Estimating Crop Residue Biomass in the Zhangjiakou Bashang Area by Integrating Optical and Radar Remote Sensing: Postprint

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Abstract

Non-photosynthetic vegetation such as crop residues plays an irreplaceable role in ecosystem material cycling and energy flow processes in arid and semi-arid regions, and also exhibits significant importance in inhibiting soil erosion, maintaining soil moisture, and promoting soil development. The Bashang area of Zhangjiakou is situated in the core zone of the capital' s "Two Districts" construction and the Beijing-Tianjin sandstorm source control. Utilizing remote sensing methods to estimate crop residue biomass in this region holds great significance for assessing wind erosion conditions, evaluating ecological environments, and studying carbon and nitrogen cycling. Based on field-measured crop residue biomass, Sentinel-2 optical imagery, and Sentinel-1 radar imagery, optical and radar remote sensing indices for crop residues were constructed. Employing optimal index normalized multiplication and multiple linear stepwise regression analysis methods, a crop residue biomass estimation model integrating optical and radar remote sensing was established to calculate and analyze crop residue biomass in the Bashang area of Zhangjiakou from 2017 to 2023. The results indicate: (1) Among optical remote sensing indices, the RI(11,12) index constructed from Sentinel-2 short-wave infrared bands (B11 and B12) demonstrated the highest correlation with crop residue biomass, with a model coefficient of determination (R2) of 0.744. Among radar remote sensing indices, the cross-polarization (VH) backscatter coefficient showed the highest correlation with crop residue biomass, with an R2 of 0.409. (2) Among the combined optical and radar remote sensing estimation models, the multiple linear stepwise regression model achieved the highest accuracy, with an R2 of 0.796 and a root mean square error (RMSE) of 8.84 g · m-2, enabling satisfactory prediction of crop residue biomass. (3) The accuracy of the constructed crop residue biomass estimation model is approximately 9.72% higher than that using optical remote sensing alone, and approximately 66.74% higher than that using radar remote

sensing alone. (4) From 2017 to 2023, the average annual crop residue biomass in the Bashang area of Zhangjiakou was 23.74$\times$104 t, displaying a fluctuating downward trend. The interannual variation of crop residue biomass is influenced by temperature and precipitation. In recent years, changes in cropping structure resulting from land transfer policy have been an important factor causing the decline in crop residue biomass in this region.

Full Text

Preamble

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Estimation of Crop Stubble Biomass in the Bashang Region of Zhangjiakou by Integrating Optical and Radar Remote Sensing

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Abstract: Non-photosynthetic vegetation such as crop stubble plays an irreplaceable role in material cycling and energy flow in arid and semi-arid ecosystems, while also contributing significantly to soil erosion prevention, moisture retention, and soil development. The Bashang region of Zhangjiakou, located in the core area of the capital' s two-zone construction and Beijing-Tianjin sandstorm source control, holds strategic importance for ecological security. Estimating crop stubble biomass in this region using remote sensing is crucial for assessing wind erosion conditions, evaluating ecological environments, and studying carbon and nitrogen cycles. Based on field-measured crop stubble biomass, Sentinel-2 optical imagery, and Sentinel-1 radar imagery, this study constructed optical and radar remote sensing indices for crop stubble. Using optimal index normalization multiplication and multiple linear stepwise regression analysis, an integrated optical-radar model was developed to estimate crop stubble biomass in the Bashang region from 2017 to 2023. The results demonstrate that: (1) Among optical remote sensing indices, the RI(11,12) index constructed from Sentinel-2 short-wave infrared bands (B11 and B12) showed the highest correlation with crop stubble biomass, achieving a coefficient of determination (R^2) of 0.744. For radar remote sensing indices, the cross-polarization (VH) backscattering coefficient exhibited the strongest correlation with crop stubble biomass, with an R^2 of 0.409. (2) The multiple linear stepwise regression model achieved the highest accuracy among all integrated models, with an R^2 of 0.796 and a root mean square error (RMSE) of 8.84 $g \cdot m^{-2}$, demonstrating reliable predictive capability for crop stubble biomass. (3) The combined optical-radar model improved estimation accuracy by approximately 9.72% compared to optical remote sensing alone and by 66.74% compared to radar remote sensing alone. (4) The average annual crop stubble biomass in the Bashang region from 2017 to 2023 was 23.74$×10^{4}$ t, showing a fluctuating downward trend. Interannual variations in crop stubble biomass were influenced by temperature and precipitation, while recent declines were primarily driven by changes in planting structure resulting from land transfer policies.

