Monitoring Maize Canopy SPAD Values Under Drought Stress Based on UAV Multispectral Remote Sensing: Postprint

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Abstract

Precise dynamic monitoring of corn canopy relative chlorophyll content under drought stress serves an important indicative role in improving drought disaster early warning capabilities and achieving precision field irrigation for corn production in China. Using UAV multispectral imagery as the data source, multiple vegetation indices with clear physical significance and strong correlation with corn canopy relative chlorophyll content SPAD (Soil and Plant Analyzer Development) values were selected. Remote sensing monitoring models for corn canopy SPAD values were established and validated using multiple stepwise regression, Support Vector Machine (SVM), and BP Neural Network (Back Propagation Neural Network, BPNN). The optimal estimation model was employed to extract corn canopy SPAD values under varying degrees of drought stress at different growth stages, analyze the variation patterns of corn canopy SPAD values across growth stages, and investigate the impacts of different drought stress levels on corn canopy SPAD values. The results demonstrated that vegetation indices sensitive to corn canopy chlorophyll differed among growth stages, and the optimal inversion models with the best estimation capability also varied for each growth stage. Among the three modeling methods, the BPNN model achieved the best performance in both modeling and validation, indicating superior estimation capability and stability, and can be recommended as the preferred method for UAV multispectral-based corn canopy SPAD value modeling. Furthermore, drought stress reduces the estimation accuracy of remote sensing monitoring models for corn canopy SPAD values, with the most pronounced effect during the seedling stage. Mild drought exhibited no significant impact on corn canopy SPAD values, suggesting that corn possesses certain adaptability and stress resistance to drought stress. Therefore, the vegetation index-based BPNN model can provide more accurate SPAD value estimation, offering a novel approach for UAV remote sensing-based SPAD value monitoring and serving as

a reference for non-destructive monitoring of summer corn canopy SPAD values and precision field water management under drought stress.

Full Text

Preamble

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Monitoring Maize Canopy SPAD Values Under Drought Stress Based on UAV Multispectral Remote Sensing

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Abstract: Accurate and dynamic monitoring of relative chlorophyll content in maize canopy under drought stress plays a crucial role in improving drought early warning capabilities and enabling precision irrigation management in China. Using UAV multispectral imagery as the data source, this study selected multiple vegetation indices with clear physical significance and strong correlation with Soil and Plant Analyzer Development (SPAD) values. Three modeling approaches—multiple stepwise regression, Support Vector Machine (SVM), and Back Propagation Neural Network (BPNN)—were employed to construct maize canopy SPAD value estimation models. The optimal estimation model was selected to extract SPAD values under varying drought stress levels across different growth stages, analyzing SPAD value variations and investigating the impacts of different drought stress severities. Results demonstrated that chlorophyll-sensitive vegetation indices differed across growth stages, and the optimal inversion models varied accordingly. Comparative analysis revealed that the BPNN model achieved the best performance in both modeling and validation, exhibiting superior estimation capability and stability, making it the preferred method for UAV multispectral-based maize canopy SPAD modeling. Additionally, drought stress reduced the estimation accuracy of remote sensing monitoring models, with the most significant impact observed during the seedling stage. Mild drought showed no significant effect on SPAD values, indicating that maize possesses certain adaptability and stress resistance. Therefore, the BPNN model based on vegetation indices provides a novel approach for SPAD monitoring via UAV remote sensing and offers valuable references for non-destructive monitoring of summer maize canopy

SPAD values and precision water management under drought stress.

Keywords: maize; UAV; multispectral remote sensing; chlorophyll relative content

1.1 Study Area Overview

The experimental site is located at Xidatan Qianjin Farm in Pingluo County, Ningxia Hui Autonomous Region (114°24 E, 35°01 N). This region exhibits typical temperate continental arid climate characteristics, with severe drought and low precipitation. The average annual precipitation is 185 mm, while annual evaporation reaches 1755 mm—approximately 9.5 times the precipitation. The area experiences large temperature variations, with an average annual temperature of 8.8 °C and extreme maximum temperatures reaching 36 °C. Solar radiation is abundant at 4226 $kJ \cdot m^{-2}$. The soil type is white stiff soil (solonetz) with severe salinization and poor fertility. The soil texture is heavy clay with poor water permeability. The soil alkalinity degree is 19.23%, total salt content is 3.85 $g \cdot kg^{-1}$, organic carbon content is 1.54 $g \cdot cm^{-3}$, and field water capacity is 23.45%. Soil salt distribution shows obvious surface accumulation, with primary salt types being Na_2SO_4 and Na_2CO_3.

