

Article

Optimization of Grassland Carrying Capacity with Grass Quality Indicators Through GF5B Hyperspectral Images

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Abstract: The accurate estimation of grassland carrying capacity (GCC) in the alpine grasslands of the Changjiang River source region is crucial for managing livestock loads and ensuring ecological security on the Qinghai-Tibetan Plateau. Previous remote sensing methods have predominantly focused on yield indicators, often neglecting quality indicators, which hampers precise GCC estimation. Here, we collected 25 samples from the Dangqu basin, analyzing various grass parameters including yield, crude protein (CP), neutral detergent fiber (NDF), and acid detergent fiber (ADF). Then, we developed models to optimize GCC using quality indicators derived from GF5B images, assessing performance through Pearson correlation coefficient (R^2), root mean square error (RMSE), and relative root mean square error (rRMSE). Results were found to show an average yield of 61.26 g/m², with CP, ADF, and NDF ranging from 5.81% to 18.75%, 45.47% to 58.80%, and 27.50% to 31.81%, respectively. Spectra in the near-infrared range, such as 1918 nm, and spectral indices improved the accuracy of the hyperspectral inversion of grass parameters. The GCC increased from 0.51 SU·hm⁻² to 0.63 SU·hm⁻² post-optimization, showing an increasing trend from northwest to southeast. This study enhances GCC estimation accuracy, aiding in reasonable livestock management and effective ecological preservation.

Keywords: alpine meadow; grass quality indicators; grassland carrying capacity; Dangqu basin



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1. Introduction

The Changjiang River, known as the mother river of China, serves as a critical ecological security barrier and a vital foundation for the development of the Chinese nation. Its source, Dangqu, is located in the hinterland of the Qinghai-Tibetan Plateau, with an altitude of more than 4500 m above sea level. The area is concentrated with many alpine swampy wetlands and is part of an important grazing economic zone [1], which is important for stabilizing the regional ecosystem and maintaining the ecological function of the plateau [2]. Animal husbandry is the predominant land use in the region [3]. The *Bos grunniens* are the most common animals in this area, which is an important source of milk, meat, fiber, and fuel [4].

However, in recent years, the ecological fragility and sensitivity of these alpine steppes and meadows have been compromised by overgrazing, leading to the ecological degradation of grasslands. The grass yield per unit area during the grazing season has seen a reduction of 30% to 50% [5]. The excessive grazing and ill-considered choice of grazing areas have resulted in grassland degradation and desertification, which severely impacts the sustainable development of animal husbandry in the Dangqu basin and threatens the ecological security of the source area of the Changjiang River [6]. In light of the escalating issue of grassland degradation in these alpine steps and meadows, gaining timely and precise insights into the growth status of extensive grasslands in this region is of utmost importance for the effective management and utilization of these degraded lands.

Methods for estimating grassland carrying capacity (GCC) are evolving from basic net productivity assessments to more sophisticated approaches that integrate remote sensing and modeling. These methods can be categorized into several types, including grass yield estimation [7], net primary productivity estimation [8], ecological models [9,10], and by estimation based on a spectral index, such as the normalized difference vegetation index (NDVI) [11]. Among these, remote sensing techniques have garnered increasing attention. Traditional GCC studies have relied heavily on a collection of aboveground biomass samples and spatial interpolation, which often come with significant drawbacks such as being time-consuming, labor-intensive, costly, and lacking in spatial resolution. Hyperspectral remote sensing enriches spectral information with more spectral wavelengths than common optical sensors, enhancing the ability to distinguish features significantly, in turn making it feasible for accurate GCC inversion.

Research on grassland productivity assessment reveals significant insights into the effects of biodiversity and grazing intensity on ecosystem health. Hector et al. [12] have demonstrated that reduced plant diversity in European grasslands led to a decline in aboveground biomass. In contrast, Tilman, et al. [13] conducted a 7-year study showing that increased species diversity and ecological niche complementarity positively impacted grassland net productivity. Additionally, Dara et al., [14] used Landsat data to document an 80% reduction in carrying capacity in Russian and Kazakh grasslands within the Eurasian Steppe Belt due to changing grazing intensities. Wang et al., [15] monitored gross primary productivity (GPP) in southern Alberta using MODIS satellite data, revealing critical links between inter-annual productivity trends and climate influences.

While remote sensing technology is increasingly employed to estimate grassland carrying capacity, research specifically targeting alpine meadows, particularly alpine wetland meadows with altitudes of above 4500 m, remains scarce. This gap is concerning because the sustainable development of the livestock sector relies not only on grass production but also on grass quality [16,17]. High-quality grass—characterized by its softness, grazing resistance, and superior nutritional value—exhibits higher crude protein content along with lower levels of acid detergent fiber (ADF) and neutral detergent fiber (NDF) [18]. Common indices for assessing forage quality, such as relative feeding value (RFV) and relative forage quality (RFQ), are available [19]. However, current research primarily emphasizes grass yield and often overlooks pasture quality, undermining a comprehensive assessment of grassland carrying capacity [20]. This oversight could pose significant risks to the sustainable development of grassland ecosystems in the long term [10].

In this study, our main objective is to estimate pasture quality and accurately determine the GCC of the Dangqu basin using advanced GF5B hyperspectral imagery. Specifically, we aim to (1) utilize GF5B hyperspectral imagery to estimate the yield and quality indicators (ADF, NDF) of alpine grassland in the Dangqu basin; (2) explore the spatial distribution of these indicators in the Dangqu basin with altitudes of above 4500 m; and (3) accurately assess the actual GCC of alpine wetlands with considering the grass quality.

2. Materials and Methods

2.1. Study Area

Dangqu, the source of the Changjiang River, originates from Xiasheriaba mountain (5395 m) in the eastern foothills of the Tanggula mountains. The basin features a triangular-shaped water system with numerous tributaries symmetrically distributed along both sides of the headwaters section (Figure 1) [21]. The Dangqu basin, located in Zadoi County within the Yushu Tibetan Autonomous Prefecture of Qinghai Province, spans coordinates from 32.40°N to 33.96°N and 92.14°E to 94.62°E, covering a total area of approximately 1.69×10^4 km² [21]. The climate is characterized by cold, low air pressure, strong solar radiation, and windy conditions. Average monthly temperatures range from −3 to −13 °C, showing an increasing trend from southeast to northwest [22]. Monthly precipitation averages between 29 mm and 54 mm, decreasing from southeast to northwest [23]. It is part of the core wetlands area of the Three Rivers Source region [24], and grassland

predominates in this region [25]. The predominant vegetation type in this area is alpine meadow, primarily consisting of *Kobresia pygmaea* and *Stipa purpurea* Griseb [26]. *Kobresia* swamp meadows are mainly distributed in intermontane basins in the east of Dangqu, while *K. pygmaea* wet meadows are primarily found in the transition zone between *Kobresia* swamp meadows and non-wetland zones (e.g., steppe meadows) [24]. Grazing is the main form of grassland utilization and the number of livestock increased between the years 2000 and 2008 according to studied results [24]. The area experiences significant warming and drying trends with global warming.

