A Remote Sensing Based Forage Biomass Yield Inversion Model of Alpine-cold Meadow during Grass-withering Period in Sanjiangyuan Area

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Abstract: Estimating forage biomass yield remotely from space is still challenging nowadays. Field experiments were conducted and ground measurements correlated to remote sensing data to estimate the forage biomass yield of Alpine-cold meadow grassland during the grass and grass-withering period in Sanjiangyuan area in Yushu county. Both Shapiro-Wilk and Kolmogorov-Smirnov two-tailed tests showed that the field training samples are normally distributed, the Spearman coefficient indicated that the parametric correlation analysis had significant differences. The optimal regression models were developed based on the Landsat Thematic Mapper Normalized Difference Vegetation Index (TM-NDVI) and the forage biomass field data during the grass and the grass-withering periods, respectively. Then an integration model was used to predict forage biomass yield of alpine-cold meadow in the grass-withering period. The model showed good prediction accuracy and reliability. It was found that this approach can not only estimate forage yield in large scale efficiently but also overcome the seasonal limitation of remote sensing inversion. This technique can provides valuable guidance to animal husbandry to resource more efficiently in winter.

Keywords: Sanjiangyuan area, Grass-withering period, Alpine-cold meadow grassland, Remote sensing inversion, NDVI

1. Introduction

The Sanjiangyuan area, where the springs of the Yangtze River, the Yellow River and the Lantsang River are all nearby, is the largest nature reserve and one of the three most important high-yield grasslands in China. It is recently declared the exclusive district with the richest biodiversity and the most fragile ecological environment among the high-altitude areas around the world. However, as a result of overgrazing, the forage yield of grass period has reduced 30%~50% per unit of area and the overloading rate of grass-withering period has reached approximately 41.5% in recent years [1]. Although remote sensing is increasingly used to study forage biomass retrieval from satellites, forage biomass estimation during grass-withering period, especially in the Sanjiangyuan area, were still rare and had to be complemented with traditional empirical methods, such as visual and sampling estimation. To date, satellite-based indices, such as the normalized difference vegetation index (NDVI), were well established in many case studies for estimating the forage biomass yield levels.

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The major limitation comes from that the remote sensing can be solely utilized only when forage is green[2-5]. For instance, Ikeda et al. [6] developed a growth model for estimation of the surface phytomass in meadow grassland using the TM data. Chen et al. [7] found both forage biomass and TM-NDVI values in sampling points are significantly correlated (correlation coefficient r>0.7) in the Sanjiangyuan area.

The objective of this study is to develop a new approach that can overcome overcoming the aforementioned the season limitation and the forage spatial heterogeneity limitation [8]. To the best knowledge of the authors, this is one of the very few, if not first, investigations on forage biomass estimation in the grass-withering season in the Sanjiangyuan area by using remote sensing inversion. The models are tested in the typical Alpine-cold meadow grassland and the performance evaluated.

2. Data collection and integration
The area of the region of interest is approximately 2412 km². It is a representative region covered by Alpine-cold meadow grassland (Figure 1) located in the eastern Qinghai-Tibet plateau (32°46′40″N-33°05′40″N, 96°45′08″E-97°06′52″E)). Additionally, the average elevation is 4493.4 m above sea level, the average annual temperature is 2.9 ℃, and the annual rainfall is 487 mm. The relatively stable climate and extensive grassland coverage are ideal for the simplification of the retrieval model with achievable regression model performance.

2.1 Thematic Mapper (TM) data
The Thematic Mapper (TM) sensor is on board the Landsat satellite. Its swath width is 185 km with 30 m spatial resolution and spectrum ranges from 0.45 μm to 3.35 μm. The Landsat5 TM data (banding/line number: 134/037), which covered the region of interest during the on-site sampling period, were downloaded from the International Scientific Data Service Platform at [FULL NAME OF CNIC] (CNIC) (http://datamirror.csdb.cn/). The TM data (version: Level 1T) were then pre-processed with radiometric calibration [9], atmospheric correction [10] and geometric correction (Gauss-Kruger coordinate system, residual error is 0.1456). NDVI values were calculated using TM3 (red band, wavelength 0.63-0.69μm) and TM4 (near-infrared band, wavelength 0.76-0.90 μm) by the following equation.
\[ NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \] (1)

2.2 Field survey data
The layout of the sample plot in the region of interest was relatively uniform in terms of forage spatial distribution, landform difference and traffic convenience. The fieldwork were carried out on six sites (“YangGou”, “NiuGou”, ”GouKou”,“ZhongXuChang”,”ShangBaTang” and “XiaBaTang”) as shown in Figure 1.

Depending on the situation of the forage community, 2-3 1m\(^2\) quadrats were archived if forage community had good consistency; otherwise 4-6 1m\(^2\) quadrats were archived. During the sample collection, the sampling time, plot name, quadrat number, forage coverage and forage fresh weight were recorded. Meanwhile, the latitude, longitude and altitude information from the GPS receiver were also logged.

