Remote Sensing Estimation of Winter Wheat Leaf Nitrogen Concentration Using UAV Hyperspectral Imagery: Postprint

Authors: Sun Fafu, Lai Ning, Geng Qinglong, Li Yongfu, Lü Caixia, Xin Huinan, Li Na, Shuhuang Chen

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Abstract

Leaf Nitrogen Concentration (LNC) is an important indicator reflecting crop photosynthesis, nutritional status, and growth status. To accurately and efficiently estimate leaf nitrogen concentration of winter wheat at different growth stages, this study took Xindong 22 as the study cultivar and utilized a UAV equipped with a Pika L hyperspectral camera to acquire winter wheat canopy reflectance data at four key growth stages. LNC-sensitive spectral indices were screened based on band optimization algorithm and correlation analysis, and estimation models for leaf nitrogen concentration of winter wheat at key growth stages were established using stepwise regression, multiple linear regression, and partial least squares regression, and these were compared with univariate estimation models. The results demonstrated that: the correlation between combined spectral indices screened based on band optimization algorithm and LNC was superior to that of traditional vegetation indices and reached a highly significant correlation level; in univariate LNC estimation models, models constructed using combined spectral indices exhibited higher accuracy than traditional vegetation indices, among which the estimation model established with Difference Spectral Index (DSI(R940, R968)) at the anthesis stage achieved the best performance, with R^2 of 0.789; all multivariate estimation models exhibited higher accuracy than univariate estimation models, among which the LNC estimation model constructed based on partial least squares regression performed the best, exhibiting superior fitting performance at both booting and anthesis stages, with model coefficients of determination of 0.923 for both stages and root mean square errors of 0.082 and 0.084, respectively. The results of this study can serve as a scientific basis for winter wheat LNC estimation and growth monitoring.

Full Text

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Sun Fafu[1,2,3], Lai Ning[1,2], Geng Qinglong[1,2], Li Yongfu[1,2], Lü Caixia[1,2], Xin Huinan[1,2], Li Na[1,2], Chen Shuhuang[1,2]

[1]Institute of Soil, Fertilizer and Water-saving Agriculture, Xinjiang Academy of Agricultural Sciences, Urumqi 830091, Xinjiang, China

[2]Agricultural Remote Sensing Center, Xinjiang Academy of Agricultural Sciences, Urumqi 830091, Xinjiang, China

[3]College of Resources and Environmental Sciences, Xinjiang Agricultural University, Urumqi 830052, Xinjiang, China

Abstract

Leaf nitrogen concentration (LNC) is a critical indicator that reflects crop photosynthetic capacity, nutritional status, and growth vigor. To accurately and efficiently estimate LNC in winter wheat across different growth stages, this study utilized the winter wheat variety Xindong 22 as the research subject. A UAV equipped with a Pika L hyperspectral camera was employed to acquire canopy reflectance data during four key growth stages. LNC-sensitive spectral indices were selected through band optimization algorithms and correlation analysis. Estimation models for winter wheat LNC were developed using stepwise regression, multiple linear regression, and partial least squares regression, with performance compared against single-variable models. The results demonstrated that: (1) The combined spectral indices selected via band optimization algorithms exhibited stronger correlations with LNC than traditional vegetation indices, reaching extremely significant levels; (2) Among single-variable LNC estimation models, those constructed with combined spectral indices outperformed traditional vegetation indices, with the difference spectral index at the flowering stage (DSI(R940, R968)) yielding the best model ($R^2 = 0.789$); (3) Multi-variable estimation models consistently surpassed single-variable models in accuracy, with the partial least squares regression model performing best. The booting and flowering stages showed optimal fitting performance, with model coefficients of determination of 0.923 and root mean square errors of 0.082 and 0.084, respectively. These findings provide a scientific basis for estimating winter wheat LNC and monitoring crop growth status.

Keywords: winter wheat; leaf nitrogen concentration; unmanned aerial vehicle; hyperspectral; partial least squares regression; combined spectral index

1. Materials and Methods

1.1 Study Area Overview

The experiment was conducted at the Qitai Cereal Crop Experimental Station of the Xinjiang Academy of Agricultural Sciences (43°59 6 N, 89°44 48 E), located at an altitude of 831 m. The region experiences a mid-temperate continental semi-arid climate with an average annual temperature of 5.5 °C, annual precipitation of 269.4 mm, and annual sunshine duration of 2280–3230 hours. The soil type is irrigated gray desert soil, with physicochemical properties detailed in .

1.2 Experimental Design

The winter wheat variety Xindong 22 was used as the test crop. The experiment employed a randomized block design with five nitrogen application gradients (0, 75, 150, 225, and 300 $kg \cdot hm^{-2}$), each replicated three times. Each plot measured 9 m × 11 m (99 m^2). Nitrogen fertilizer (urea) was applied entirely through drip irrigation, with distribution ratios of 20%, 25%, 25%, 20%, and 10% across the regreening, jointing, booting, flowering, and grain-filling stages, respectively. Phosphorus (P_2O_5 150 $kg \cdot hm^{-2}$) and potassium (K_2O 45 $kg \cdot hm^{-2}$) fertilizers were also applied via drip irrigation. Plot planting and management practices followed local conventional field methods.