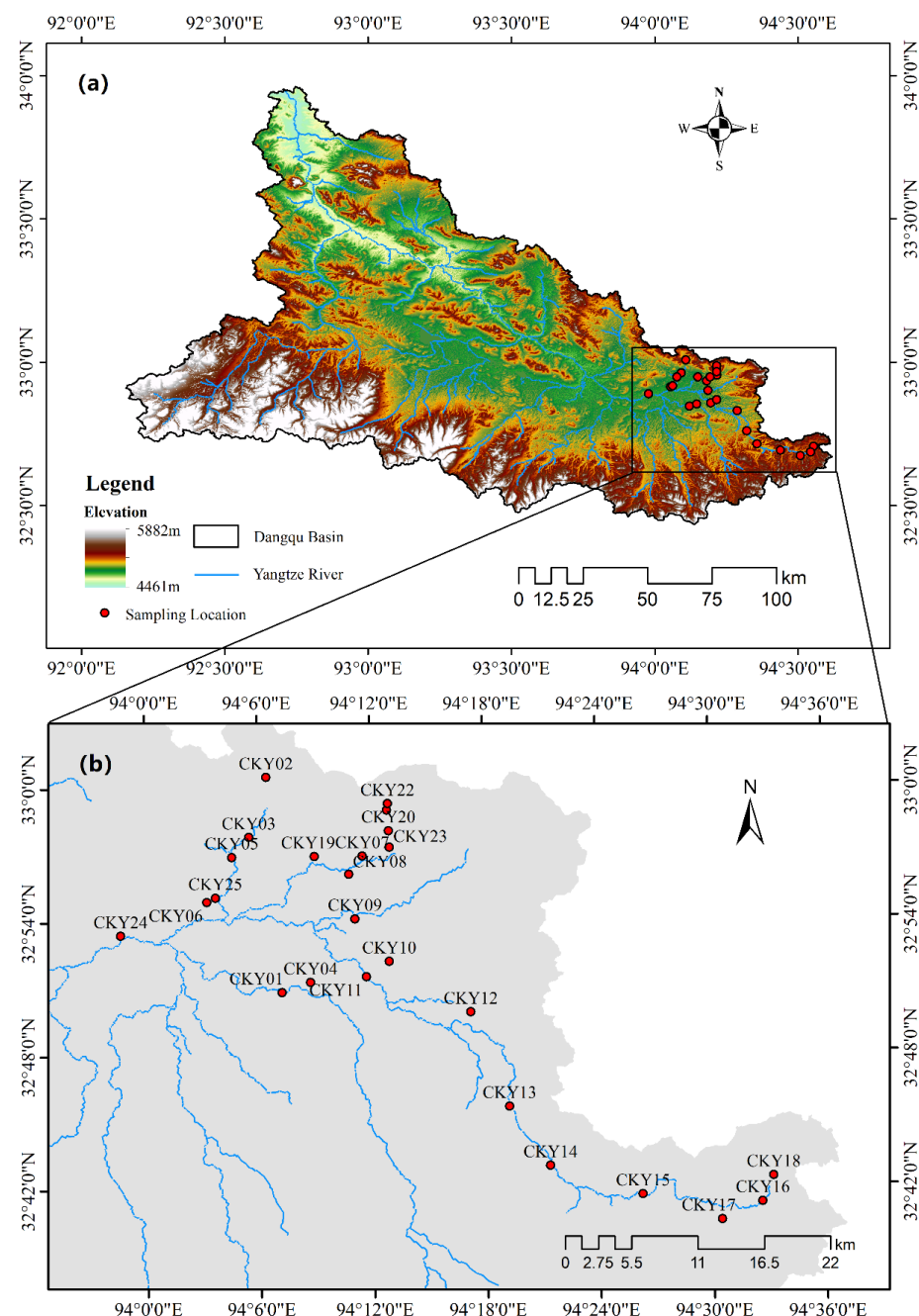


Figure 1. Dangqu basin (a) and sampling distribution (b).

2.2. Data Acquisition

2.2.1. Gaofen-5B and Pre-Processing

Gaofen-5B (GF-5B) is the first hyperspectral satellite that offers both wide coverage and extensive spectral bands. The data utilized in this study are sourced from the Advanced

Hyperspectral Imager (AHSI), which features a spatial resolution of 30 m and encompasses 330 spectral bands within the range of approximately 380 to 2500 nm. In comparison to Hyperion, a well-known hyperspectral instrument, the AHSI boasts an imaging width that is eight times greater, an increase of hundreds of spectral bands, and a fourfold improvement in signal-to-noise ratio (SNR) [27].

During the growth period of grasses in the Dangqu basin from July through August 2022, the GF-5B hyperspectral images were selected based on the geographic extent of the Dangqu basin and the sample collection time, with imaging timed to coincide with field sampling. In order to realize the high-precision inversion of the subsequent grass indicators, we set the cloud coverage to less than 30% to screen the GF-5B hyperspectral images to ensure image quality.

Pre-processing of the remote sensing images was conducted using ENVI 5.6 (ITT Visual Information Solutions, Inc., McLean, VA, USA), involving processes such as radiometric calibration, atmospheric correction, orthorectification, and mosaic cropping. The conventional process of the AHSI ground processing system produces L1-level product data with the master file in GeoTiff format. The first process performed on the AHSI L1-level data is the radiometric calibration, which converts the recorded raw DN values to apparent reflectance and the luminance grayscale values of the images to absolute radiometric brightness. Next, the radiometrically calibrated data were atmospherically corrected using the FLASH tool 5.6. Hyperspectral data are commonly used in quantitative remote sensing applications, where radiometric calibration and atmospheric correction are mandatory steps. Finally, the RPC orthometric correction is performed on the results of the atmospheric correction. The AHSI L1 level of Gaofen-5B includes RPC files, and after undergoing processes such as radiometric calibration and atmospheric correction, ENVI can still maximize the preservation of metadata information, and will automatically embed the RPC in the processing results (in the hdr header file).

