements were taken from 9:00 AM to 17:00 PM of sunny days from late July to early August when plants are in their peak growth stage.

Fresh biomass weight was measured by species once being mowed and the dry weight was measured after being dried at 60°C for 48 hours. Then, plants in a plot were thoroughly mixed to measure the organic carbon content at the community level based on the principle of classical potassium dichromate oxidation-outer heating method. It is well established that leaf total nitrogen content is closely related with leaf maximum carbon fixation rate and community aggregated nitrogen content scales linearly with ecosystem carbon fixation capacity (Musavi et al., 2016; Reich et al., 1997). H₂SO₄·H₂O₂ digestion method was employed to determine plant total nitrogen.

Acquisition of RPAS remote sensing images

We used a RPAS equipped with an optical camera to acquire remote sensing images of the four landscapes before in-situ plot survey. The windy and low oxygen environments on the TP severely limit the time window for stably flying RPAS. To guarantee the image quality, we selected a high-performance four rotor RPAS of DJI Phantom 4 RTK (DJI Inc., Shenzhen, China) loaded with FC6310R visible spectral sensor.

Aerial missions were carried on between 10:00–12:00 AM across the four landscapes to achieve standardized illumination. The flying altitude was set to 10 m to ensure a spatial resolution of 2.5 cm after resampling. The course overlap and side overlap rate were set to 80 and 65%, respectively. Three 50 × 50 cm PVC plates with black and white crisscross lines were used as the positioning plate and evenly laid on the ground in each landscape. The center point of the PVC plate was treated as the image control point to record the latitude and longitude information. We only fly RPAS in clear sky and when wind speed is <5 m/s.
Figure 1. Alpine grassland plot network. (A) The location of Alpine grassland plot network in the Tibet Plateau; (B–E) distribution of field plots in each region. Each red dot represents a field plot of 0.5 × 0.5 m in size.
### Table 1. Summary of the study landscapes.

| Region name | Damxung County | Baingoin County | Nagqu County | Degraded area |
|-------------|----------------|-----------------|--------------|---------------|
| Grassland type | Alpine steppe | Alpine desert steppe | Alpine meadow steppe | Alpine mixed steppe |
| Mean annual temperature/°C | 1.3 | -1 | -1.2 | -1.2 |
| Mean annual precipitation/mm | 480 | 310 | 380 | 380 |
| Number of plots | 10 | 12 | 34 | 21 |
| Species pool | Eritrichium hemisphaericum; Potentilla saundersiana; Potentilla bifurca; Kobresia pygmaea; Heteropappus bowerii (Hems.) Grierson; Anaphalis xylorhiza Sch.-Bip. ex Hook. f.; Carex praecoxa; Microgynoecium tibeticum; Stipa purpurea | Festuca coelestis (St.-Yves) Krecz. et Bobrowska; Festuca coelestis (St.-Yves) Krecz. et Bobrowska; Incanvillea youngusbandii Sprague; Astragalus tibetanus Benth. ex Bunge; Kobresia macrantha; Androsace mariae; Kanit; Oxypia biflora; Androsace graminifolia; Leontopodium nanum; Crepis flexuosa; Artemisia demissa; Dimorphostemon glandulosus (Kar et Kir) Golub; Arenaria kansuensis Maxim.; Gentiana crenulatotruncata (Marq.) T. N. Ho; Polygonum macrophyllum D. Don; Poa annua L.; Oxytropis stracheyana Bunge; Stipa purpurea | Eritrichium hemisphaericum; Potentilla saundersiana; Potentilla bifurca; Lasiocaryum munroi (Clarke) Johnst.; Taraxacum mongolicum Hand.-Mazz.; Saussurea tibetica C. Winkl; Youngia terminalis Babcock et Stebbins; Astragalus tibetanus Benth. ex Bunge; Leontopodium nanum; Kobresia pygmaea; Carex praecoxa; Potentilla cuneata; Gentiana crenulatotruncata (Marq.) T. N. Ho; Poa annua L.; Lithospermum erythrorhizon Sieb. et Zucc.; Festuca coelestis (St.-Yves) Krecz. et Bobrowska; Microgynoecium tibeticum; Stipa purpurea | Crepis flexuosa; Androsace umbellata (Lour.) Merr.; Potentilla saundersiana; Potentilla multifida; Potentilla anserina; Potentilla bifurca; Saussurea tibetica C. Winkl; Heteropappus bowerii (Hems.) Grierson; Youngia terminalis Babcock et Stebbins; Astragalus tibetanus Benth. ex Bunge; Leontopodium nanum; Oxytropis stracheyana Bunge; Potentilla anserina L.; Callianthemum pimpinelloides; Lancea tibetica; Trietum bifidum; Kobresia pygmaea; Carex praecoxa; Lagotis ramalana Batal; Potentilla cuneata; Aster himalaicus C. B. Clarke; Arenaria kansuensis Maxim.; Poa pratensis L.; Swertia racemosa; Lithospermum erythrorhizon |
Figure 2. Cross-validation of PLSR prediction results against in-situ measurements of the ecosystem traits. RMSE means the root mean squared error. The subscript CV and CD denote the values from cross-validation datasets and calibration datasets, respectively. CVC, community vegetation coverage; CSN, community species number; CIN, community individual number; SHDI, Shannon’s Diversity Index; SHEI, Shannon’s Evenness Index; AGB, above ground biomass; OC%, original carbon content; TN%, total nitrogen content.

