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RESEARCH PAPER

Unique contributions of chlorophyll and nitrogen to predict crop photosynthetic capacity from leaf spectroscopy

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Abstract

The photosynthetic capacity or the CO_2-saturated photosynthetic rate (V_{max}), chlorophyll, and nitrogen are closely linked leaf traits that determine C_4 crop photosynthesis and yield. Accurate, timely, rapid, and non-destructive approaches to predict leaf photosynthetic traits from hyperspectral reflectance are urgently needed for high-throughput crop monitoring to ensure food and bioenergy security. Therefore, this study thoroughly evaluated the state-of-the-art physically based radiative transfer models (RTMs), data-driven partial least squares regression (PLSR), and generalized PLSR (gPLSR) models to estimate leaf traits from leaf-clip hyperspectral reflectance, which was collected from maize (*Zea mays* L.) bioenergy plots with diverse genotypes, growth stages, treatments with nitrogen fertilizers, and ozone stresses in three growing seasons. The results show that leaf RTMs considering bidirectional effects can give accurate estimates of chlorophyll content (Pearson correlation r=0.95), while gPLSR enabled retrieval of leaf nitrogen concentration (r=0.85). Using PLSR with field measurements for training, the cross-validation indicates that V_{max} can be well predicted from spectra (r=0.81). The integration of chlorophyll content (strongly related to visible spectra) and nitrogen concentration (linked to shortwave infrared signals) can provide better predictions of V_{max} (r=0.71) than only using either chlorophyll or nitrogen individually. This study highlights that leaf chlorophyll content and nitrogen concentration have key and unique contributions to V_{max} prediction.

Keywords: Bioenergy crop, chlorophyll, CO_2-saturated photosynthetic rate, hyperspectral leaf reflectance, maize, nitrogen, partial least squares regression, radiative transfer model.

Introduction

Photosynthesis captures and converts solar radiation into chemical energy to drive CO_2 fixation into carbohydrates that ultimately power ecosystems and feed humanity (Ainsworth, 2018). The conservation of photosynthetic proteins and enzymes has aided the mathematical modeling of photosynthetic processes (Farquhar *et al.*, 1980; von Caemmerer and Furbank, 1999). In C_4 photosynthesis models, carbon assimilation is limited by phosphoenolpyruvate (PEP) carboxylation in mesophyll and Rubisco carboxylation of bundle sheath cells (von Caemmerer, 2000; Sage and Kubien, 2007). With the ability to concentrate CO_2 around Rubisco, the photosynthesis of C_4 crops (e.g. *Zea mays*, *Miscanthus sinensis*, and *Panicum virgatum*) under current atmospheric conditions is often limited by the CO_2-saturated photosynthesis rate V_{max}, which corresponds to the maximal Rubisco carboxylation rate (Leakey *et al.*, 2019). However, due to limited *in situ* measurements and knowledge of V_{max}, most crop and terrestrial ecosystem models ignore such variability and specify a fixed value of V_{max} for each plant functional type (Kattge *et al.*, 2009). Inaccurate temporal and spatial representation of V_{max} can cause significant uncertainties in photosynthesis models and crop yield predictions (Hu *et al.*, 2014). Thus, accurate, timely, rapid, non-destructive, and cost-effective approaches to estimate V_{max} are greatly needed for yield forecasting, bioenergy production, and agricultural management.