2.3 Data integration
In collocate satellite observations and field measurements of forage biomass, the 30 m resolution TM-NDVI were matched with corresponding quadrat values multiplied by 30×30. Forage fresh weight was matched with NDVI image according to geographic coordinate. In addition, the normal distribution was tested by checking whether the Shapiro-Wilk coefficient or Kologorov-Smirnov coefficient are greater than 0.05 (Table 1). The Spearman correlation coefficient calculated between the grass and the grass-withering periods (Table 2) was greater than 0.7.

| Parameters                     | Shapiro-Wilk Coefficient | Kologorov-Smirnov coefficient |
|--------------------------------|---------------------------|------------------------------|
| Forage biomass in grass period | 0.160                     | 0.230                        |
| Forage biomass in grass-withering period | 0.136             | 0.018                        |
| NDVI                           | 0.017                     | 0.084                        |

Table 2. Spearman correlation coefficient

|                          | Forage biomass in grass period | Forage biomass in grass-withering period |
|--------------------------|--------------------------------|----------------------------------------|
| NDVI                     | 0.776**                        | 0.824**                                |

** means the correlation is very significant (p<0.001, N=23)

3. Methods
Since remote sensing was not used in the estimation of forage biomass during the grass-withering period in previous studies and the remote sensing inversion of forage biomass in the grass period are already validated (Figure 2), a systematic analysis was conducted on the seasonal variation of the vegetation index in different vegetation coverage conditions (Figure 3). Figure 3 illustrated that the high values of NDVI appeared in the grass period (June to mid-September), and the higher the coverage, the greater the vegetation index values. However, vegetation index dropped below 0.2 during the rest of the year. In addition, curvilinear trend had nothing to do with either vegetation index types or coverage. The consequently of the encountered conditions were that the remotely sensed forage biomass of the grass period have been fully, whereas the forage biomass of the grass-withering period couldn’t be sensed indirectly by satellites [11].
4. Results and discussion

Theoretically, the air-dry nutrients of forage, harvested in the grass-withering period, could be calculated by the highest wet weight of forage in the year, which is usually reaches its maximum in the grass period. Therefore, the forage biomass in the grass period was chosen as a representative exhibiting the largest forage biomass of the year. Meanwhile, the satellite based NDVI was chosen as an index to calculate forage yield in the grass period. To evaluate the feasibility and precision of the model parameters, the average estimation accuracy and the median error were used from the macro and partial levels, respectively.

The formulas are presented as follows:

\[ MEA = (1 - \frac{\bar{x}_0 - \bar{x}_p}{\bar{x}_0}) \times 100\% \]  
\[ ME = 0.6745 \sqrt{\frac{\sum (x_0 - x_p)^2}{(n-1)}} \]  

where MEA is the mean estimation accuracy, \( \bar{x}_0 \) is the mean measured value, \( \bar{x}_p \) is the mean simulative value; ME is the median error, \( x_0 \) is the measured value, \( x_p \) is the simulative value, and \( n \) is the number of observed values.

4.1 Evaluation of the forage biomass model based on NDVI for the grass period

The grass period quadrats and the matched NDVI values both followed the normal distributions (Table 1). The correlation coefficient between the forage biomass and NDVI was 0.776 (Table 2), indicating a highly significant correlative relation between the two variables (p=0.000<0.001). We further built a regression model using the matched NDVI and the forage fresh weight values as predictor of forage biomass. The results are similar to Wang et al. (2005), who reported that the linear and exponential functions were most matured and widely applied in the forage yield estimation. In contrast secondary and higher polynomial functions were used rarely due to unclear physical interpretations and over-fitting [12]. The statistics from the linear and exponential forage biomass estimation models are listed in Table 3. For the grass period, the optimal model was found as \( Y = 0.286e^{10.858x} \) (\( R^2=0.761; \) MEA=71.07%, ME=27.98%), similar to what was found by Zhang et al. [13] and Yu et al. [14].
Table 3. The inversion model of Remote Sensing

| Model Pattern       | Regression Model | $R^2$ | p   | MEA | ME  |
|---------------------|------------------|-------|-----|-----|-----|
| Grass Period        | Linear           | 0.602 | 0.000 | 84.06% | 46.30% |
|                     | Exponential      | 0.761 | 0.000 | 71.07% | 27.98% |
| Grass-withering Period | Linear         | 0.68  | 0.000 | 90.80% | 30.42% |
|                     | Exponential      | 0.62  | 0.000 | 67.78% | 33.23% |
| Model integration   | Exponential      |       |      | 90.26% | 54.13% |

4.2 Empirical forage biomass estimation model for the grass-withering period
Over the region of interest, winter rangeland was separated from livestock and human activities in the grass period. Therefore, the forage nutrition in the grass period, including Crude Protein (CP), Neutral Detergent Fiber (NDF) or Acid Detergent Fiber (ADF), are the most reliable indicator for forage in the grass-withering period. While it can be interpreted easily in terms of vegetation growth cycle, the seasonal evolution of vegetation communities is rather complex and the exact mechanisms that modulate community evolution are still poorly known. As shown in table 3, the optimal seasonal model for the grass-withering period was linear ($Y=0.142X+35.634$, $R^2=0.68$; MEA=90.80%; ME=30.42%) with slight better performance over the exponential model.

4.3 Model integration
In table 3, an integration model was also provided. The integration combines remote sensing and seasonal empirical model to quantitatively estimate forage biomass at a macro scale. The model was selected was $Y = 0.040612e^{10.858X} + 32070.6$ with an average estimation accuracy of 95.91% indicating a very good precision of the model at macro scale. With a median error of 54.13%, the model is expected feasible for partial scale despite of increased uncertainty from in situ sampling differences.

5. Conclusion
A remote sensing based forage biomass yield model was developed and evaluated in this study. The technology roadmap recommended in the article is proven fully executable. The NDVI-based empirical model of the forage yield in the grass-withering period meets the actual application requirements. The precision of the integration model and of the biomass estimation model at macro scale is acceptable for alpine-cold meadow in the Sanjiangyuan area during the grass-withering period, although this model may have potential limitation over certain regions because of quadrats’ complex
variation. This tested approach not only can estimate forage yield accurately in large scale but also overcome the seasonal limitation of remote sensing inversion. It provides valuable guidance to animal husbandry to use resources in winter more efficiently.

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