Keywords: crop stubble; biomass; optical remote sensing; radar remote sensing; Zhangjiakou Bashang region

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1 Introduction

Crop stubble refers to the residues remaining in farmland after crop harvest. As a critical component of agricultural ecosystems, it significantly influences material and energy cycling while reducing greenhouse gas emissions and protecting cultivated land. Crop stubble contains substantial carbon (40.74%-45.83%), nitrogen (14.66%-23.45%), potassium (0.60%-1.00%), and phosphorus (0.45%-1.97%), along with other trace elements. Upon decomposition, these residues increase soil organic carbon, potassium, and available phosphorus content, thereby alleviating nutrient loss, compensating for inorganic fertilizer deficiencies, and promoting crop growth. Soil organic carbon accumulation represents a vital source of carbon sequestration in farmland ecosystems, and crop stubble serves as a primary source of soil organic carbon that enhances carbon sequestration capacity by increasing organic carbon and its active components.

Farmland in arid and semi-arid regions accounts for 11.57% of China' s total cultivated area, where soil wind erosion occurs frequently, causing severe resource loss. Crop stubble cover represents a key conservation tillage practice in these regions. The protective effects of crop stubble on soil moisture retention, soil development, and wind erosion inhibition manifest in two primary ways. First, surface residue cover directly reduces evaporation, maintaining soil moisture while improving saturated hydraulic conductivity and water infiltration. Second, as a roughness element in wind erosion processes, crop stubble reduces wind shear stress and surface exposure area, thereby suppressing farmland wind erosion. Consequently, efficient crop stubble utilization constitutes an essential component of agricultural modernization in arid and semi-arid regions, with accurate biomass assessment being the critical prerequisite.

Traditional assessments of crop stubble quantity and distribution rely on field surveys and provincial agricultural statistics, which suffer from poor timeliness and inaccurate spatial representation. Remote sensing technology, characterized by broad coverage, continuous time series, and rich spectral information, has become an effective tool for biomass estimation. Current research predominantly utilizes optical remote sensing data to establish relationships between biomass and spectral bands, indices, or texture features. However, optical imagery is vulnerable to weather conditions, particularly during cloudy and rainy seasons when data quality deteriorates. In contrast, synthetic aperture radar (SAR) operates independently of weather conditions and can accurately capture crop stubble orientation information. Existing radar-based monitoring primarily establishes linear relationships between backscattering coefficients and biomass, though accuracy remains limited due to factors such as incidence angle, surface soil moisture, and soil roughness.

Given the complementary characteristics of optical and radar remote sensing, integrating both data sources can overcome the limitations of single-source approaches, representing a feasible and effective pathway for large-scale crop stubble biomass estimation. This study constructed optical and radar remote sensing indices based on Sentinel-2 and Sentinel-1 data, respectively, to determine their relationships with crop stubble biomass. By combining these indices, an optimal estimation model was developed to enhance the accuracy of remote sensing-based crop stubble biomass retrieval.