Figure 3. Moran’s I and P values for each ecosystem trait from the spatial autocorrelation analysis. The null hypothesis is that there is no spatial autocorrelation of the predicted variables. We cannot reject the null hypothesis with $P > 0.05$. 

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In each region, more than 2000 images were acquired. Software of Agisoft Photoscan was applied to perform position calibration and splicing operations on the raw images. After obtaining the orthographic image, radiation calibration was conducted in reference to the white and black pixels of the PVC plates (Fig. S2). DN values of each pixel located in the black and white parts of the plates were regarded as \(RGB (0, 0, 0)\) and \(RGB (255, 255, 255)\), respectively (Mojsilovic, 2005). Image normalization (see Part 1 of appendix for more details) can eliminate the data bias caused by weather conditions and digital camera system errors.

**Computing ecosystem traits from in situ measurements**

By integrating field measurements and remote sensing, we scaled up species-based traits to a community level and obtained the community vegetation coverage (CVC), community species number (CSN) and community individual number (CIN). Species richness is a core index indicating biodiversity and plays a critical role in determining ecosystem productivity and stability (Zhang et al., 2019a). Among the set of indices, alpha diversity comprises information on species number, and also the number of each species within a community. Thus, we calculated Shannon’s Diversity Index (SHDI) and Shannon’s Evenness Index (SHEI) using *in-situ* measurements. The above five indices were employed to characterize the physical traits of the target grassland ecosystem.

We calculated above ground biomass (AGB) as the aboveground live plant organic substances in each plot. Organic carbon content and nitrogen content samples were extracted from the mixed AGB of each entire plot. Thus, community organic carbon content (OC%) and community total nitrogen content (TN%) embody the weight of each species in the plot. The above three indices characterize the chemical traits of our target ecosystem.

**Table 2. Predictions of different band combinations on ecosystem traits.**

| Ecosystem traits | Number of components | Variables       | \(R^2_{CV}\) | RMSE\(_{CV}\) |
|------------------|----------------------|-----------------|--------------|--------------|
| CVC              | 4                    | BM + BSD       | 0.8614       | 9.5292       |
|                  | 3                    | BM              | 0.8572       | 9.6747       |
|                  | 2                    | BSD             | 0.1235       | 23.9661      |
| CSN              | 3                    | BM + BSD       | 0.1152       | 2.8404       |
|                  | 3                    | BM              | 0.0374       | 2.9626       |
|                  | 2                    | BSD             | 0.0000       | 3.0824       |
| CIN              | 3                    | BM + BSD       | 0.6757       | 130.7308     |
|                  | 3                    | BM              | 0.6749       | 130.0698     |
|                  | 2                    | BSD             | 0.1028       | 217.4360     |
| SHDI             | 4                    | BM + BSD       | 0.4028       | 0.4036       |
|                  | 3                    | BM              | 0.3787       | 0.4117       |
|                  | 3                    | BSD             | 0.0460       | 0.5102       |
| SHEI             | 4                    | BM + BSD       | 0.2833       | 0.1067       |
|                  | 3                    | BM              | 0.2529       | 0.1089       |
|                  | 3                    | BSD             | 0.0435       | 0.1232       |
| AGB              | 3                    | BM + BSD       | 0.4793       | 24.0417      |
|                  | 3                    | BM              | 0.4772       | 24.0897      |
|                  | 2                    | BSD             | 0.0091       | 33.1638      |
| OC%              | 6                    | BM + BSD       | 0.2659       | 2.8631       |
|                  | 3                    | BM              | 0.2323       | 2.9278       |
|                  | 2                    | BSD             | 0.1599       | 3.0627       |
| TN%              | 6                    | BM + BSD       | 0.1732       | 0.2387       |
|                  | 3                    | BM              | 0.1623       | 0.2402       |
|                  | 3                    | BSD             | 0.0812       | 0.2516       |