1.2 Experimental Plot Design

The geographical location, plot layout, and irrigation levels are shown in [Figure 1: see original paper]. The total experimental area is approximately 1.58 hm^2. Four irrigation levels were established, with impermeable membranes laid on both sides of each plot's ridges to prevent lateral water seepage. Each irrigation level comprised three replicate plots, with 80 cm protective rows between plots to eliminate cross-contamination. Following the "Technical Specification for Field Investigation and Classification of Maize Disasters," drought stress levels were defined. Due to scarce precipitation and high evaporation throughout the maize growth period, and considering the uniform local distribution of rainfall, precipitation interference was negligible. The CK plots received sufficient irrigation (approximately 80% of field water capacity) and served as the non-stressed control. The T1 plots were maintained at 65% of field water capacity (mild drought stress). The T2 plots were maintained at 50% of field water capacity (moderate drought stress). The T3 and T4 plots received severe and extreme drought stress treatments (35% and 20% of field water capacity, respectively). Soil moisture was monitored regularly at 0–10 cm, 10–20 cm, 20–30 cm, 30–40 cm, and 40–50 cm depths using soil augers, and irrigation amounts were calculated to maintain soil relative humidity at the designed field capacity levels. The test variety was spring maize Ningdan 58, sown on April 25 at a depth of 5 cm with row spacing of 25 cm. Except for irrigation levels, all plots received identical field management practices including fertilization and planting density.

1.3 Data Collection

Data collection was conducted on May 30, June 28, July 26, and September 13, 2021, corresponding to the seedling, jointing, tasseling, and maturity stages when maize canopy spectral changes were most pronounced. UAV multispectral data acquisition and ground measurements were synchronized to ensure data consistency.

1.3.1 UAV Multispectral Data Acquisition

This study utilized a SenseFly fixed-wing UAV platform equipped with a Parrot Sequoia multispectral camera for high-throughput phenotypic information extraction. The main parameters of the UAV and camera are listed in . Before each flight, appropriate takeoff and landing positions were selected based on field conditions, and flight paths were planned using eMotion software. Radiometric calibration was performed prior to flight to convert image brightness grayscale values to true ground reflectance. Flights were conducted around noon (12:00) under good lighting conditions with no wind or light breeze and cloudless skies. The flight altitude was set at 120 m with a speed of 6 $m \cdot s^{-1}$. Forward and side overlaps were both set at 80%, following pre-programmed flight routes.

1.3.2 Ground Measurement Data Acquisition

Ground measurements were synchronized with UAV image acquisition, with a total of 12 field measurements conducted throughout the maize growth period. A SPAD-502 handheld chlorophyll meter was used to measure SPAD values in each plot. Within each replicate plot, three uniformly growing maize plants were randomly selected. For each plant, three leaves were randomly measured for SPAD values, with three measurements recorded per leaf. The average of these nine values was recorded as the SPAD value for that sampling point, while handheld GPS recorded the coordinates. A total of 108 samples were collected per growth stage, with 70% (76 samples) randomly selected as the modeling dataset and the remaining 30% (32 samples) used as the validation dataset to evaluate model stability using different regression analysis methods.

1.4 Multispectral Image Preprocessing and Vegetation Index Selection

The acquired UAV multispectral images were preprocessed using Pix4Dmapper software following three steps: geometric correction, image mosaicking, and radiometric calibration. After initial mosaicking, geographically accurate composite images were obtained. The Pix4Dmapper agricultural multispectral standard template was applied to perform radiometric correction on the green, red, red-edge, and near-infrared bands individually, yielding reflectance images for each band.