2.2.2. Field Sampling and Chemical Analysis

During the growth period of grasses in the Dangqu in early July 2022, a total of 25 sampling sites were set up through the survey, which was centrally distributed along the main stream of the Dangqu headwaters (Figure 1). Each plot featured a 3×3 m sample square, with three 1×1 m sub-squares positioned along the diagonal. All three sub-squares were sampled once, and the same method was used for all three sub-squares. The above-ground vegetation was mowed, and auxiliary information, such as latitude, longitude, and elevation, of each plot was recorded. All samples were oven-dried at 60°C for 48 h in the laboratory, and then a chemical analysis was conducted to determine crude protein (CP) content and neutral (acid) detergent fiber content. CP was measured using the Kjeldahl method [28], while the contents of neutral detergent fiber (NDF) and acid detergent fiber (ADF) were assessed according to the Van Soest method [29]. Nutrient composition analyses were conducted on a dry matter basis, with CP, ADF, and NDF values calculated as the average of the three sub-squares.

2.3. Methods

2.3.1. Band Selection

To avoid the Hughes phenomenon and to construct an inversion model, the spectral bands and indices that are sensitive to the change of grass indicators are selected as the independent variables of the subsequent model calibration and validation.

To enhance vegetation information, we also calculated indices derived from relevant bands of the remote sensing images apart from the reflectance data from 330 bands. Drawing on prior inversion experiences and considering the spectral wavelengths of GF-5B images [30–33], we calculated indices and other variables, including the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), difference vegetation index (DVI), ratio vegetation index (RVI), transformed vegetation index (TVI), modified soil adjustment vegetation index (MSAVI), optimization of soil regulatory vegetation index

(OSAVI), the reflectance at green peak (ρ_g), the reflectance at red valley (ρ_r), the reflectance at green peak/the reflectance at red valley (RVIgr), and the normalized difference vegetation index of the reflectance at green peak and the reflectance at red valley (NDVIgr), as detailed in Table 1.

Table 1. The variables for modeling grass yield based on GF-5B.

Indices	Formula
NDVI	$(\rho_{836} - \rho_{665}) / (\rho_{836} + \rho_{665})$
EVI	$2.5(\rho_{836} - \rho_{665}) / (\rho_{836} + 6 \cdot \rho_{665} - 7.5 \cdot \rho_{481} + 1)$
DVI	$\rho_{836} - \rho_{665}$
RVI	ρ_{836} / ρ_{665}
TVI	$\sqrt{\text{NDVI} + 0.5}$
MSAVI	$0.5(2\rho_{836} + 1) / \sqrt{(2\rho_{836} + 1)^2 - 8(\rho_{836} - \rho_{665})}$
OSAVI	$1.16(\rho_{836} - \rho_{665}) / (\rho_{836} + \rho_{665} + 0.16)$
ρ_g	Maximum band reflectance in the wavelength range 510~560 nm
ρ_r	Wavelength 650~690 nm minimum reflectance in the range of 650~690 nm
RVIgr	ρ_g / ρ_r
NDVIgr	$(\rho_g - \rho_r) / (\rho_g + \rho_r)$

$\rho\lambda$ is the spectral reflectance of wavelengths with a center wavelength of λ in [nm].

Pearson's correlation analysis and principal component analysis (PCA) were conducted to extract spectral bands and spectral information that were sensitive to the change of forage parameters. Principal component analysis (PCA) was performed on 330 bands, the results of PCA analysis are shown in Table 2. Pearson's correlation analysis was employed to assess the relationship between quality parameters and principal components, while the first four principal components (total contribution rate > 95%) were selected to explain the spectral characteristics. Furthermore, the spectral bands and the abovementioned indices with high correlation ($r > 0.5$) and significance ($p < 0.01$) were also selected as independent variables, facilitating the establishment of modeling relationships between these variables and yield.

Table 2. Contributions of the principal components 1 to 4 based on 330 bands.

Principal Component	PC1	PC2	PC3	PC4
Contribution rate	0.8204	0.0721	0.0412	0.0187
Total contribution rate	0.8204	0.8925	0.9337	0.9524

The correlation analysis formula is as follows:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

where, X_i denotes the i th variable indicator and Y_i denotes the i th yield (quality) indicator. Based on the r absolute value magnitude, characterizing variables sensitive to grass yield (quality) indicators were screened.

2.3.2. Model Calibration and Validation

Multiple linear stepwise regression (MLR) was used to establish the relation between grass indicators and selected bands and indices, followed by an evaluation using root mean square error (RMSE) and the relative root mean square error (rRMSE). Due to limited samples, cross-validation was used to evaluate the accuracy of the model.

Given the complexity of alpine grassland types and high spatial heterogeneity, modeling with single variables results in limited accuracy. MLR was thus used for model-

ing [34,35], which incorporates or removes one variable at a time and identifies model variables based on the coefficient of determination (R^2). The stepwise regression method determines whether to retain or eliminate independent bands or indices by assessing the significance of newly added variables. When new independent bands or indices are introduced, previously included bands and indices are re-evaluated to determine their continued relevance in the model. This process is repeated until no further bands and indices can be added or removed. Because of the likely overfitting, it is necessary to choose an appropriate number of variables. Model fitting usually starts with a single variable, and then the variable numbers of the model increase gradually via the constant repetition of this process. Ultimately, models comprising multiple characteristic bands and indices are identified to explain the forage parameter.

The derived regression function was used to predict the grass quality, and these prediction results were compared with the measured values to assess accuracy. The evaluation parameters included the coefficient of determination (R^2), the root mean square error (RMSE), and the relative root mean square error (rRMSE). While RMSE is influenced by the magnitude of the selected bands and indices, rRMSE is not, making it a reliable metric for reflecting the modeling accuracy. The formulas for calculating the above parameters are as follows:

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$$

$$RMSE = \sqrt{\frac{SSE}{n}} = \sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n}}$$

$$rRMSE = \frac{RMSE}{\bar{Y}}$$

where Y_i is the measured value of grass quality indicators, $\bar{Y}$ is the measured average of grass quality indicators, $\hat{Y}_i$ is the predicted value of grass quality indicators, and n is the number of samples.

After obtaining the inversion model, the selected bands or indices of all regions in the study area were input into the model to obtain the grass indicators of the whole study area. Then, the inversion results were imported into ArcGIS 10.5 to realize the spatial mapping to reveal the spatial distribution pattern of the grass indicators.

