Hyperspectral Data-Based Assessment of Maize Leaf Area Index and Biomass (Postprint)

Authors: Shu Meiyan, Chen Xiangyang, Wang Xiqing, Ma Yuntao

Date: 2023-02-17T00:00:00+00:00

Abstract

Utilizing hyperspectral technology to acquire corn agronomic parameter information contributes to enhancing precision management in corn production. Based on a field experiment with three planting densities and five corn materials, this study obtained ground-based ASD hyperspectral data and UAV hyperspectral imagery at the large trumpet stage of corn, analyzed the Leaf Area Index (LAI) and above-ground biomass per plant for different genetic materials under various planting densities, constructed hyperspectral estimation models for LAI and above-ground biomass per plant based on full bands, sensitive bands, and vegetation indices, and comparatively analyzed the monitoring capabilities of the two types of hyperspectral data for corn phenotypic trait parameters. The results indicated that the canopy spectral reflectance of wild-type corn material in the near-infrared band increased with increasing planting density; the spectral reflectance of wild-type corn material under the same planting density was the lowest in both visible and near-infrared bands. At the spectral peak of 550 nm in the visible band, the spectral reflectance of the four transgenic materials was 4.52%–19.9% higher than that of the wild-type corn material, and at the spectral peak of 870 nm in the near-infrared band, the spectral reflectance of the four transgenic materials was 23.64%–57.05% higher than that of the wild-type corn material. The model constructed based on 21 hyperspectral vegetation indices achieved the best estimation performance for LAI, with a coefficient of determination (R^2) of 0.70, Root Mean Square Error (RMSE) of 0.92, and relative Root Mean Square Error (rRMSE) of 15.94% for the test set. Sensitive band reflectance (839–893 nm and 1336–1348 nm) yielded the best estimation performance for above-ground biomass per plant in corn, with R^2 of 0.71, RMSE of 12.31 g, and rRMSE of 15.89% for the test set. In summary, ground-based non-imaging hyperspectral and UAV imaging hyperspectral data demonstrate good consistency in estimating corn LAI and biomass, enabling rapid and effective extraction of agronomic parameter information at the field scale. This study can provide a reference for the application of hyperspectral technology in

precision agricultural management at the plot scale.

Full Text

Estimation of Maize Leaf Area Index and Aboveground Biomass Based on Hyperspectral Data

Shu Meiyan, Chen Xiangyang, Wang Xiqing, Ma Yuntao
Smart Agriculture, 2021, 3(1): 29-39

Abstract

Monitoring leaf area index (LAI) and aboveground biomass is critical for assessing maize growth status and predicting yield. This study investigated the use of ground-based and unmanned aerial vehicle (UAV) hyperspectral data combined with partial least squares (PLS) regression to estimate maize LAI and biomass. Field experiments were conducted using five maize materials (wild type and four transgenic lines of biotechnology material 807) under three planting densities (60,000, 90,000, and 120,000 plants/ha). Canopy hyperspectral reflectance was measured using an ASD FieldSpec spectrometer (350–2500 nm) and a Resonon Pika-L imaging sensor (400–1000 nm). Eighteen vegetation indices were calculated, and sensitive bands were identified through 100 repeated modeling iterations. PLS models were developed using full spectra, selected sensitive bands, and vegetation indices. The sensitive-band model achieved the best performance for LAI estimation (R^2 = 0.70, RMSE = 0.92, rRMSE = 15.94%) and aboveground biomass estimation (R^2 = 0.71, RMSE = 12.31 g, rRMSE = 15.89%). Results demonstrate that hyperspectral data combined with PLS regression provides a reliable non-destructive method for monitoring maize LAI and biomass, with band selection improving model efficiency and accuracy.

Keywords: hyperspectral remote sensing; leaf area index; aboveground biomass; partial least squares regression; maize

1. Introduction

Leaf area index (LAI) and aboveground biomass are fundamental parameters for monitoring crop growth, predicting yield, and managing agricultural practices. Traditional destructive sampling methods are labor-intensive and time-consuming, limiting their application for large-scale monitoring. Remote sensing technology, particularly hyperspectral imaging, offers a non-destructive alternative by capturing detailed spectral information related to crop physiological and biochemical status.

Previous studies have established relationships between vegetation indices derived from multispectral and hyperspectral data and crop biophysical parameters. However, the full potential of hyperspectral data lies in utilizing complete spectral information rather than pre-defined indices. Partial least squares (PLS) regression has proven effective for handling high-dimensional collinear spectral data, offering advantages over traditional stepwise regression. Machine learning and deep learning approaches have also been applied, though they require large datasets and computational resources. This study aims to develop robust PLS models for estimating maize LAI and biomass while identifying optimal spectral bands to improve model parsimony and interpretability.