V_{max} is sensitive to leaf nitrogen, temperature, ozone, and pathogens, and shows spatial, temporal, and developmental variability (Bernacchi *et al.*, 2001; Ainsworth *et al.*, 2014; Kucharik *et al.*, 2016). Leaf nitrogen is often cited as the primary mechanism controlling V_{max}, as multiple studies have shown that V_{max} standardized to a certain temperature shows a strong relationship with leaf total nitrogen content or concentration (Walker *et al.*, 2014; Dechant *et al.*, 2017; Yendrek *et al.*, 2017). Other studies, however, reveal that the V_{max} and nitrogen relationships are complicated. For instance, plants in soils with low nitrogen availability can achieve high V_{max} per leaf nitrogen (Ainsworth and Rogers, 2007). Miner and Bauerle (2019) found that nitrogen content and the Rubisco carboxylation rate were not correlated for sunflower. The Rubisco activity of soybean did not significantly correlate to leaf nitrogen due to the excessive nitrogen storage in leaves (Koester *et al.*, 2016). For tree species aspen, maple, and ash, Croft *et al.* (2017) found that Rubisco carboxylation rates were more sensitive to chlorophyll (Chl) than leaf nitrogen content. The high correlation between Chl and V_{max} could be explained by the nitrogen resource optimality allocation (Dewar, 1996; Evans and Clarke, 2019; Smith *et al.*, 2019). As light and dark reactions should be well coordinated to maximize leaf photosynthesis, nitrogen investment in light-harvesting Chl and Rubisco should be optimized. Although these studies imply strong connections among nitrogen, Chl, and V_{max}, it is still debated whether the use of Chl (Houborg *et al.*, 2015; Croft *et al.*, 2017), nitrogen content/concentration (Yendrek *et al.*, 2017; Dechant *et al.*, 2017), or their derivatives [e.g. Chl×carotenoids (Car) Chou *et al.*, 2020)] as the proxy for V_{max}.

Traditional methods to estimate leaf V_{max} by A/C_i (net photosynthesis/intercellular CO_2 concentration) curves from leaf gas exchange experiments (von Caemmerer, 2013) provide accurate measurements, but are time-consuming and not suitable for high-throughput crop monitoring in the context of field phenotyping and precision agriculture. Sensing techniques such as optical reflectance, solar-induced fluorescence, or thermal infrared data are rapid, non-destructive, and cost-effective ways to quantify crop traits (Houborg *et al.*, 2013; Serbin *et al.*, 2015; Guan *et al.*, 2017). In particular, spectroscopy can exploit spectral information of the entire optical range (400–2500 nm) through either physically based radiative transfer models (RTMs; e.g. Jacquemoud and Baret, 1990; Vilfan *et al.*, 2019) or data-driven methods (Serbin *et al.*, 2012; e.g. Ainsworth *et al.*, 2014; Yendrek *et al.*, 2017) to estimate traits. These estimates include photosynthetic traits (Chl, nitrogen, and V_{max}), structural parameters, chemical composition, and photo-protective pigments (Townsend *et al.*, 2003; Weber *et al.*, 2012; Singh *et al.*, 2015). The information of diverse traits from spectroscopy provides opportunities to interpret the linkage of leaf traits and V_{max} to evaluate using Chl, nitrogen, or other traits as the proxy of V_{max}.

The RTM approaches, for instance the pre-calibrated generalized plate-based turbid medium PROSPECT (Jacquemoud and Baret, 1990) or PROSPECT-DyN (Z. Wang *et al.*, 2015, 2018) models, have merits to operationally predict foliar traits such as Chl, nitrogen, and water content across species, growth stages, and environmental conditions. However, the accuracy and number of predictable traits from RTMs are limited (Verrelst *et al.*, 2019). For instance, due to the weak absorption features of Rubisco protein, existing RTMs do not include the spectral absorption coefficients of Rubisco protein to directly predict V_{max}. The prediction of V_{max} through RTMs often relies on statistical regression with RTM-based traits (Houborg *et al.*, 2013; Croft *et al.*, 2017; Dechant *et al.*, 2017) or detecting photosynthetic functioning (Zheng and Chen, 2017; Bayat *et al.*, 2018; Vilfan *et al.*, 2019). Additionally, leaf RTMs are developed with hemispherical reflectance measured with integrating spheres. These reflectance measurements are different from conical reflectance (Schaepman-Strub *et al.*, 2006) collected by the leaf-clip, which is the high-throughput approach for spectra collection in the field. To solve the above issues, the close-range spectral imaging of leaves model (COSINE; Jay *et al.*, 2016), which accounts for bi-directional reflectance factors, needs to be combined with PROSPECT to simulate leaf conical reflectance. Conversely, data-driven approaches, such as partial least squares regression (PLSR), can flexibly fit leaf spectra with diverse measured traits with high predictive performance. For instance, a few studies have