1.1 Study Area Overview

The Bashang region of Zhangjiakou is located in northern Hebei Province, on the southern edge of the Inner Mongolian Plateau, encompassing Kangbao County, Zhangbei County, Guyuan County, and Shangyi County, with a total area of approximately 1.38×10^{4} km^{2}. The region features elevations ranging from 1,200 to 1,800 m, with a terrain dominated by hills and plains that slopes from southeast to northwest [Figure 1: see original paper]. As a typical soil wind erosion area in northern China, this region holds a special ecological position in ensuring water resources and environmental security for the capital, playing an irreplaceable role in constructing the capital' s water conservation functional zone and ecological environment support zone. The area experiences a continental monsoon climate with harsh natural conditions characterized by cold temperatures, drought, and strong winds. The mean annual temperature is 1.2°C, with precipitation ranging from 90 to 120 days and an annual average of 400 mm.

1.2 Data Sources and Processing

1.2.1 Image Data Acquisition and Processing Optical Imagery: Sentinel-2 data were obtained from the Sentinel-2A and Sentinel-2B satellites, which provide a combined revisit period of 5 days. The data comprise 13 spectral bands, with visible and near-infrared bands (B2–B8) at 10 m resolution and short-wave infrared bands (B11–B12) at 20 m resolution. This study utilized the "COPERNICUS/S2" dataset via the Google Earth Engine platform. Since the harmonized dataset excludes the short-wave infrared cirrus band (B10), the analysis employed the remaining 12 bands. The platform provides Level-1C data preprocessed with radiometric calibration, atmospheric correction, and geometric correction. Additional processing included cloud removal, image mosaicking, vector clipping, and resampling to 10 m resolution.

Radar Imagery: Sentinel-1 data were acquired from the active microwave remote sensing satellite constellation consisting of two polar-orbiting satellites with a 12-day revisit cycle. The C-band SAR sensor operates in four imaging modes; this study employed the Interferometric Wide Swath (IW) Ground Range Detected (GRD) product with 10 m spatial resolution, providing both cross-polarization (VH) and vertical co-polarization (VV) modes. Data were obtained from the Alaska Satellite Facility and processed through orbit correction, radiometric calibration, speckle filtering, terrain correction, and conversion to decibels, yielding VH and VV backscattering coefficient images.

1.2.2 Field Measurement Data Spring wheat and naked oats in the Bashang region are sown in mid-May and harvested in late August. Field data collection was conducted from August 20–30, 2023, following harvest. A total of 50 sample plots were established across the region, each containing a 10 m × 10 m sampling unit within which a 1 m × 1 m quadrat was randomly selected and georeferenced. Stubble within each quadrat was cut at ground level, bagged, labeled, and air-dried. The average weight of stubble from three quadrats per plot was measured using a digital balance and recorded as the plot’ s crop stubble biomass.

1.3 Methods

1.3.1 Construction of Optical Remote Sensing Indices Post-harvest farmland primarily comprises crop stubble and soil. The spectral characteristics of crop stubble and soil are highly similar, differing only in wavelength amplitude. Single-band analysis is susceptible to soil interference, hindering stubble information extraction. Studies demonstrate that arithmetic operations between bands effectively suppress interference while enhancing spectral signals related to target absorption features. Following established vegetation index formulations, this study generated normalized difference indices (NDI) and ratio indices (RI) from all two-band combinations of Sentinel-2 data, calculating correlation matrices with measured stubble biomass to establish empirical relationships:

$$NDI(i,j) = \frac{R(i) - R(j)}{R(i) + R(j)}$$

$$RI(i,j) = \frac{R(i)}{R(j)}$$

where $R(i)$ and $R(j)$ represent spectral reflectance at bands i and j from Sentinel-2 imagery, and $NDI(i,j)$ and $RI(i,j)$ are the corresponding normalized difference and ratio indices.

1.3.2 Construction of Radar Indices Synthetic aperture radar data are sensitive to crop stubble vertical structure, providing indirect biomass information. This study utilized VH and VV backscattering coefficients and their polarimetric combinations to establish empirical relationships with crop stubble biomass:

$$\sigma^0_{VH+VV} = \sigma^0_{VH} + \sigma^0_{VV}$$

$$\sigma^0_{VH-VV} = \sigma^0_{VH} - \sigma^0_{VV}$$

$$\sigma^0_{VH\times VV} = \sigma^0_{VH} \times \sigma^0_{VV}$$

$$\sigma^0_{\frac{VH}{VV}} = \frac{\sigma^0_{VH}}{\sigma^0_{VV}}$$

where σ^0_{VH} and σ^0_{VV} represent backscattering coefficients in cross- and co-polarization modes, respectively.