1.3 UAV Hyperspectral Data Acquisition and Processing

A DJI M600Pro UAV equipped with a Resonon Pika L hyperspectral imager was used to acquire winter wheat canopy hyperspectral images on April 28, May 15, May 30, and June 14, 2022, corresponding to the jointing, booting, flowering, and grain-filling stages, respectively. The hyperspectral imager parameters are listed in . Prior to data collection, UAV flight paths were planned with an altitude of 100 m, a vertical downward camera angle, and a field of view of 17.6°. Target cloths were laid in the experimental area for radiometric calibration. Post-processing was performed using MegaCubeV 2 software for radiometric calibration and geometric correction, followed by seamless mosaic stitching and cropping in ArcGIS. Finally, reflectance calculation and region of interest (ROI) construction were conducted in ENVI 5.3, with mean values within each ROI serving as the plot's spectral reflectance.

1.4 Agronomic Parameter Acquisition

Immediately following UAV hyperspectral image acquisition, 30 representative wheat plants were destructively sampled from each spectral measurement area. Plants were separated into stems, leaves, and spikes, placed in paper bags, and oven-dried at 105 °C for 30 minutes, then at 75 °C to constant weight before dry weight measurement. Dried leaf samples were ground and analyzed for nitrogen concentration using the Kjeldahl method.

1.5 Spectral Index Selection

Spectral transformation and vegetation index construction effectively reduce interference from soil background, atmospheric moisture, and other environmental factors on crop canopy reflectance. Previous studies have demonstrated that combined vegetation indices exhibit stronger correlations with winter wheat LNC than traditional spectral indices. This study constructed three types of spectral indices through band optimization: (1) 12 traditional vegetation indices reported in literature as correlated with crop nitrogen content; (2) normalized difference spectral index (NDSI), difference spectral index (DSI), and ratio spectral index (RSI) from arbitrary two-band combinations across 400–1000 nm; (3) combined spectral indices. Definitions are provided in .

1.6 Model Construction and Validation

From each growth stage and treatment, 12 plots were randomly selected for model development, with the remaining 3 plots used for validation. A total of 180 spectral and LNC samples were collected across the four growth stages (144 for modeling, 36 for validation). Four regression methods were employed: simple linear regression, multiple linear regression, stepwise regression, and partial least squares regression. Model performance was evaluated using coefficient of determination (R^2) and root mean square error (RMSE), where R^2 approaching 1 indicates better stability and fit, and RMSE approaching 0 indicates smaller deviation between predicted and actual values.

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2. Results and Analysis

2.1 Correlation Analysis Between Vegetation Indices and LNC

Correlations between vegetation indices and LNC across growth stages are shown in [Figure 2: see original paper]. At the jointing stage, CIred exhibited the highest correlation ($r = 0.721$). During the booting stage, CIred also showed the strongest correlation ($r = 0.742$). At flowering, RNDRE achieved the maximum correlation ($r = 0.768$), while CIred performed best during grain-filling ($r = 0.683$). All correlations were extremely significant ($P < 0.01$), with red-edge position-based indices (RNDRE, CIred) generally outperforming others.

2.2 Correlation Analysis Between Combined Spectral Indices and LNC

Correlation isopleth maps between three types of two-band spectral indices and LNC were computed and plotted in Matlab ([Figure 3: see original paper]). Regions with correlation coefficients > 0.463 ($P < 0.01$) indicated extremely significant correlations. Optimal combined spectral indices for each growth stage are listed in . The best performing indices were NDSI(R644, R688) at jointing ($r = 0.784$), NDSI(R708, R736) at booting ($r = 0.818$), NDSI(R940, R968) at flowering (r = 0.829), and NDSI(R980, R996) at grain-filling (r = 0.796). All correlations were extremely significant.

2.3 LNC Estimation Models

2.3.1 Single Spectral Parameter Models Using spectral indices from as independent variables and LNC as the dependent variable, models were developed using linear, exponential, quadratic, and power functions. Linear functions consistently showed the lowest accuracy. Combined spectral index models outperformed traditional vegetation indices across all stages. At jointing, the exponential model based on NDSI(R644, R688) performed best (R^2 = 0.615). Booting stage optimal model was quadratic using NDSI(R708, R736) (R^2 = 0.669). Flowering stage achieved highest accuracy with the exponential model based on DSI(R940, R968) (R^2 = 0.789). Grain-filling stage optimal model was power function using NDSI(R980, R996) (R^2 = 0.634). Detailed results are presented in .