demonstrated that V_{max} can be accurately estimated from leaf spectra (Serbin *et al.*, 2012; Yendrek *et al.*, 2017; Wu *et al.*, 2019). However, the performance of PLSR models can vary significantly depending on species, plant growth stages, and sensor configurations (Wang *et al.*, 2019). In addition, PLSR requires sufficient samples of measured traits for model training, which is less operational compared with RTMs. The pre-trained generalized PLSR (gPLSR) models, which were developed from a large database of *in situ* observations, can be promising for applications lacking measured trait data for modeling training (Wang *et al.*, 2020). The traits Chl, nitrogen, and V_{max} can be retrieved from leaf spectra through RTMs, PLSR, or gPLSR, but it remains uncertain for the performance comparison of these approaches. A comprehensive evaluation of these approaches to quantify Chl, nitrogen, and V_{max} for high-throughput crop monitoring is greatly needed.

Maize (*Zea mays* L.), one of the major nitrogen-deficient staple and bioenergy crops, represents a model for species with the C_4 photosynthesis pathway. Due to environmental factors or management strategies (e.g. shortage of nitrogen fertilizers), maize V_{max} is often suppressed and the average yield reaches only 64% of maximum potential globally (Neumann *et al.*, 2010). In this study, we collected leaf gas exchange measurements, leaf-level hyperspectral reflectance, nitrogen, and Chl data from maize experimental plots with various genotypes, growth stages, treatments with nitrogen fertilizers, and ozone stress during three growing seasons. The objective was to develop and evaluate spectroscopy approaches for estimating photosynthetic traits from leaf-clip spectra and to understand the relationship among Chl, nitrogen, and V_{max}. Two key questions were addressed. (i) Among RTMs, PLSR, and gPLSR approaches, which method performs best to estimate Chl and nitrogen from the leaf-clip reflectance? (ii) Can we utilize leaf spectra or spectra-based traits to accurately estimate V_{max}? If so, what are the key spectra or traits for V_{max} prediction? By answering these questions, this study aimed to identify the operational approaches to predict photosynthetic traits using leaf hyperspectral reflectance and understand the linkage among Chl, nitrogen, and V_{max} prediction.

Materials and methods

Leaf spectra and photosynthetic trait measurements

The maize experimental plots of diverse genotypes were treated with nitrogen fertilizers (maize nitrogen plots; see Supplementary Fig. S1 at *JXB* online) and ozone (SoyFACE; Supplementary Fig. S1) in Champaign, Illinois, and measured during the growing seasons of 2014, 2015, and 2019. The ozone experiment was previously described by Yendrek *et al.* (2017), along with hyperspectral reflectance, gas exchange, and biochemical data from the ozone experiments. The nitrogen experiment was designed with management practices of different nitrogen fertilization amounts (0, 50, 100, 150, 200, and 250 pounds per acre), time (planting, V6, and V10 stages), and approaches (middle-row injection and in-row dribble). The ozone and nitrogen fertilization experiments provided test cases to evaluate the approaches to retrieve photosynthetic traits from leaf-clip spectra, and further to identify the relationship among leaf V_{max}, nitrogen, and Chl.