CVC, community vegetation coverage; CSN, community species number; CIN, community individual number; SHDI, Shannon’s Diversity Index; SHEI, Shannon’s Evenness Index; AGB, above ground biomass; OC%, original carbon content; TN%, total nitrogen content; BM and BSD, band mean and band standard deviation of DN values from all the 400 pixels within each 50 x 50 cm plot; CV indicates the results were from cross-validation datasets.

**Construction of ecosystem trait model**

By comparing the several conventionally used regression models, we proved that Partial Least Squares Regression (PLSR) achieved the best performance on the dataset (see Part 2 of appendix for more details). Therefore, we applied PLSR to predict in-situ ecosystem traits (including physical traits and chemical traits) from RPAS remote sensing. PLSR first reduces the predictors to a thinner set of uncorrelated variables by projection transformation and then performs a least squares regression on the remaining subset of variables (Ferreira et al., 2017). We calculated band mean and band standard deviation of DN values from all the 400 pixels within each 50 x 50 cm plot, which represent between-site difference and within-site heterogeneity, respectively. Thus, a total of three BMs and three BSDs were calculated to predict ecosystem traits.

We applied PLSR to predict ecosystem traits at a landscape scale and then evaluated model performance using the leave-one-out cross-validation (LOOCV) (Volpe et al., 2011). The optimal number of components used in the PLSR model was obtained by minimizing the prediction residual error sum of squares (PRESS) (Ma et al., 2019). We calculated coefficient of determination (\(R^2_{CD}\)) and root mean squared error (RMSE\(_{CV}\)) to evaluate model performance against the cross-validation dataset. \(R^2_{CD}\) and RMSE\(_{CD}\) were also calculated. The subscript CV and the subscript CD denotes the results from cross-validation datasets and calibration datasets, respectively. The variable importance of projection (VIP) score of each band was measured to quantify their relative contribution to the fitted PLSR model.
Figure 4. The variable importance of projection (VIP) score of each variable in the PLSR model for predicting ecosystem traits. The red columns represent the VIP score of band mean value (BM) and the black ones represent the VIP score of band standard deviation (BSD). CVC, community vegetation coverage; CSN, community species number; CIN, community individual number; SHDI, Shannon’s Diversity Index; SHEI, Shannon’s Evenness Index; AGB, above ground biomass; OC%, original carbon content; TN%, total nitrogen content.

Figure 5. Statistics of ecosystem traits of alpine grassland plot network from regional results of remote sensing retrieval. The height of the column represents the average value of the trait, and the bar means standard deviation. The same lowercase letter indicates that there are no significant differences in ecosystem traits among different regions, and different lowercase letters indicate that there are significant differences in traits among different regions. CVC, community vegetation coverage; CSN, community species number; CIN, community individual number; SHDI, Shannon’s Diversity Index; SHEI, Shannon’s Evenness Index; AGB, above ground biomass; OC%, original carbon content; TN%, total nitrogen content.
Results

Relations between ecosystem traits and RPAS images

The associations between the six indices (the BMs and BSDs of three visible bands) from RPAS images and the eight ecosystem traits from *in-situ* plot measurements were established through PLSR (Fig. 2). Both cross-validation and calibration datasets achieved good predictions on ecosystem traits. For the physical traits, the predictions of spectral reflectance on CVC and CIN were the best, with $R^2_{cv}$ reaching 0.86 and 0.68, respectively. The second-best predictions were on SHDI and SHEI, with $R^2_{cv}$ of 0.40 and 0.28, respectively. The prediction turned out the lowest accuracies on CSN, with $R^2_{cv}$ of only 0.12.
When predicting chemical traits, the explained variations were all lower than 0.5, among which the model generated the highest prediction on AGB, with $R^2_{cv}$ of 0.48 and RMSECV of 0.41. The proportion for spectral reflectance explaining variations of OC% and TN% was 0.27 and 0.17, respectively.