1.3.3 Integrated Optical-Radar Estimation Model Construction To effectively combine optical and radar remote sensing for crop stubble biomass estimation, this study employed two approaches:

(1) Optimal Index Normalized Multiplication: The best-performing radar index was normalized and multiplied with relatively well-performing optical indices to create integrated optical-radar indices. Relationships between these combined indices and crop stubble biomass were then established.

(2) Multiple Linear Stepwise Regression: This method introduces variables sequentially while testing existing variables for significance, eliminating those that are not significant or cause multicollinearity. Using SPSS software, optical indices, radar backscattering coefficients, and radar indices served as independent variables, with field-measured biomass as the dependent variable, to construct estimation models.

1.3.4 Accuracy Assessment Model performance was evaluated using coefficient of determination (R^2) and root mean square error (RMSE):

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

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

where $\bar{Y}$ is the mean measured biomass, Y_i is the measured biomass of quadrat i, $\hat{Y}_i$ is the predicted biomass, and n is the number of samples.

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2 Results and Analysis

2.1 Correlation Between Optical Remote Sensing Indices and Measured Biomass

Correlation matrices were generated from 66 optical indices constructed from Sentinel-2 bands B1–B12. The correlation patterns showed consistent distributions, with indices involving the B12 band (2100–2280 nm) exhibiting the highest correlations with crop stubble biomass. Indices constructed without B12 showed low correlations ($R^2 < 0.3$), indicating that B12 is a sensitive band for crop stubble, capable of distinguishing stubble from soil based on unique absorption features.

Based on the correlation matrices, the six optical indices with highest correlations were selected: NDI(11,12), NDI(9,12), NDI(8A,12), RI(11,12), RI(12,11), and RI(9,12). Linear regression results show that RI(11,12) achieved the highest R^2 of 0.744, followed by RI(12,11) and RI(9,12) with R^2 values of 0.714 and 0.709, respectively. All models were statistically significant ($P < 0.01$).

2.2 Correlation Between Radar Indices and Measured Biomass

Correlation analysis was performed between backscattering coefficients, radar indices, and measured biomass [Figure 4: see original paper]. The VH backscattering coefficient showed the strongest correlation with crop stubble biomass ($R^2 = 0.409$), followed by the VH×VV index ($R^2 = 0.402$). The VH polarization demonstrated good potential for biomass estimation with an RMSE of 14.74 $g \cdot m^{-2}$. Other backscattering coefficients and radar indices showed weaker or non-significant correlations.

2.3 Integrated Optical-Radar Estimation Models

Optimal Index Normalized Multiplication: Six integrated models were developed by normalizing and multiplying the optimal VH backscattering coefficient with optical indices. Results show that VH×NDI(11,12), VH×NDI(9,12), and VH×NDI(8A,12) achieved R^2 values of 0.758, 0.759, and 0.751, respectively, with RMSE values around 10.4–12.6 $g \cdot m^{-2}$. While these models improved upon single-source radar models, they did not significantly outperform optical-only models.

Multiple Linear Stepwise Regression: This approach incorporated optical indices, backscattering coefficients, and radar indices as independent variables. After eliminating non-significant variables and addressing multicollinearity, the final model integrated RI(9,12), RI(11,12), and VH+VV, achieving the highest accuracy with $R^2 = 0.796$ and RMSE = 8.84 g・m^{-2}. This represents improvements of 0.052 and 0.387 over the best optical and radar single-source models, respectively, and reductions in RMSE of 0.86 g・m^{-2} and 5.90 g・m^{-2}.