Leaf reflectance spectra (500–2400 nm) were acquired from the central section of the leaf adaxial surface using ASD FieldSpec 4 Standard Res full-range spectroradiometers (Analytical Spectral Devices Inc., CO, USA) equipped with an illuminated leaf-clip contact probe. A/C_i curves were measured with LI-COR 6400 and 6800 portable photosynthesis systems (LI-COR Inc., Lincoln, NE, USA) after measurements of leaf-clip reflectance. The A/C_i measurements were conducted with the leaf positioned in the chamber with air humidity of 55% and leaf temperature close to ambient conditions (25–32 °C). The leaf adaxial side was placed facing the light source with an intensity of 2000 μmol m^{-2} s^{-1}. For each A/C_i curve, the ambient CO_2 concentrations were set to the sequences of 400, 50, 100, 150, 250, 350, 500, 700, 900, and 1200 ppm. To ensure the accuracy of measured V_{max} from gas exchange measurements, we have tested the reproducibility of LiCOR machines in our experiments. This study followed the protocol of Yendrek *et al.* (2017) to use the horizontal asymptote of a four parameter non-rectangular hyperbolic function to process the measured A/C_i curves to estimate V_{max}. Furthermore, we collected V_{max} measurements of the same leaves with different leaf temperatures to quantify the V_{max} temperature response curve using the Q10 formula and temperature inhibition curves (Leuning, 2002). By using the fitted temperature response curve of maize, V_{max} measurements of this study were standardized to the reference temperature; 25 °C is a commonly used reference temperature to normalize the temperature impacts on V_{max}. However, this study selected 27 °C as the reference temperature due to the following reason: 60% of the field V_{max} measurements were collected at 27 °C, and using $V_{max,27}$ could reduce uncertainties of temperature normalization. Furthermore, as 27 °C is close to ambient temperature in the peak growing season of our study site, using $V_{max,27}$ agrees with our desire to estimate biochemical limitations to photosynthesis close to growth temperature. Additionally, with the measured temperature correction curve of Supplementary Fig. S3, all $V_{max,27}$ relationships of this study can be converted to $V_{max,25}$ ($V_{max,25}$=0.875$V_{max,27}$).

After A/C_i measurements, leaf tissues were sampled using a cork borer and stored in liquid nitrogen. The wet laboratory experiments were conducted to measure Chl content and nitrogen concentration of leaf samples. For Chl, one leaf disc (~1.4 cm^2) was incubated in 96% (v/v) ethanol to determine Chl content using the equations of Lichtenthaler and Wellburn (1983). Three leaf discs were dried in an oven (60 °C) for 3 weeks to determine leaf dry mass. An analytical balance (ME204TE/00, Mettler Toledo Inc., OH, USA) was used to measure the dry matter weight per area (Cdm, g cm^{-2}) of leaf samples. The dried leaf tissues were ground to a fine powder and combusted with oxygen in an elemental analyzer (Costech 4010, Costech Analytical Technologies Inc., CA, USA). The nitrogen per mass (N_{mass}, %) was determined by comparing experimental samples with an acetanilide standard curve. In total, we collected 460 leaf spectra, 297 leaf V_{max} measurements, 177 leaf Chl measurements, and 350 leaf N_{mass} and Cdm measurements. Raw data and experiment sources of these measurements can be found in Supplementary Dataset S1. A correlation matrix among the measured photosynthetic traits of $V_{max,27}$, Chl, N_{mass}, and nitrogen per area (N_{area}, N_{mass}×Cdm, mg cm^{-2}) was calculated to characterize their relationships.

Models to predict traits from leaf spectra

Radiative transfer modeling

The PROSPECT models (Jacquemoud and Baret, 1990) were employed in this study to simulate leaf hemispherical reflectance over the optical domain from 400 nm to 2500 nm to retrieve the photosynthetic traits Chl and nitrogen. PROSPECT-D can utilize leaf reflectance to estimate multiple traits, such as a leaf structure parameter (N), leaf Chl content (Chl, μg cm^{-2}), equivalent water thickness (Cw, cm), leaf mass per area (Cdm, g cm^{-2}), and the senescent (brown) materials (Féret *et al.*, 2017).

Table 1. Model parameters and their typical ranges for PROSPECT-D, PROSPECT-DyN, and COSINE leaf radiative transfer models.