In addition, Moran’s I test was run on the residuals of the PLSR model (Fig. 3). For the eight ecosystem traits, the $P$ values of all the tests were $>0.05$, which indicate that there existed no spatial autocorrelation of the PLSR model in predicting ecosystem traits.

**Performances of bands in predicting ecosystem traits**

We conducted different strategies of band combinations to assess the predicting power of BMs and BSDs on ecosystem traits (Table 2). For both physical and chemical traits, BMs performed much better than BSDs in the PLSR model. When using only BMs as independent variables, the highest explained variations by the model can reach 0.86, while those by sole BSDs as independent variables are only 0.16. The $R^2$ difference between using BMs and BSDs was largest on predicting AGB and least when predicting OC%.

The VIP scores of each variable represent their relative contributions to predicting ecosystem traits (Fig. 4). Except for predicting CSN, BMs scored overall higher VIP than BSDs did. For sole BMs (except for the trait of CSN), the VIP score of band $R$ was the largest in predicting SHEI with a value of 2.86 and the smallest in predicting OC% with a value of 1.94. Band $G$ scored 1.79 for predicting SHDI and 2.69 for predicting CVC. Band $B$ scored the least no matter predicting physical traits or chemical ones, with all the VIP values $<1.5$. BMs of $R$ scored higher than those of $G$ when predicting CIN, SHDI and SHEI for physical traits and TN% for chemical traits.
Predict ecosystem traits of alpine grassland plot network

We retrieved ecosystem traits of alpine grasslands to a landscape scale using the PLSR model. The ecosystem traits exhibited high differences among the four regions (Fig. 5). CVC and CIN were 13.61% and 126.30 for BG, 33.51% and 281.23 for DX, 52.10% and 497.11 for DA and 69.53% and 575.08 for NQ, respectively. Physical traits of CSN, SHDI and SHEI displayed an opposite pattern, with their largest and smallest values in BG and NQ, respectively. Chemical traits of AGB, OC% and TN% were all the lowest in BG (23.99 g/m², 38.38 and 1.78%, respectively). AGB and OC% were the greatest in NQ (84.10 g/m² and 41.98%, respectively) while TN% was the greatest in DA (2.07%).

Based on mapped ecosystem traits, their spatial variations were revealed (Figs. 6 and 7). The ecosystem traits exhibited the greatest spatial heterogeneity in DA, with the highest values occurring approximately in the center of the study region. The highest CVs of CVC, CIN, CSN, SHDI, SHEI, AGB, OC% and TN% were 32.63, 25.89, 33.51, 281.23, 52.10, 497.11, 69.53% and 575.08 for NQ, respectively. Physical traits exhibited the highest spatial homogeneity in BG while OC% and TN% embodied the highest spatial consistency in NQ. Spatially, CVC, CIN, AGB, OC% and TN% increased significantly while SHDI and SHEI decreased significantly in the right half of BG and the lower parts of NQ, respectively.

Discussion

A new framework for efficiently monitoring alpine grassland ecosystem traits

This research combined RPAS high spatial resolution remote sensing and in-situ plot measurement to detect ecosystem traits in alpine grasslands at a landscape scale. As an ecosystem distributed in the environmental gradient of being extremely cold, semi-arid and high altitude, information on ecosystem traits at a landscape is in high scarcity, which significantly inhibits our understanding on its structures and processes. This study represents a pioneering research on ecosystem traits of the alpine TP and opens up a new window for investigating its responses to global changes.

Along the environment gradient from tropical to the alpine cold, plant size decreases gradually and the difficulties of mapping their structures strengthens. In terms of plant size, alpine grassland is one of the smallest (Bhandari & Zhang, 2019; Zhang et al., 2019b). Traditional medium resolution satellite remote sensing achieved low accuracies in retrieving plant biomass or other functional traits of the alpine ecosystems, and was even worse in structure recognition. Moreover they failed to capture the subtle differences over time of low-statured grasses for their longer and fixed revisit period, while RPAS remote sensing can avoid these constraints and well capture traits in time. This study proposed a new pathway to map ecosystem traits at a scale beyond site with high spatial and temporal resolution data.