2.3.3. Grassland Carrying Capacity Assessment Considering the Grass Quality Indicators

The relative feed value (RFV) index for hay quality rating was introduced by the hay marketing task force in 1978 [36]. However, RFV's simplicity and reliance on just two parameters—neutral detergent fiber and acidity—limit its effectiveness. To overcome the limitations, relative feed quality (RFQ) was proposed [37], incorporating newer analyses and more comprehensive equations. RFQ is based on the concept of total digestible nutrients (TDN) for standard grass; thus, grasses with a higher RFQ provide more energy when compared with standard grass, and vice versa. Its formula is as follows [17]:

$$RFQ = DMI \times TDN / 1.23$$

$$TDN = (CP \times 0.87) + (FA \times 0.97 \times 2.25) + \left[NDFn \times \left(\frac{NDFDP}{100} \right) \right] + (NFC \times 0.98) - 10$$

$$DMI = -2.318 + 0.442 \times CP - 0.01 \times CP^2 - 0.0638 \times TDN + 0.000922 \times TDN^2 + 0.18 \times ADF - 0.00196 \times ADF^2 - 0.00529 \times CP \times ADF$$

and can be understood as follows:

- NDFn = nitrogen free NDF = NDF – NDFCP, also estimated as NDFn = NDF × 0.93
- NDFCP = neutral detergent fiber crude protein

- NDFD = 48 h in vitro NDF digestibility (% of NDF), taken as 55%.
- NFC = nonfibrous carbohydrate (% of DM) = $100 - (\text{NDFn} + \text{CP} + \text{EE} + \text{Ash})$
- EE = ether extract (% of DM), taken as 2%. Ash, taken as 9%.
- $\text{NDFDp} = 22.7 + 0.664 \times \text{NDFD}$

Because the dominant species in the Dangqu basin differs from the typical standard grass (generally *Medicago sativa*), the RFQ for the standard grass was recalibrated. Considering the grass quality, we computed the ratio of the predicted grass RFQ to that of the standard grass. This study recalculated RFQ based on the dominant species, *Kobresia pygmaea*, using the following parameters: CP at 11%, NDF at 55%, ADF at 30%, EE at 2%, Ash at 9%, and 48h NDF digestibility at 55%.

Considering the quality, we developed the following yield formula:

$$Y_o = Y \times \text{RFQ}_i / \text{RFQ}_s$$

where Y_o is the grass yield with consideration of grass quality, Y is the original grass yield, RFQ_i is the predicted relative feed quality, and RFQ_s is the relative feed quality of standard grass, calculated as 125.30.

Based on the studies [38,39], the following formula was utilized to calculate the grass carrying capacity within the study area:

$$C = \frac{10 \times Y_o \times G \times E}{I \times D}$$

where C is the theoretical carrying capacity of grassland ($\text{SU} \cdot \text{hm}^{-2}$); Y_o (g/m^2) is the grass yield with consideration of grass quality; G is the utilization rate of grassland in the whole year, which is 50% according to the LY/T3320-2022 standard [40]; E is the proportion of edible grass of grassland, which was determined to be 90% according to the LY/T3320-2022 standard [40]; I is the daily feed of 1.33 kg hay for the standardized sheep unit, with the water content of 1.8 kg of standard hay being converted to 1.548 kg of hay without water according to the LY/T3320-2022 standard [40]; and D is grazing time in each year (365 days).

3. Results

3.1. Models of Grass Quality Indicators and Grass Yield

The models and the bands selected via MLR modeling are presented in Tables 3–6, and all models were found to be statistically significant at the 0.05 level ($p < 0.05$). The selected bands included in the model are as follows: CP content can be modeled using ρ_{1497} , ρ_{733} , ρ_{2516} , and ρ_{1918} ; NDF content was modeled with ρ_{1884} , ρ_{2347} , and ρ_{404} ; and ADF content was represented by ρ_{1918} and ρ_{2415} (Tables 3–5). The R^2 values of CP ranged from 0.197 to 0.462 while RMSE values varied between 3.551 and 3.126 and rRMSE ranged from 0.253 to 0.223. The R^2 of NDF ranged from 0.07 to 0.316 with RMSE values between 3.889 and 3.499 and rRMSE ranging from 0.074 to 0.066, while the R^2 of ADF were between 0.112 and 0.245 with RMSE and rRMSE of between 2.380 and 2.247 and 0.080 to 0.076, respectively. As the number of variables increased, the R^2 values of all three regression models improved, while RMSE and rRMSE decreased, indicating enhanced accuracy.

In contrast with the quality indicators, grass yield could be predicted via line regression by EVI and multiple regression by ρ_{1396} and the third principal component (PC3) (Table 6) with R^2 of more than 0.650 and confidence at the $p < 0.001$ level. The three regression models exhibited the following ranges: R^2 from 0.654 to 0.815, RMSE between 25.857 and 33.676, and rRMSE spanning 0.286 to 0.372. As the number of variables increases, R^2 consistently rises, reaching a maximum of 0.815, while RMSE and rRMSE decline, indicating an improvement in the model's simulation accuracy.

Table 3. The CP model in the Dangqu basin and evaluation parameters.

Regression Model (CP)	p	R^2	RMSE	rRMSE
$34.066\rho_{1497} + 7.369$	0.03	0.197	3.551	0.253
$66.273\rho_{1497} - 62.336\rho_{733} + 16.130$	0.01	0.346	3.279	0.233
$67.714\rho_{1497} - 75.221\rho_{733} - 72.528\rho_{2516} + 24.155$	0.01	0.409	3.194	0.227
$46.735\rho_{1497} - 77.126\rho_{733} - 99.366\rho_{2516} + 326.639\rho_{1918} + 21.464$	0.01	0.462	3.126	0.223

$\rho\lambda$ is the spectral reflectance of wavelengths with a center wavelength of λ [in nm].

Table 4. The NDF model in the Dangqu basin and accuracy assessment.

Regression Model (NDF)	p	R^2	RMSE	rRMSE
$541.555\rho_{1884} + 44.229$	0.21	0.07	3.889	0.074
$1129.065\rho_{1884} - 62.772\rho_{2347} + 44.841$	0.05	0.242	3.593	0.068
$1414.260\rho_{1884} - 112.185\rho_{2347} + 114.522\rho_{404} + 43.558$	0.05	0.316	3.499	0.066

$\rho\lambda$ is the spectral reflectance of wavelengths with a center wavelength of λ [in nm].

Table 5. The ADF model in the Dangqu basin and accuracy assessment.

Regression Model (ADF)	p	R^2	RMSE	rRMSE
$-193.723\rho_{1918} + 35.056$	0.11	0.112	2.38	0.080
$-494.601\rho_{1918} + 68.076\rho_{2415} + 34.942$	0.05	0.245	2.247	0.076

$\rho\lambda$ is the spectral reflectance of wavelengths with a center wavelength of λ [in nm].

Table 6. The grass yield model in the Dangqu basin and accuracy assessment.

Regression Model	p	R^2	RMSE	rRMSE
$492.479\text{EVI} - 43.931$	<0.001	0.654	33.676	0.372
$474.011\text{EVI} - 587.408\rho_{1396} + 19.456$	<0.001	0.764	28.474	0.315
$379.747\text{EVI} - 561.583\rho_{1396} + 104.802\text{PC3} + 17.824$	<0.001	0.815	25.857	0.286

$\rho\lambda$ is the spectral reflectance of wavelengths with a center wavelength of λ [in nm].