Vegetation indices were constructed based on the spectral absorption characteristics of vegetation, which form unique spectral signatures due to chlorophyll, water, and dry matter content. These indices effectively enhance vegetation features while reducing interference from soil, atmosphere, and sensor factors. Referencing existing research and the band characteristics of the Parrot Sequoia multispectral sensor, 15 vegetation indices with clear physical significance and strong correlation with SPAD values were selected for model construction. The specific names, calculation formulas, and sources of these indices are provided in .

1.5 Maize Canopy SPAD Value Inversion Model Construction

This study employed three methods to construct maize canopy SPAD value inversion models: multiple stepwise regression, SVM, and BPNN. First, correlation relationships were established between vegetation indices and measured SPAD values. The stepwise regression model performed simple regression between SPAD values and individual vegetation indices, gradually introducing additional indices while automatically deleting non-significant variables to improve accuracy and eliminate multicollinearity, implemented using SPSS 26 software. The SVM model used kernel functions to implicitly map data into high-dimensional space, employing training set cross-validation and grid search for parameter optimization, implemented using Matlab R2020a. The BPNN model learned and stored input-output mapping relationships, continuously adjusting network weights and thresholds through backpropagation to minimize error sum of squares. In this study, vegetation indices served as the input layer and maize canopy SPAD values as the output layer, implemented using Matlab R2020a.

1.6 Model Evaluation Metrics

The coefficient of determination (R^2) and root mean square error (RMSE) were used as fundamental metrics to evaluate training and validation model performance. The formulas are:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

where n is the sample size, y is the estimated value, $\hat{y}_i$ is the mean of estimated values, and y is the measured value. R^2 evaluates regression model fit, with values closer to 1 indicating better fit and higher estimation accuracy. RMSE measures deviation between estimated and measured values to test model estimation capability, with a minimum value of 0; values closer to 0 indicate smaller estimation errors and higher precision. For modeling results, larger R^2 and smaller RMSE indicate better estimation capability; for validation results, larger R^2 and smaller RMSE indicate better model stability.

2.1 Correlation Analysis Between Maize Canopy SPAD Values and Vegetation Indices

Pearson correlation analysis was performed between measured maize canopy SPAD values and vegetation index values across all plots (). During the seedling stage, overall correlations between vegetation indices and SPAD values were relatively low, with only OSAVI, GNDVI, and GOSAVI showing significant correlation. During the jointing stage, all vegetation indices except OSAVI showed extremely significant correlation with SPAD values, with correlation coefficients above 0.50 for GNDVI and GOSAVI. During the tasseling stage, all vegetation indices showed extremely significant correlation with SPAD values, with coefficients above 0.65, and GOSAVI exceeding 0.70. During the maturity stage, all vegetation indices except REDVI reached extremely significant correlation levels, with coefficients above 0.50. Overall, OSAVI, GNDVI, and GOSAVI maintained high correlation levels with maize canopy SPAD values across all growth stages, with correlations during the tasseling stage superior to other stages. This indicates that red and near-infrared bands exhibit higher sensitivity to SPAD values compared to green bands.

2.2 Construction and Validation of Maize Canopy SPAD Value Remote Sensing Monitoring Models

Based on the correlation analysis results, sensitive vegetation indices were selected to construct SPAD value remote sensing monitoring models for different growth stages. The modeling and validation results are presented in . All models achieved modeling set R^2 values above 0.50, demonstrating the feasibility of UAV multispectral inversion for maize canopy SPAD values in arid regions. During the seedling stage, the BPNN model performed best with R^2 of 0.62. During the jointing stage, the BPNN model was slightly superior with R^2 of 0.71. During the tasseling stage, R^2 values ranked from highest to lowest as BPNN > SVM > stepwise regression, with BPNN achieving R^2 of 0.81. During the maturity stage, BPNN again performed best with R^2 of 0.75. The BPNN model's R^2 values were 0.05–0.23 higher than SVM and 0.09–0.27 higher than stepwise regression, while its RMSE values were 1.21–2.34 and 1.65–3.21 lower than SVM and stepwise regression, respectively. Validation results showed that BPNN maintained the highest R^2 and lowest RMSE across all growth stages, indicating optimal performance.