2.4 Biomass Inversion in the Bashang Region

Based on these results, the multiple linear stepwise regression model was applied to estimate crop stubble biomass across the Bashang region from 2017 to 2023 [Figure 5: see original paper]. Spatial analysis reveals distinct distribution patterns and regional variations. Areas with biomass <80 g・m^{-2} were primarily concentrated in Kangbao County, while 80–120 g・m^{-2} zones were distributed across northern Shangyi County and central/southern Guyuan County. High-biomass areas (>120 g・m^{-2}) appeared sporadically, with notable concentrations in eastern Kangbao and Zhangbei counties during certain years.

The average annual biomass showed a fluctuating downward trend [Figure 6: see original paper], with values of 109.30, 115.51, 113.19, 113.98, 107.94, 114.90, and 94.67 g・m^{-2} for 2017–2023, respectively. The 2023 value represented the lowest point in the study period.

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3 Discussion

3.1 Optical Remote Sensing for Crop Stubble Biomass Retrieval

Optical remote sensing of crop stubble biomass is primarily influenced by soil moisture, texture, and organic matter, as soil and stubble share similar spectral characteristics. To suppress soil interference, this study employed band arithmetic operations to enhance spectral signals related to stubble absorption features. The correlation matrices revealed that indices incorporating the B12 band (2100–2280 nm) showed consistently high correlations with biomass. This sensitivity arises from absorption features unique to stubble components (hemicellulose, cellulose, lignin, proteins, and soluble sugars) near 2100 nm, which are absent in green vegetation and bare soil. Consequently, the RI(11,12) index achieved an R^2 of 0.744, demonstrating high potential for optical-based biomass estimation.

3.2 Radar Remote Sensing for Crop Stubble Biomass Retrieval

Radar remote sensing sensitivity to crop stubble biomass derives from its response to vertical structure. This study utilized dual-polarization backscattering coefficients and their combinations to model biomass relationships. The VH polarization showed the highest correlation ($R^2 = 0.409$) because cross-polarization is more sensitive to volume scattering from vegetation, while VV polarization responds primarily to surface scattering. Post-harvest stubble remains mostly upright (with inclination angles <15°), creating complex volume scattering that VH polarization detects effectively. While radar demonstrates potential for biomass retrieval, accuracy is limited by incidence angle, soil moisture, surface roughness, planting patterns, and stubble morphology. Additionally, Sentinel-1' s limited polarization modes (VH and VV only) constrain further optimization; the potential of HH polarization and advanced polarimetric combinations warrants investigation.

3.3 Integrated Optical-Radar Remote Sensing Approach

Optical and radar remote sensing operate through different mechanisms—optical sensors detect spectral responses while radar captures structural information through active microwave scattering. Despite these differences, the two modalities provide complementary information about crop stubble characteristics. This study' s integration approach, particularly the multiple linear stepwise regression model ($R^2 = 0.796$, RMSE = 8.84 $g \cdot m^{-2}$), significantly improved estimation accuracy compared to single-source models. This enhancement provides a novel framework for remote sensing-based crop stubble biomass estimation, with important implications for identifying and promoting conservation tillage practices and studying carbon sequestration effects in the Bashang region.

3.4 Interannual Variations and Influencing Factors

Total crop stubble biomass in the Bashang region exhibited a fluctuating downward trend from 2017 to 2023 [Figure 7: see original paper], with values of 26.28\$$\times 10^{\{4\},25.74\times 10}\{4\}, 24.91\times 10^{\{4\},25.36\times 10}\{4\}, 23.74\times 10^{\{4\},24.89\times 10}\{4\}, and 19.35\times 10$^{4}\$ t, respectively. These variations correlate with climate conditions and changes in grain crop planting area. Wheat and naked oats are sown in mid-May and harvested in late August. In 2022, despite reduced planting area (2044.29 km^2), increased precipitation (422.34 mm) and temperature (17.68°C) during the growing season enhanced crop growth and stubble biomass. Conversely, in 2023, expanded planting area (2192.03 km^2) was offset by reduced precipitation (278.17 mm) and lower temperatures (16.11°C), resulting in decreased biomass.