---

2. Materials and Methods

2.1 Study Area and Experimental Design The field experiment was conducted at a research station located at 124°82 E, 43°50 N. The region has a mean temperature of 5.6°C, annual precipitation of 594 mm, and a growing season of approximately 150 days. The experimental design included five maize materials: wild type (control) and four transgenic lines (OE1–OE4) derived from biotechnology material 807. Three planting densities were implemented: 60,000, 90,000, and 120,000 plants/ha. The field plot distribution is shown in [Figure 1: see original paper].

2.2 Data Collection Hyperspectral Reflectance Measurements
Canopy spectral reflectance was acquired using two instruments: (1) an ASD FieldSpec 4 spectroradiometer (Analytical Spectral Devices, Inc.) covering 350-2500 nm with 1 nm spectral resolution, and (2) a Resonon Pika-L hyperspectral imager mounted on a DJI S1000 UAV, covering 400–1000 nm with 2.1 nm resolution. Ground-based measurements were collected between 12:00-13:00 at 1 m above the canopy. UAV flights were conducted at 100 m altitude with 3 cm spatial resolution. Spectral data were preprocessed using ENVI 5.3 software, with noisy bands removed (1350–1500 nm, 1800–2000 nm, and 2400–2500 nm).

LAI Measurement
LAI was measured non-destructively using a Yaxin-1242 plant canopy analyzer at 30-minute intervals across sampling periods.

Aboveground Biomass Measurement
Destructive sampling was performed by harvesting three representative plants per plot. Fresh samples were dried at 80°C and 120°C to constant weight for dry biomass determination.

2.3 Vegetation Indices Eighteen hyperspectral vegetation indices were calculated based on key wavelengths sensitive to chlorophyll content, leaf structure, and biomass (Table 1). These included normalized difference vegetation indices (NDVI variants), green NDVI (GNDVI), modified chlorophyll absorption ratio index (MCARI), modified normalized difference index (MND705), modified simple ratio (MSR705), and MERIS terrestrial chlorophyll index (MTCI).

2.4 Partial Least Squares Modeling PLS regression models were developed using the *pls* package in R. The dataset was randomly split into training (70%) and test (30%) sets, with 100 iterations to ensure robustness. Three modeling approaches were compared:

1. **Full-spectrum model**: Using all available bands (350-2500 nm)
2. **Sensitive-band model**: Using bands selected through iterative modeling
3. **Vegetation index model**: Using the 18 calculated indices

Sensitive bands were identified by counting selection frequency across 100 model runs; bands selected $ $50 times were considered core bands (threshold indicated by dashed lines in figures).

Model performance was evaluated using coefficient of determination (R^2), root mean square error (RMSE), and relative RMSE (rRMSE).

---

3. Results

3.1 Descriptive Statistics Basal statistical results for LAI and aboveground biomass across all treatments are presented in Table 2. LAI values ranged from 1.2 to 5.8, with mean biomass of 77.45 g/plant. Significant variation was observed across planting densities and genotypes.

3.2 Effects of Planting Density and Genotype Both LAI and per-plant biomass were significantly affected by planting density and genotype ($P < 0.05$) [Figure 2: see original paper]. LAI increased with planting density, with the highest values observed at 120,000 plants/ha. Transgenic lines OE1 and OE2 showed significantly higher LAI than wild type at this density. Aboveground biomass per plant decreased with increasing density due to competition, though total plot biomass increased.

3.3 Spectral Response Characteristics Spectral curves varied significantly among planting densities [Figure 3: see original paper] and genotypes [Figure 4: see original paper]. The wild type exhibited typical vegetation spectral signatures with clear red-edge inflection. At higher planting densities, NIR reflectance (750-1000 nm) increased while visible reflectance decreased due to greater canopy closure. Transgenic lines showed subtle spectral differences in the red-edge region (700-750 nm) compared to wild type.

3.4 Sensitive Band Selection Iterative PLS modeling identified optimal spectral bands for LAI and biomass estimation. For LAI, core sensitive bands clustered in two regions: 839-893 nm and 1336-1348 nm [Figure 5: see original paper]. For aboveground biomass, sensitive bands were distributed across 550 nm, 516-525 nm, and 569-609 nm regions [Figure 7: see original paper]. These bands correspond to key physiological features including leaf structure, water content, and pigment absorption.

3.5 Model Performance LAI Estimation

The full-spectrum PLS model achieved $R^2 = 0.65$, RMSE = 0.98, and rRMSE = 17.00% . The sensitive-band model improved accuracy to $R^2 = 0.70$, RMSE = 0.92, and rRMSE = 15.94%. The vegetation index model performed similarly to full-spectrum ($R^2 = 0.64$, rRMSE = 18.12%). Measured vs. predicted values are shown in [Figure 6: see original paper].

Aboveground Biomass Estimation

Biomass models showed comparable patterns . The sensitive-band model outperformed others with $R^2 = 0.71$, RMSE = 12.31 g, and rRMSE = 15.89%, compared to full-spectrum ($R^2 = 0.56$, rRMSE = 18.92%) and vegetation index models ($R^2 = 0.51$, rRMSE = 17.54%). Predicted vs. measured biomass is plotted in [Figure 8: see original paper].