2.3 Impact of Drought Stress on Maize Canopy SPAD Value Estimation Accuracy

Using the optimal inversion models for each growth stage, remote sensing monitoring models for maize canopy SPAD values under different drought stresses were constructed and evaluated to investigate drought stress impacts on estimation accuracy. shows that under mild drought stress, SPAD estimation accuracy showed no significant differences across growth stages. As drought stress intensified, estimation accuracy decreased significantly across all growth stages, though the tasseling stage showed smaller declines and maintained better estimation accuracy under different drought stresses. Validation results for each growth stage are shown in [Figure 2: see original paper]. During the seedling stage, the BPNN validation set R^2 was highest at 0.58, with SVM and stepwise regression models showing similar performance. During the jointing stage, BPNN and SVM validation set R^2 values were close and both higher than stepwise regression. During the tasseling stage, BPNN validation set R^2 was slightly higher than SVM, with stepwise regression being the lowest. During the maturity stage, BPNN validation set R^2 was highest at 0.71, with all models showing acceptable performance. Overall, the BPNN model based on vegetation indices demonstrated the best modeling and validation results across growth stages, proving to be a reliable method for obtaining SPAD values under drought stress, with tasseling stage being optimal for monitoring.

2.4 Spatial Distribution of Maize Canopy SPAD Values Under Different Drought Stress Levels

Based on the optimal inversion models for each growth stage, vegetation indices calculated from each pixel of UAV multispectral images across growth stages were input into the models to generate pixel-level SPAD value distributions. As shown in [Figure 3: see original paper], higher drought severity within the same growth stage caused more severe impacts on chlorophyll. During the seedling and jointing stages, maize canopy SPAD values were relatively low, reaching maximum levels at maturity. The CK (no stress) and T1 (mild stress) plots showed minimal SPAD variation across growth stages. Compared to CK, the T2 (moderate stress) plots began showing substantial SPAD decreases, with T4 (extreme stress) showing the largest decline. Additionally, moderate, severe, and extreme drought stress treatments exhibited significantly more bare soil area and reduced vegetation coverage compared to no stress and mild stress treatments. Regions with low chlorophyll levels during the seedling stage remained low throughout subsequent development, indicating that drought stress directly affects the entire growth period, causing slow growth or even plant death.

2.5 Analysis of Maize Canopy SPAD Value Changes Across Growth Stages

As shown in [Figure 4: see original paper], maize canopy SPAD values exhibited a gradual increasing trend with growth stage progression, peaking at maturity (55.32). The seedling to jointing stage represented a rapid growth period, increasing from 21.97 to 38.45, indicating rapid leaf development and greening. Due to low plant height and small leaf size during the seedling stage, combined with the multispectral sensor's optimal resolution of 1.2$×10^{-2}$ m, SPAD values may be underestimated. From tasseling to maturity, canopy SPAD values continued increasing but at a significantly reduced rate with smaller variation amplitude, consistent with plant height patterns. This occurs because early growth focuses on stem and leaf development for plant elongation and leaf expansion, while post-tasseling stages emphasize rapid development of vegetative and reproductive organs.

2.6 Response of Maize Canopy SPAD Values to Different Drought Stress Levels at Various Growth Stages

Under different drought stress treatments, SPAD values generally showed decreasing trends, though no significant differences existed between mild stress and no stress treatments. Starting from moderate stress, SPAD value reduction became significant. As drought stress intensified, SPAD values across growth stages converged, particularly under severe and extreme stress where tasseling and maturity stage SPAD values were extremely similar. This indicates that severe drought stress impedes maize growth progression, resulting in non-significant chlorophyll level changes. Standard errors of SPAD values increased significantly with drought stress severity, demonstrating that drought stress causes growth inhibition or cessation, leading to varying growth rates under the same stress level and consequently different canopy chlorophyll levels.

3.1 Relationship Between Vegetation Indices and SPAD Values

Effective spectral band selection is fundamental to spectral index modeling. With diverse band combination approaches, crop phenotypic information remote sensing models based on multi-band vegetation indices achieve higher accuracy than single-band models while eliminating atmospheric and soil background interference. UAV remote sensing has been widely applied in crop phenotypic information extraction. This study screened vegetation indices showing good correlation with maize canopy SPAD values across different growth stages under drought stress. Results indicated that red and near-infrared bands exhibited higher SPAD sensitivity than green bands, consistent with Zhou et al.'s findings on wheat canopy SPAD estimation. Vegetation indices constructed from near-infrared and red-edge bands effectively inverted SPAD values, aligning with Mao et al.'s conclusions from UAV multispectral maize phenotyping studies. The inherent significant differences between red and near-infrared bands form the theoretical basis for vegetation indices, as these bands correlate with plant pigments and are sensitive to leaf structure. Tasseling stage showed superior SPAD-vegetation index correlations compared to other stages, similar to Feng's findings, because SPAD values peaked and remained relatively stable with concentrated value distribution during this period, demonstrating favorable statistical properties.