The optimal inversion models for CP, NDF, ADF, and grass yield were identified by comparing R^2 , RMSE, and rRMSE across all of the models. The results indicate that incorporating more factors into the model improves the prediction accuracy. The optimal models are displayed in Figure 2. The x coordinate of the scatter plot represents the field detection value of the sample grassland, and the y coordinate represents the predicted grassland value of the remote sensing image corresponding to the sample coordinates. The whole figure can be used to analyze the fitting effect of the model.

Their optimal models were as follows :

$$Y_{\text{CP}} = 46.735\rho_{1497} - 77.126\rho_{733} - 99.366\rho_{2516} + 326.639\rho_{1918} + 21.464$$

$$Y_{\text{NDF}} = 1414.260\rho_{1884} - 112.185\rho_{2347} + 114.522\rho_{404} + 43.558$$

$$Y_{\text{ADF}} = -494.601\rho_{1918} + 68.076\rho_{2415} + 34.942$$

where Y_{CP} , Y_{NDF} , and Y_{ADF} represent the predicted values of crude protein, neutral detergent fiber, and acid detergent fiber, respectively.

$$Y_{\text{yield}} = 379.747\text{EVI} - 561.583\rho_{1396} + 104.802\text{PC3} + 17.824$$

where Y_{yield} is the forage yield, EVI represents the enhanced vegetation index, and PC3 represents the third principal component in the principal component analysis of all spectral bands.

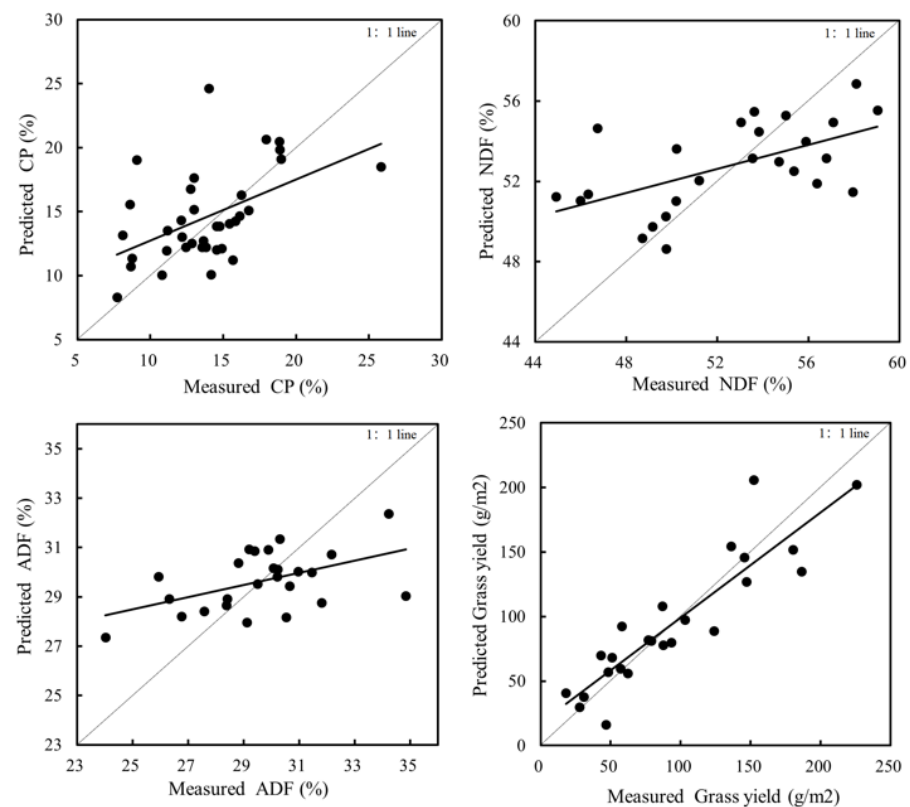


Figure 2. The scatterplots between measured and predicted grass quality indicators or yield.

3.2. Grass Parameters Prediction and Their Spatial Distribution

The quality indicators and RFQ of the alpine meadow in the Dangqu basin were predicted using the optimal multiple linear regression models, and the spatial distribution maps generated are presented below (Figures 3–6).

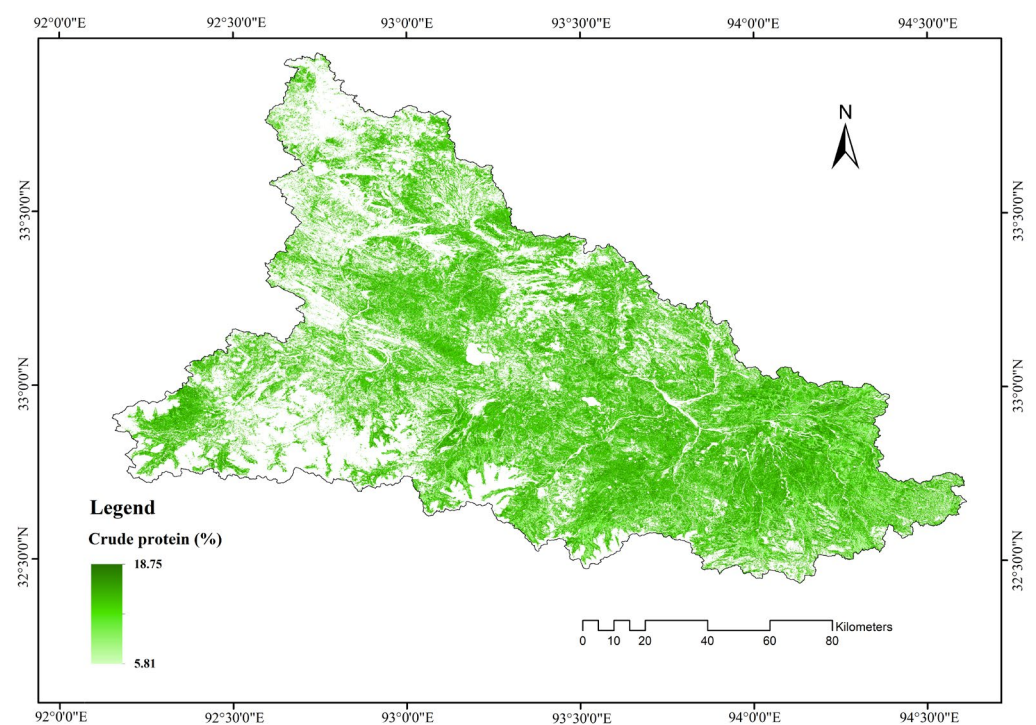


Figure 3. The spatial distribution of crude protein in the Dangqu basin.