Long-term trends show grain crop planting area declining from 2328.49 km^2 in 2017 to 2078.48 km^2 in 2019, then fluctuating around 2100-2200 km^2 through 2023. This decline reflects implementation of the Beijing-Tianjin sandstorm source control project, which converts cropland to shrubs and grassland, and the increasing prevalence of land transfer policies that shift from smallholder farming to large-scale operations. Many wheat and naked oat fields have been converted to oil crops, medicinal herbs, and potatoes, which leave minimal post-harvest residue. Consequently, the area capable of producing crop stubble has decreased, reducing total biomass. Recent implementation of water-saving policies has gradually increased grain crop area, but biomass recovery remains limited by these structural changes.

4 Conclusions

1. **Optical Remote Sensing Performance:** Among optical indices, the RI(11,12) index derived from Sentinel-2 short-wave infrared bands (B11 and B12) showed the highest correlation with crop stubble biomass (R^2 = 0.744). For radar indices, the VH backscattering coefficient demonstrated the strongest correlation (R^2 = 0.409).

2. **Integrated Model Superiority:** The multiple linear stepwise regression model combining optical and radar data achieved the highest accuracy (R^2 = 0.796, RMSE = 8.84 $g \cdot m^{-2}$), providing reliable crop stubble biomass predictions.

3. **Accuracy Improvements:** The integrated optical-radar model improved estimation accuracy by approximately 9.72% over optical-only models and 66.74% over radar-only models.

4. **Spatiotemporal Patterns:** From 2017 to 2023, average annual crop stubble biomass in the Bashang region was 23.74$×10^{4}$ t, showing a fluctuating downward trend. While interannual variations were influenced by temperature and precipitation, recent declines were primarily driven by planting structure changes associated with land transfer policies.

References

[1] Daughtry C S T, Hunt E R, Mcmurtrey J E. Assessing crop residue cover using shortwave infrared reflectance[J]. Remote Sensing of Environment, 2004, 90(1): 126-134.
[2] Kumar K, Goh K M. Crop residues and management practices: Effects on soil quality, soil nitrogen dynamics, crop yield, and nitrogen recovery[M]. United States: Academic Press, 1999: 197-319.
[3] Fu B, Chen L, Huang H Y, et al. Impacts of crop residues on soil health: A review[J]. Environmental Pollutants and Bioavailability, 2021, 33(1): 164-173.
[4] Zhao Mingyue, Liu Yuanxin, Zhang Xueyan. A review of research advances on carbon sinks in farmland ecosystems[J]. Acta Ecologica Sinica, 2022, 42(23): 9405-9416.
[5] Chang Linxi, Liang Xinran, Wang Lei, et al. Research progress on characteristics and influencing factors of soil organic carbon sink in paddy fields in China[J]. Solis, 2023, 55(3): 487-493.
[6] Zhang Yue, Chen Siyu, Bi Hongru, et al. Characteristics and parameterization of farmland soil wind erosion in arid and semi-arid areas of China: Progress and challenges[J]. Journal of Desert Research, 2022, 42(3): 105-117.
[7] Wu Yingying, Wang Zhenting. Risk assessment of soil wind erosion in Hetao Plain[J]. Arid Land Geography, 2023, 46(3): 418-427.