---

4. Discussion

The study demonstrates that hyperspectral data combined with PLS regression can effectively estimate maize LAI and aboveground biomass with acceptable accuracy. The sensitive-band selection approach improved model performance while reducing dimensionality by >90%, enhancing computational efficiency and model interpretability. The identified sensitive bands align with known physiological features: the 839–893 nm region captures leaf structure and biomass effects, while 1336–1348 nm relates to water absorption.

Planting density significantly affected both parameters and spectral signatures, confirming the importance of accounting for management practices in model development. The transgenic lines exhibited spectral differences, suggesting potential for genotype-specific model calibration.

Compared to vegetation indices alone, full-spectrum and sensitive-band approaches captured more information, resulting in higher accuracy. This supports the advantage of hyperspectral data over multispectral systems for precision agriculture applications.

---

5. Conclusion

This study developed reliable PLS regression models for estimating maize LAI and aboveground biomass using ground-based and UAV hyperspectral data. The band selection strategy effectively identified core wavelengths, improving model efficiency without sacrificing accuracy. These results support the operational use of hyperspectral remote sensing for non-destructive crop monitoring in precision agriculture systems. Future work should validate these models across broader environmental conditions and growth stages.

References

[1] Meng, et al. *Remote Sensing for Agriculture*, 2019, 39(11): 3553-3559.

Table 1
Hyperspectral vegetation indices used in the research

Index	Formula	Description
GNDVI	$(R_{750} - R_{550})/(R_{750} + R_{550})$	Green Normalized Difference Vegetation Index
MCARI	$[(R_{700} - R_{670}) - 0.2\times(R_{700} - R_{550})] \times (R_{700}/R_{670})$	Modified Chlorophyll Absorption Reflectance Index
MND705	$(R_{750} - R_{705})/(R_{750} + R_{705})$	Modified Normalized Difference Index
MSR705	$(R_{750}/R_{705} - 1)/\sqrt{(}R_{750}/R_{705} + 1)$	Modified Simple Ratio
NDVI	(R - R)/(R + R)	Normalized Difference Vegetation Index (multiple variants)
MTCI	$(R_{750} - R_{705})/(R_{705} - R_{680})$	MERIS Terrestrial Chlorophyll Index
DDI	$(R_{750} - R_{705}) - (R_{680} - R_{550})$	Double Difference Index

Table 2
Basal statistical results of LAI and aboveground biomass

Parameter	Mean	Std. Dev.	Range
LAI	3.5	1.2	1.2–5.8
Biomass (g/plant)	77.45	15.6	45.2–120.3

Table 3
Test set results of PLS model for estimating LAI based on different parameters

<table>
<tr><th>Model Input</th><th>R^2±Std</th><th>RMSE±Std</th><th>rRMSE±Std (%)</th></tr>
<tr><td>Full spectrum (350-2500 nm)</td><td colspan="3">0.65$±0.04|0.98±0.11|17.00±1.94||*Sensitivebands*|0.70±0.02|0.92±0.13|15.94±2.27||*Ve*</td></tr>
</table>

Table 4
Test set results of PLS model for estimating aboveground biomass based on different parameters

<table>
<tr><th>Model Input</th><th>R^2±Std</th><th>RMSE±Std (g)</th><th>rRMSE±Std (%)</th></tr>
<tr><td>Full spectrum (350-2500 nm)</td><td colspan="3">0.56$±0.04|14.66±5.32|18.92±6.87||Sensitivebands|0.71±0.02|12.31±3.98|15.89±5.14||V</td></tr>
</table>

Figure Captions

[Figure 1: see original paper] Image of field plots distribution showing the arrangement of five maize materials under three planting densities.

[Figure 2: see original paper] Effects of planting density and line on LAI and aboveground biomass. Different lowercase letters indicate significant differences ($P < 0.05$) among materials at the same density during the large trumpet stage.

[Figure 3: see original paper] Spectral curves of wild type material under three planting densities (60,000, 90,000, and 120,000 plants/ha).

[Figure 4: see original paper] Spectral curves of five materials at the density of 120,000 plants/ha.

[Figure 5: see original paper] Screening results of sensitive bands for leaf area index. The dashed line represents the threshold where bands were selected as core variables in $ $50 of 100 modeling runs.

[Figure 6: see original paper] Results of measured and predicted LAI from the PLS model using sensitive bands (R^2 = 0.70, RMSE = 0.92).

[Figure 7: see original paper] Screening results of sensitive bands for aboveground biomass. The dashed line represents the threshold where bands were selected as core variables in $ $50 of 100 modeling runs.

[Figure 8: see original paper] Results of measured and predicted aboveground biomass from the PLS model using sensitive bands (R^2 = 0.71, RMSE = 12.31 g).

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

Source: ChinaXiv —Machine translation. Verify with original.