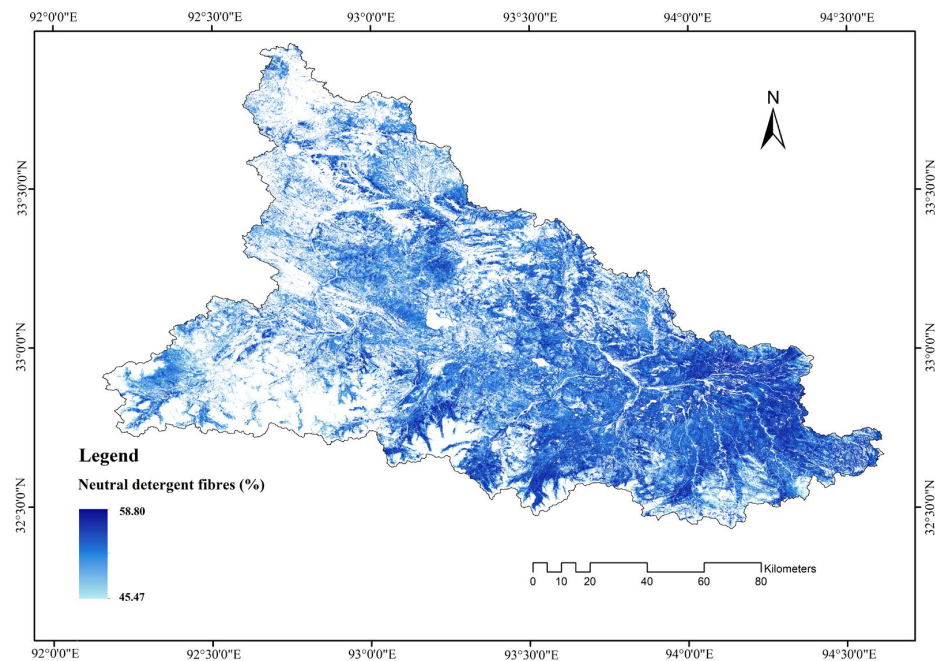


Figure 4. The spatial distribution of neutral detergent fiber in the Dangqu basin.

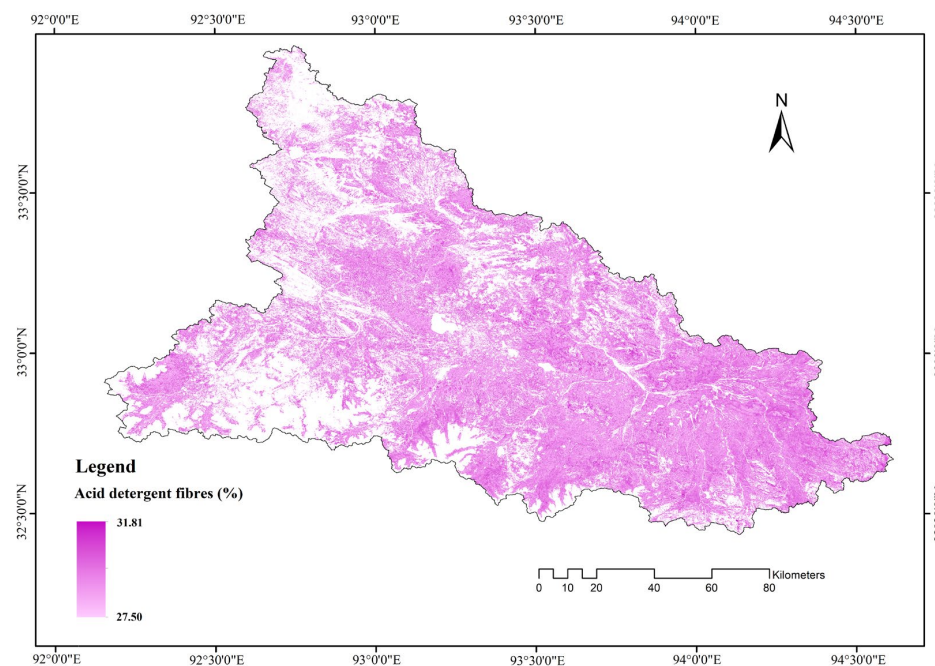


Figure 5. The spatial distribution of acid detergent fiber in the Dangqu basin.

The CP (Figure 3) varied between 5.81% and 18.75%, averaging at 11.25%. Its contents increased from west to east, with higher concentrations observed in the foothills of the southwestern region. The region with the lower CP was mainly distributed in the north and in the southwest. The NDF (Figure 4) ranged from 45.47% to 58.80%, with an average of 54.36%, while ADF (Figure 5) varied from 27.50% to 31.81%, averaging 28.90%. The NDF exhibited a trend of higher concentrations in the southeast and lower concentrations in the northwest. Specifically, elevated NDF levels were found in the southern Tanggula foothills and near Chatan township in the northeast, while certain areas along the northwestern banks of the Dangqu main stream also showed high NDF content. Conversely, the central-west region displayed generally low NDF levels. The distribution of ADF revealed localized areas of high value, especially in the southern Tanggula foothills and southwestern regions.

Conversely, certain parts of the central northern basin, near the Dangqu main stream, featured scattered zones with elevated ADF, while most other areas exhibited generally lower ADF. The RFQ (Figure 6) ranged from 116.99 to 181.93, with an average of 159.65. RFQ values were higher in the west and east, while lower in the south. Notably, there were several areas of exceptionally high relative feeding value in the foothills of the Tanggula mountains in the southeast, as well as additional pockets of high RFQ near Chadang township in the northeast.

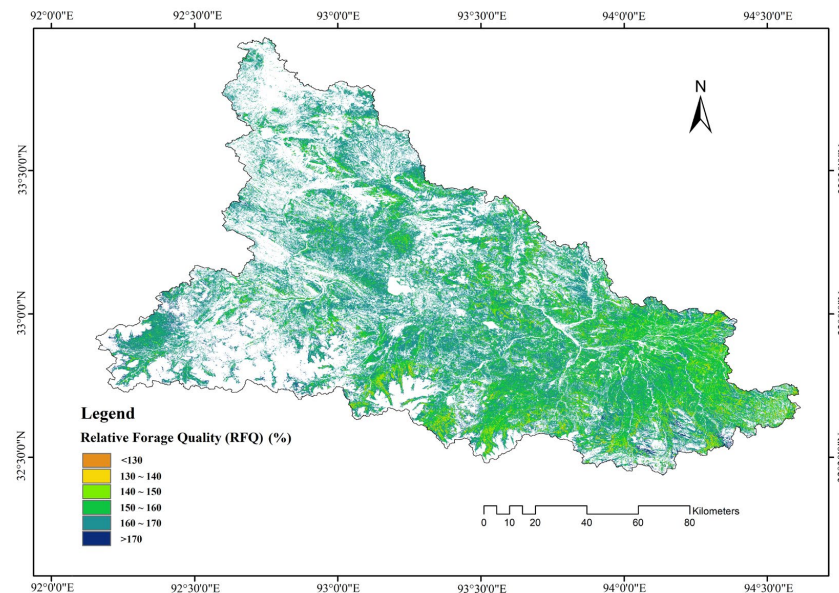


Figure 6. The spatial distribution of relative forage quality in the Dangqu basin.