[8] Guo Rui, Fu Shuai, Hou Mengjing, et al. Remote sensing retrieval of nature grassland biomass in Menyuan County, Qinghai Province experimental area based on Sentinel-2 data[J]. Acta Prataculturae Sinica, 2023, 32(4): 15-29.
[9] Verhulst N, Nelissen V, Jespers N, et al. Soil water content, maize yield and its stability as affected by tillage and crop residue management in rainfed semi-arid highlands[J]. Plant and Soil, 2011, 344(1-2): 73-85.
[10] Zhang Yifu, Li Hongwen, He Jin, et al. Effects of maize straw mulching on runoff and sediment process of slope[J]. Transactions of the Chinese Society of Agricultural Engineering, 2015, 31(7): 118-124.
[11] Zhao Xia, Wang Xiuping, Liu Tianxue, et al. Effects of wheat stubble treatment methods on soil evaporation and water use efficiency of summer maize[J]. Tillage and Cultivation, 2008(4): 9, 32.
[12] Zhang Miao, Li Qiangzi, Meng Jihua, et al. Review of crop residue fractional cover monitoring with remote sensing[J]. Spectroscopy and Spectral Analysis, 2011, 31(12): 3200-3205.
[13] Tan Jin, Wu Xiuqin, Ruan Yongjian, et al. Effects of crop residues on farmland wind erosion in Cyperus esculentus planting area[J]. Arid Land Geography, 2022, 45(2): 546-556.
[14] Feng Zhe, Liu Ruijuan, Bai Yuchen, et al. Variation characteristics of the fetch effect of near-surface aeolian sand flux for farmlands[J]. Arid Land Geography, 2022, 45(5): 1500-1512.
[15] Cui Zhong, Wan Wei, et al. Estimation of maize residue cover on the basis of SAR and optical remote sensing image[J]. National Remote Sensing Bulletin, 2021, 25(6): 1308-1323.
[16] Gao Liwei, Ma Lin, Zhang Weifeng, et al. Estimation of nutrient resource quantity of crop straw and its utilization situation in China[J]. Transactions of the Chinese Society of Agricultural Engineering, 2009, 25(7): 173-179.
[17] Xie Guanghui, Wang Xiaoyu, Ren Lantian. China' s crop residues resources evaluation[J]. Chinese Journal of Biotechnology, 2010, 26(7): 855-863.
[18] Munyati C. Detecting the distribution of grass aboveground biomass on a rangeland using Sentinel-2 MSI vegetation indices[J]. Advances in Space Research, 2022, 69(2): 1130-1145.
[19] Lei Buyun. Estimation of winter wheat residue biomass based on full polarimetric radar data[D]. Nanjing: Nanjing University, 2017.
[20] Kushwaha A, Dave R, Kumar G, et al. Assessment of rice crop biophysical parameters using Sentinel-1 C-band SAR data[J]. Advances in Space Research, 2022, 70(12): 3833-3844.
[21] Zhao Yue, Xu Dawei, Fan Kaikai, et al. Estimating aboveground biomass in grassland using Landsat 8 and machine learning in Mongolian Plateau[J]. Transactions of the Chinese Society of Agricultural Engineering, 2022, 38(24): 138-144.
[22] Lin Arong, Zhou Dongmei, Ma Jing, et al. Evaluation of wind prevention and sand fixation function in Shule River Basin based on RWEQ model[J]. Arid Land Geography, 2024, 47(1): 58-67.
[23] Clark R N, Gallagher A J, Swayze G A, et al. Material absorption band depth mapping of imaging spectrometer data using a complete band shape least

squares fit with library reference spectra[J]. Proceedings of the Second Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) Workshop, 1990, 90-54: 176-186.
[24] Elvidge C D. Visible and near infrared reflectance characteristics of dry plant materials[J]. Remote Sensing, 1990, 11(10): 1775-1795.
[25] Gaparovi M, Dobrini D. Comparative assessment of machine learning methods for urban vegetation mapping using multitemporal Sentinel-1 imagery[J]. Remote Sensing, 2020, 12(12): 1952.
[26] Vreugdenhil M, Wagner W, Bauer-Marschallinger B, et al. Sensitivity of Sentinel-1 backscatter to vegetation dynamics: An Austrian case study[J]. Remote Sensing, 2018, 10(9): 1396.

Note: Figure translations are in progress. See original paper for figures.