2.3.2 Multiple Spectral Parameter Models Multi-variable models generally exhibit superior accuracy and robustness compared to single-variable approaches. To address multicollinearity and overfitting risks, six vegetation indices and four optimal combined spectral indices with high overall correlation were selected as independent variables. As shown in , multi-variable models substantially outperformed single-variable models across all growth stages. Partial least squares regression yielded the optimal models, followed by multiple linear regression, with stepwise regression performing worst. Optimal model R^2 values were 0.887, 0.923, 0.923, and 0.868 for jointing, booting, flowering, and grain-filling stages, respectively.

2.3.3 Validation of Optimal LNC Estimation Models Validation was performed using the independent validation dataset, with R^2 and RMSE as evaluation metrics. Scatter plots of measured versus predicted values approaching the 1:1 line indicate good model performance. Validation results demonstrated that multi-variable models consistently outperformed single-variable models across all growth stages. The jointing stage model achieved R^2 = 0.851 with uniform scatter distribution. Booting stage showed the highest validation accuracy (R^2 = 0.904), with points tightly clustered near the 1:1 line. Flowering stage exhibited the steepest slope (0.923) and minimal RMSE (0.084), indicating strong predictive capability. Grain-filling stage validation yielded R^2 = 0.841 and RMSE = 0.091, though scatter was more dispersed. Validation scatter plots are presented in [Figure 4: see original paper].

2.4 Remote Sensing Mapping of Winter Wheat LNC

Based on validation results confirming the superior accuracy and stability of the partial least squares regression model, this approach was applied to predict LNC across all four growth stages. Predicted values were processed using pseudo-color rendering to generate spatial distribution maps of winter wheat LNC ([Figure 5: see original paper]). Spatial patterns revealed lower LNC in southeastern, northern, and central regions, with higher values in other areas, generally consistent with actual field conditions. These maps enable intuitive monitoring of wheat growth status across different zones, providing a basis for precision fertilization management.

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3. Discussion

Leaf nitrogen concentration is a primary parameter reflecting crop growth status and nitrogen nutrition, enabling quantitative assessment of nitrogen deficiency. This study investigated quantitative relationships between both traditional vegetation indices and arbitrary two-band combined spectral indices with LNC in winter wheat in northern Xinjiang. Results demonstrated that combined spectral indices significantly improved correlation strength and model accuracy compared to traditional indices, consistent with previous research. Yang et al. found that band-optimized combined spectral parameters for potato nitrogen concentration could overcome saturation issues in traditional indices while substantially improving diagnostic model accuracy. Luo et al. reported that combined spectral indices significantly enhanced estimation accuracy and stability for wheat canopy chlorophyll content. Lai et al. concluded that arbitrary two-band combined spectral indices outperformed traditional vegetation indices for estimating tobacco leaf chlorophyll content across all growth stages.

Single-variable models are prone to saturation effects, prompting this study to employ multiple linear regression, stepwise regression, and partial least squares regression for multi-variable LNC estimation. Results confirmed that multi-parameter models achieved superior accuracy and stability compared to single-parameter models across all growth stages, aligning with existing research. Among modeling methods, partial least squares regression consistently produced the optimal LNC estimation models, consistent with Ban et al. who found partial least squares regression outperformed neural network models for rice leaf phosphorus content estimation, and Zhang et al. who reported partial least squares regression as the best method for cotton leaf nitrogen content estimation.

This study validated models using data from a single location; applicability to other regions, soil types, and wheat varieties requires further investigation. Future research should expand to multi-location, multi-variety experiments to explore the effects of different spectral transformations and fitting methods on LNC estimation, ultimately developing robust models to support winter wheat growth monitoring and smart farming practices.

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4. Conclusion

1) Correlation analysis revealed that optimal combined spectral indices constructed from arbitrary two bands consistently outperformed traditional vegetation indices for LNC estimation across all growth stages from jointing to grain-filling, with correlation coefficients reaching extremely significant levels. The best combined spectral indices were NDSI(R644, R688) at jointing (r = 0.784), NDSI(R708, R736) at booting (r = 0.818), NDSI(R940, R968) at flowering (r = 0.829), and NDSI(R980, R996) at grain-filling (r = 0.796).

2) Among single-variable and multi-variable models constructed using simple linear regression, multiple linear regression, stepwise regression, and partial least squares regression, multi-variable models demonstrated substantially improved accuracy and stability across all growth stages. Partial least squares regression models performed optimally for all four key growth stages, with modeling R^2 values of 0.887, 0.923, 0.923, and 0.868, respectively. In validation, the booting stage achieved highest accuracy (R^2 = 0.904, RMSE = 0.082), followed by flowering stage (R^2 = 0.904, RMSE = 0.084). The booting and flowering stage models exhibited optimal stability and precision, enabling remote sensing inversion mapping to visually assess plot-level nitrogen status and support variable-rate fertilization decisions.

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