The grass yield and its spatial distribution are presented in Figure 7. The results indicate that grass yield in the alpine meadows ranged from 0 to 238.41 g/m², with an average of 61.26 g/m². Grass yield demonstrated an increasing trend from northwest to southeast, and the central northern region generally had low yields, interspersed with pockets of higher yields. High values were primarily concentrated in the southeastern wetlands.

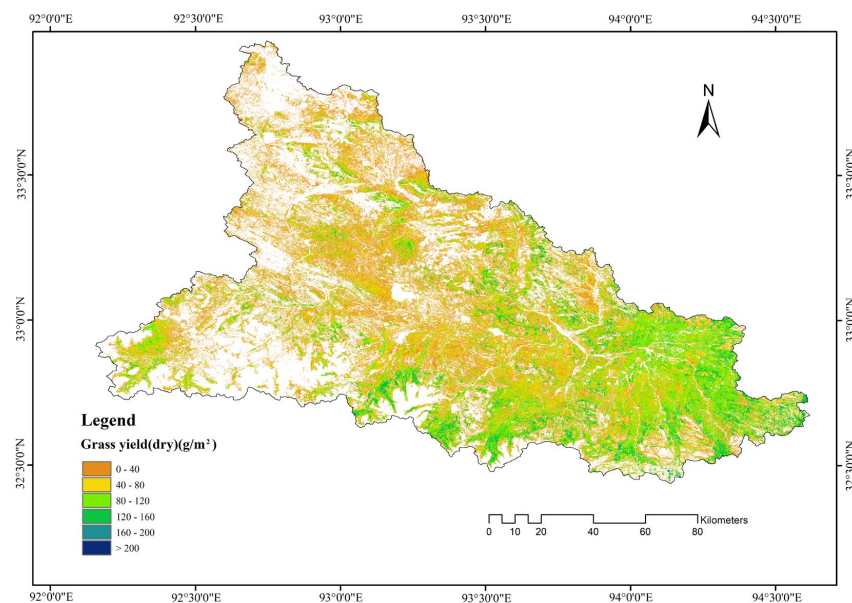


Figure 7. The spatial distribution of grass yield in the Dangqu basin.

3.3. Assessment and Optimization of Grassland Carrying Capacity in the Dangqu Basin

The statistical information of GCC and optimized GCC of the Dangqu basin are calculated in Table 7. Grasslands accounted for about 57% of the total area. Without consideration of grass quality, the GCC varied from 0 to $1.92 \text{ SU} \cdot \text{hm}^{-2}$, with an average of $0.51 \text{ SU} \cdot \text{hm}^{-2}$. Over 30% of the land had a GCC of $0\text{--}0.5 \text{ SU} \cdot \text{hm}^{-2}$, while 22% fell in the range of $0.5\text{--}1.0 \text{ SU} \cdot \text{hm}^{-2}$. Less than 5% of the land had a carrying capacity greater than $1.0 \text{ SU} \cdot \text{hm}^{-2}$. Following the optimization of grass quality parameters, the GCC changed. The GCC with consideration of grass quality was distributed in the range of 0 to $2.44 \text{ SU} \cdot \text{hm}^{-2}$, with an average of $0.63 \text{ SU} \cdot \text{hm}^{-2}$. Approximately 23% of the total area was found to show a GCC of $0\text{--}0.5 \text{ SU} \cdot \text{hm}^{-2}$, 21% of which lies between $0.5\text{--}1.0 \text{ SU} \cdot \text{hm}^{-2}$. While about 10% of the area had a carrying capacity exceeding $1.0 \text{ SU} \cdot \text{hm}^{-2}$, less than 1% exceeded $1.5 \text{ SU} \cdot \text{hm}^{-2}$. Compared with the unoptimized GCC, which peaked at $0\text{--}0.5 \text{ SU} \cdot \text{hm}^{-2}$, the optimized capacity was now more concentrated in the range of 0.5 to $1.0 \text{ SU} \cdot \text{hm}^{-2}$.

Table 7. Statistical characteristics of grassland carrying capacity in the Dangqu basin.

Grassland Carrying Capacity ($\text{SU} \cdot \text{hm}^{-2}$)	km^2		Percentage	
	Before	Optimization	Before	Optimization
0–0.5	5256.242	3917.186	31.121%	23.193%
0.5–1.0	3798.278	3657.282	22.489%	21.654%
1.0–1.5	578.461	2001.626	3.425%	11.851%
1.5–2.0	8.636	64.680	0.051%	0.383%
>2.0	0.000	0.807	0.000	0.005%
Total	9641.581	9641.581	57.087%	57.087%

The spatial distribution of the optimized GCC is displayed in Figure 8. Similar to the grass yield, the GCC also showed an increasing trend from northwest to southeast, with high values distributed in the southeastern wetlands. Most of the region had a GCC of less than $1.0 \text{ SU} \cdot \text{hm}^{-2}$, and the region between 92° and 93°E had a GCC of essentially less than $0.5 \text{ SU} \cdot \text{hm}^{-2}$. The region with a GCC exceeding 1 was primarily found in the southwestern portion of the Dangqu basin, accounting for about 30% of the total grassland area. This region encompassed the Chatan wetland, the highest elevation wetland of the Changjiang River source, characterized by abundant water resources and extensive alpine meadows. It serves as a vital pasture area in Chatan township, aligning well with the actual conditions observed.