3.2 Impact of Drought Stress on Maize Canopy SPAD Values at Key Growth Stages

Chlorophyll is the primary substance for light absorption and conversion in photosynthesis, playing a vital role in obtaining light energy and producing reducing power. Its content directly determines photosynthetic capacity, material accumulation capability, and serves as an important indicator for evaluating plant drought tolerance. This study found that mild drought did not significantly affect SPAD values, while moderate stress and above significantly impacted SPAD, consistent with Yuan et al.'s research on SPAD variation under different irrigation levels. The mechanism involves drought stress accelerating plant cell senescence, causing abnormal metabolism and gene expression that hinder chlorophyll synthesis and decomposition. Severe drought causes leaf yellowing and wilting. Drought stress impacts differed across growth stages, with seedling and jointing stages being more vulnerable due to initial vegetative growth requiring substantial water and having weaker stress resistance. During tasseling, maize exhibited stronger antioxidant and osmotic regulation capabilities, mitigating drought damage to chloroplast ultrastructure. Consequently, SPAD decline slowed under equivalent drought stress during later growth stages, consistent with U Rina et al.'s findings.

3.3 Inversion Model Accuracy for Maize Canopy SPAD Values at Key Growth Stages Based on Vegetation Indices

Establishing SPAD inversion models based on spectral indices is an effective method for obtaining field SPAD values. UAV multispectral monitoring enables rapid and accurate assessment of field crop growth status. Current research on SPAD estimation from multispectral imagery primarily focuses on single key growth stages and relies on single models, with limitations due to crop type, region, and stress type differences. Stepwise regression models are susceptible to crop type, growth stage, and climate conditions, limiting universal application. SVM efficiency is greatly affected by sample size, prone to local optima, and time-consuming. Therefore, combining temporal analysis with multi-model comprehensive estimation is necessary to obtain optimal inversion models throughout the growth period. This study compared three modeling methods, with BPNN demonstrating superior estimation accuracy and stability, consistent with Peng et al.'s conclusions. Since optimal inversion models differed across growth stages, this study analyzed SPAD estimation accuracy under various drought stresses, revealing that vegetation index-based BPNN models generally performed well, making BPNN a reliable method for drought-stressed maize canopy SPAD retrieval, with tasseling stage being optimal for monitoring.

4 Conclusions

Through irrigation experiments simulating drought stress levels in summer maize, this study monitored SPAD value changes under different drought stresses using UAV multispectral remote sensing. Multiple stepwise regression, SVM, and BPNN methods were employed to construct quantitative SPAD models, which were validated and compared to select the optimal modeling approach. The main conclusions are:

1) Chlorophyll-sensitive vegetation indices differed across maize growth stages. OSAVI, GNDVI, and GOSAVI maintained high correlations with SPAD values throughout all growth stages, with tasseling stage showing superior correlations compared to other stages.

2) Optimal inversion models varied across growth stages. Among the three modeling methods, BPNN demonstrated the best estimation accuracy and stability, making it the preferred method for UAV multispectral-based maize canopy SPAD modeling.

3) Drought stress reduced the estimation accuracy of maize canopy SPAD remote sensing monitoring models, with the most significant impact on the seedling stage and minimal impact on the tasseling stage. Mild drought did not significantly affect SPAD values, demonstrating maize's adaptability and stress resistance. Moderate drought stress and above significantly impacted SPAD values.

4) As growth stages progressed, the impact of equivalent drought stress levels on SPAD values decreased. This study provides a new approach for SPAD monitoring based on UAV remote sensing and offers references for non-destructive monitoring of summer maize canopy SPAD values and precision field water management under drought stress.

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