To standardize and calibrate spectral information among different locations, we configured PVC plates with uniform specifications, which can also assist in the precise location of each landscape (Table S2). Taking the spectral information of the PVC plate as a calibration reference, we standardized the images obtained under different lighting conditions and corrected different camera biases, thereby laying the foundation for ecosystem traits comparison among heterogeneous conditions.

The retrieved ecosystem traits as obtained from the present study are the actual trait averages weighted by proportion of each species and highly reflect the ecosystem traits within a community, which are out of considerations in traditional field sampling. Through the proposed framework, a set of standardized operating procedures was built up to obtain ecosystem traits on alpine grassland. This method provides a feasible pathway to complement our data pool on grassland ecosystems, including both physical and chemical traits, thereby advancing our understanding on ecosystem functions.

The feasibility of RGB image in monitoring ecosystem traits

Images with more spectrums convey more information, and can better reveal the actual situations of the research target. Thus, hyperspectral remote sensing overall achieves higher accuracies in predicting ecosystem traits than the RGB images do (Croft et al., 2020; Gonzalezjaramillo et al., 2019; Halme et al., 2019). However, the unstable and severe weather conditions in the TP set constraints on the hyperspectral measurement operations. In addition, hyperspectral is usually accompanied by relatively low spatial image resolution. Then its efficiencies on low-statured grasses might not be ideal.

The PLSR model established in this study achieved high predictions for grassland ecosystem traits. The determination coefficient $R^2$ from our model reached 0.86 for physical traits and 0.48 for chemical traits, which are comparable based on hyperspectral data for physical traits (Feng et al., 2020; Sankey et al., 2017; Wang et al., 2019; Yi et al., 2018) and for chemical ones (Corti et al., 2019; Ma et al., 2019b; Martin et al., 2008). Besides, our proposed model directly took the spectral signatures as
dependent variables and the results were much better than those explained by 17 of 19 visible vegetation indexes used in the study (Fig. S3). By incorporating both RGB mean and standard deviation values as covariates, we significantly improved model performances in predicting ecosystem traits and efficiently overcame the constraints stemmed from the only three bands combination in the visible vegetation indexes.

Normally, the explained variations by our model on predicting physical traits were greater than on chemical ones, of which the model interpretations on CVC and CIN were almost triple those of OC% and TN%. This difference is related to the capability of lens in capturing spectral information of the target attributes (Quiros & Khot, 2016). Visible lens tend to perform better in capturing spectral differences caused by changes in land cover rather than by internal differences of objects (Jones, 1985). The higher CIN means greater vegetation coverage in a given area so that subtle changes in CVC and CIN can be well captured, which leads to a better correlation between physical traits and the spectral reflectance. SHDI and SHEI were the secondary indices calculated from individual numbers, thus they can also be well predicted by our model. In summary, our framework on grassland ecosystem traits perform solidly on attributes related to vegetation coverage and individual numbers in terms of physical traits. Among the three chemical traits investigated in our study, AGB and OC% were both well predicted while the retrieval on TN% exhibited low accuracies. This may be related to the low TN% in grasses and variations among regions were lower than 0.5%, which causes the poor retrieval performances. Remote sensing retrieval normally works well on traits and species with high light requirements and those traits highly correlated with canopy structure (Anderson & Gaston, 2013).

The RGB images embody high accuracies in predicting ecosystem traits. Relatively band R and G contributed more to the prediction model than band B did, which is associated with the spectral characteristics of plants. The chlorophyll absorption peaks fall in the two spectral bands of 0.45 μm (blue) and 0.65 μm (red), and the reflection peak is near 0.54 μm (green) in the visible region (Wang et al., 2019). Thus, all the three bands contribute to the model to some extents. However, the wavelength of band B is less than 480 nm, whose short wavelength results in strong scattering and is not conducive to the capture of relevant information by remote sensing lens (Hao et al., 2012; Pesic, 2008). Besides, the absorption efficiency of chlorophyll in the blue spectral range is only half of that of red-orange spectral range, leading to a lower contribution of band B in predicting ecosystem traits. Previous studies have proven that the reflectivity of "green peak" increases with increased vegetation coverage (Kai et al., 2014). Alpine meadow grassland in the Tibet Plateau is usually densely covered, although with low-statute height, which leads to the higher contribution of band G than band B in the PLSR model.