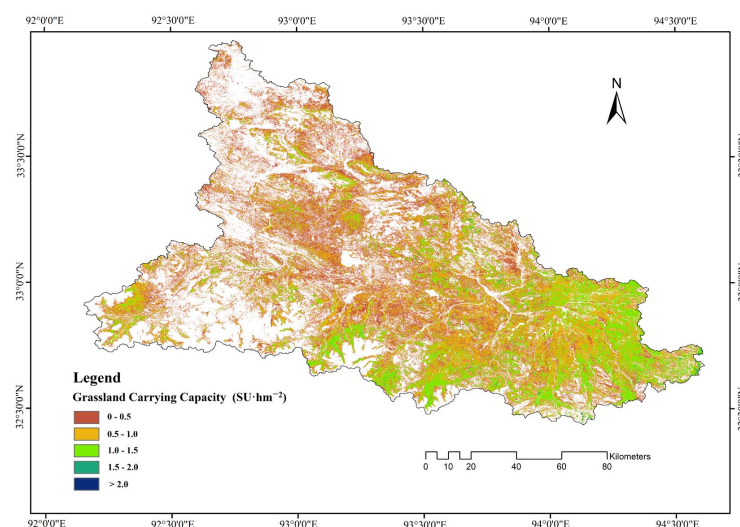


Figure 8. The spatial distribution of grassland carrying capacity in the Dangqu basin.

4. Discussion

It was found to be feasible for GF5B hyperspectral images to estimate physicochemical parameters of alpine grassland with altitudes of above 4500 m. The R^2 of optimal models of CP, NDF, ADF, and yield estimation were 0.462, 0.316, 0.245, and 0.815, respectively. Spectral wavelengths of GF5B ranged from 390 nm to 2516 nm with 330 spectral bands, including enriched spectral information. The sophisticated sensors and a swath width of 60 km make it possible to quickly acquire large-scale hyperspectral images of the Dangqu basin with a spatial resolution of 30 m, providing reliable data for quantitative and qualitative monitoring [41].

The results indicate that the wavelengths of the optimal models for the CP prediction of grassland vegetation in the study area were 733 nm, 1497 nm, 1918 nm, and 2516 nm, which is consistent with the previous research. These studies indicate that the dominant wavelengths for CP estimation were mainly distributed in the range from 700 nm to 750 nm [42,43]. Wijesingha et al. [42] conducted a study in northern Hesse, Germany, utilizing UAV-borne hyperspectral data combined with support vector regression to predict CP contents, achieving a normalized RMSE (nRMSEp) of 10.6%. They identified reflectance at 718 nm as the best variable for CP modeling. Similarly, Geipel et al. [43] employed the partial least squares regression (PLSR) to assess the potential of in-season airborne hyperspectral imaging for CP estimation, achieving a high level of accuracy with an error of 11.7%. They found that the center wavelengths of the most dominant wavelengths in the CP model were 720 nm and 725 nm. This aligns with our finding, where 733 nm was one of the optimal predictors for the CP model. The spectral wavelengths of the optimal model contained a range that was sensitive to changes in chlorophyll, nitrogen content, and water content, implying that they may influence the CP content of grass in Dangqu [44].

Although the model accuracy of NDF and ADF should be improved, it provided an alternative for the rapid monitoring of ADF and NDF at a large scale. The selected wavelengths of the optimal NDF prediction model include two bands at 1884 nm and 2347 nm which were found to be sensitive to water vapor absorption, along with one band at 404 nm that was sensitive to chlorophyll change, while that for ADF was 1918 nm and 2415 nm. Pullanagari et al. [45] utilized hyperspectral data to predict NDF and ADF content in commercial New Zealand grass, achieving high accuracy with errors of 10.6% and 8.5%, respectively; they noted that wavelengths near 805 nm were significant for predicting feed quality parameters. Schut et al. [46] reported even smaller errors of 3% and 5%. These studies highlight a strong correlation between reflectance in the near-infrared region (NIR) and NDF.

Compared with quality indicator estimation, yield estimation showed higher accuracy, with an R^2 of above 0.80. Except for single wavelengths, the optimal model for yield estimation also included the spectral index (EVI) and the third principal component of all spectral bands. A yield estimation can be achieved with an R^2 of 0.654 and an RMSE of 33.676 using only the spectral index EVI, and the accuracy gradually increased to 0.815 when a single wavelength (1396 nm) and spectral principal component were added stepwise. These results indicate that typical spectral indices (such as EVI) and PCA can extract spectral information that is sensitive to yields, but it was more difficult to extract spectral information that is sensitive to grass quality indicators. Therefore, subsequent research could explore new spectral information extraction algorithms or construct new indices to improve the accuracy of grass quality index estimation.

The GCC calculated using the previously determined grass yield of 61.26 g/m², was 0.49 SU·hm⁻². When considering the grass quality, the GCC increased to 0.63 SU·hm⁻², reflecting a 28.88% improvement. This optimization method enhances the livestock stocking rate of high-quality grass, which is crucial for the rational use of grasslands in the source area of the Changjiang River, the sustainable development of the livestock industry, and ecological environmental protection. Zhang et al. [47] estimated grassland yield and GCC in the Sanjiangyuan area based on MODIS data and analyzed its spatial distribution characteristics, finding a corresponding average stocking capacity of 0.51 SU·hm⁻² and

an average grass yield of 46.57 g/m² in 2010, with a decreasing trend from the east and southeast to the west and northwest, which aligns closely with our findings. Similar to Zhang's findings, another study also found that high values of grass production and grassland carrying capacity are primarily concentrated in the eastern and southern regions, with a decline toward the northwest [47]. This pattern is likely linked to the distribution of precipitation and temperature in the Dangqu basin. Precipitation in the southeast is higher than in the northwest, while temperatures in the central and northern areas are warmer than in the south [22,23], creating conditions more conducive to grass growth.

The spatial distribution of grass yields and GCC in the Dangqu basin showed a consistent trend of low northwest and high southeast. However, the GCC was found to be dynamically evolving and grass quality indicators also varied during the different vegetation periods [48]. In this study, we explored the feasibility of using hyperspectral images to optimize the GCC of the Dangqu basin during the growth period in early July 2022. In future studies, it is necessary to explore a universal dynamic assessment method of GCC, one which not only takes into account grass quality indicators but also grass physiological alternations, so as to predict the dynamic trend of GCC and provide more accurate data for a reasonable livestock stocking rate and for environment protection.

5. Conclusions

In this study, we first estimated the grass quality and yield of alpine grassland using GF-5B satellite hyperspectral data, and then used the quality indicators (CP, NDF, and ADF) to optimize the GCC of the Dangqu basin based on grass yield. The results demonstrate the feasibility of utilizing GF-5B hyperspectral images to quickly estimate grass quality indicators and assess GCC in the Dangqu basin at a large scale. The grass yield ranged from 0 to 238.41 g/m², with an average of 61.26 g/m². The GCC that considered the grass quality varied from 0 to 2.44 SU·hm⁻², averaging 0.63 SU·hm⁻², and was primarily concentrated in the southeastern region. This prediction of GCC reflected well the way in which higher-quality grass contains more total digestible nutrients (TDN), aligning closely with the actual conditions of the grassland. This study helps to improve the accurate GCC estimation of the source region of Changjiang River, providing technical support for the sustainable development of the livestock industry and ecological safety.

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