**Field application**

Upon the direct linkage established between ecosystem traits and spectral reflectance of RGB images derived from RPAS, we applied this method to a landscape scale and mapped ecosystem traits including physical and chemical ones. Based on the mapped ecosystem traits, we are able to conduct a comparison of ecosystem traits among varied community types (Fig. 5), which is beyond traditional field measurements and coarse resolution satellite remote sensing. Physical traits of CVC and CIN were found to be the highest in NQ and CSN, SHDI and SHEI were the highest in BG. This spatial pattern is caused mostly by local climatic conditions (Bhandari & Zhang, 2019; Zhang et al., 2018). The hydrothermal conditions in NQ are relatively favorable in supporting a higher vegetation coverage and also suitable for communities dominated by Kobresia pygmaea. BG has a higher altitude and worse precipitation conditions, leading to a transitory vegetation type from Meadow Steppe to Steppe, where species richness and biodiversity are relatively higher. These ecosystem trait patterns at a landscape scale provide us a deeper insight into the relationship between environments and alpine grassland ecosystems.

The generated ecosystem trait maps also provide a venue in identifying local variations, which are beyond most prior related studies (Figs. 6 and 7). Information on subtle changes in spatial patterns of functional traits provide impetus to gain deeper insights into ecosystem functions. For example, two of the study landscapes contain a comparison between two land use types of grazing and non-grazing. As shown, AGB and TN% are higher, while SHDI and SHEI are lower in the grazing forbidden regions of NQ. This allows for an improved understanding of grazing activities on grassland ecosystems. Besides, our method provides a new pathway to explore relationships between ecosystems and local environments (Part 4 of appendix). The proposed method framework demonstrated high applicability in retrieving environmental factors (Table S4), such as soil moisture (Fig. S4). Based on the retrieved ecosystem traits and environmental factors, we find that soil moisture plays a significant role in influencing ecosystem traits at a local scale. Physical traits of CVC and CIN increase with enhanced soil moisture while CSN, SHDI and SHEI are negatively correlated with soil moisture. The higher the soil moisture is, the significantly greater are the AGB, OC% and TN% (Table S5).
Our proposed method framework has evidenced its high efficiencies in alpine grasslands of the TP. Although the plot network is only distributed in three regions, the total 77 plots contain four most important community structures of alpine grasslands on the TP. In addition, these plot distributions range in altitude from 4000 to 4600 m, with an average annual precipitation from 310 to 480 mm and an average annual temperature from −1.2 to 1.3°C. The 77 plots also include land use types of grazing and degradation. Such plot network setup ensures more natural and man-made environments being considered as far as possible to guarantee the reliability of our results in a wide range of applications. When it is applied on other ecosystems such as forests, hyperspectral images might be needed, plus other sourced remote sensing images, to address their complex canopy structures. In addition, this study only used images in vegetation peak growing stage. A time series images might further boost the retrieval accuracies on the set of ecosystem traits.

Conclusions

In echoing the new developed concept of ecosystem traits, this study selected an ecosystem with high difficulty of remotely sensing its physical and chemical traits and proposed a new method to generate ecosystem traits at a landscape scale. Through the acquired high spatial resolution RGB images from RPAS, we scaled up the plant functional traits from a plot scale to a landscape scale. We proved that RPAS-based high spatial resolution RGB images are capable of retrieving and predicting grassland ecosystem traits in the TP. The visible spectrums predicted physical traits better than chemical traits and band R and G contributed more than band B in the prediction. Our study offers a new pathway to explore ecosystem traits at a scale beyond a site and provides a novel insight into the relationship between traits and functions.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. List of plot information used in this study.
Figure S1. Illustrations of the plot design and an in-situ photograph of one plot after above ground biomass clipping. (left) a 50 × 50 cm sampling frame with 100 grids.
Table S2. Significant performance parameters of flight and images.
Figure S2. Schematic diagram of the PVC plate used for spatial positioning.
Table S3. Visible vegetation indices for estimating ecosystem traits and environmental factors.
Figure S3. Pearson correlation of vegetation indexes (VIs) and ecosystem traits and environmental factors; (left) results from VI means; (right) results from VI standard deviations (VI SDs).
Table S4. Comparison of Linear regression and PLSR for prediction on community traits.
Figure S4. Statistics of environmental factors of PLSR for prediction on community traits.
Figure S5. Environmental factors of alpine grasslands.
Table S5. Relationships between community soil moisture (CSM) and ecosystem traits.