Model	Parameter	Description and unit	Typical range
PROSPECT-D	N	Leaf structure parameter (unitless)	0–5
	Chl	Chlorophyll content (μg cm^{-2})	0–100
	Car	Carotenoids content (μg cm^{-2})	0–60
	Ant	Anthocyanin content (μg cm^{-2})	0–5
	Cs	Senescent (brown) materials (unitless)	0–5
	Cw	Leaf water thickness (cm)	0–0.1
	Cdm	Dry matter content (g cm^{-2})	0–0.02
PROSPECT-DyN	Cp	Protein content (g cm^{-2})	0–0.02
	Ccl	Cellulose and lignin content (g cm^{-2})	0–0.02
COSINE	θs	Sensor view angle (°)	0–180
	θi	Light incident angle (°)	0–90
	B	Specular term to account for the bidirectional reflectance factor [unitless]	–0.2 to 0.6

The PROSPECT-DyN model was utilized to incorporate protein, cellulose, and lignin by recalibrating spectral absorption coefficients (Z. Wang *et al.*, 2015, 2018). As leaf protein strongly linearly correlates with nitrogen (Yeoh and Wee, 1994), estimated protein content was converted to the nitrogen content. PROSPECT was developed to simulate the hemispherical reflectance of leaves, but the leaf-clip reflectance collected in this study was conical. To convert the conical to the hemispherical reflectance, the COSINE model (Jay *et al.*, 2016) was implemented with PROSPECT models. Detailed information about the parameters of these three models can be found in Table 1.

The retrieval of foliar traits was conducted through a numerical inversion of RTMs by minimizing the root mean square deviation (RMSD) between the measured leaf-clip and simulated reflectance. The numerical optimization procedure used the same constrained Powell's line-search method as in Féret *et al.* (2017). As nitrogen is sensitive to the shortwave infrared, a two-step retrieval following Wang *et al.* (2015) was performed. The first step was to use the entire optical domain 500–2400 nm to invert the leaf structural parameter (N) and Chl content (Chl). Then we applied the shortwave infrared domain 2100–2300 nm to invert PROSPECT-DyN to estimate the protein content (Cp), which was further converted to nitrogen content using the ratio of 4.43 (Z. Wang *et al.*, 2018).

Partial least squares regression

The PLSR approach has been widely applied to process hyperspectral reflectance with high collinearity. PLSR can minimize predictor variables to a few orthogonal latent components (Geladi and Kowalski, 1986; Wold *et al.*, 2001). In this study, we selected PLSR to develop models to predict photosynthetic traits (i.e. Chl, nitrogen, and V_{max}) from the measured leaf spectra. We conducted 4-fold cross-validation to split the collected spectra and traits into training and testing. In each training data set, the model between leaf spectra and traits was developed. Then this model was tested using the independent testing data set. The uncertainty analysis of the PLSR models was conducted by splitting the training dataset via 100 permutations and generating the new model coefficients following Meerdink *et al.* (2016). Then we used the ensemble mean of PLSR models to predict the photosynthetic traits. By doing so, we obtained both predictive values and uncertainties for traits. Notably, the leaf reflectance from 500 nm to 2400 nm was utilized to develop the PLSR models between spectra and V_{max} or Chl. However, as nitrogen is well known to be linked to the shortwave infrared (Curran, 1988; Serbin *et al.*, 2012; Yendrek *et al.*, 2017), we used leaf reflectance of 1500–2400 nm to generate PLSR models to predict nitrogen. To avoid overfitting between spectra and foliar traits, we optimized the number of PLSR components by minimizing the prediction residual sum of squares (PRESS) statistic (e.g. Meerdink *et al.*, 2016). PRESS of successive model components was calculated through a cross-validation analysis. We selected model components corresponding to the minimum PRESS statistic until successive PLSR components did not significantly increase the model predictive accuracy (Serbin *et al.*, 2012).

Generalized partial least squares regression

The generation of PLSR models requires sufficient measured traits to be collected for modeling training, which could limit the applicability of PLSR in a fast and operational manner. To deal with such limitations, we tested the pre-trained gPLSR models (Wang *et al.*, 2020) to predict leaf Chl and nitrogen. The gPLSR models were generated from a database of leaf spectra and traits of 40 species (including maize) across NEON field sites in the Eastern USA (data available from doi:10.21232/e2jt-5209 and model code at ecosml.org). The pre-trained gPLSR model has advantages of free calibration and of only requiring leaf spectra data to predict foliar traits. In this study, we tested whether such gPLSR models can be applied to agricultural sites with different environmental conditions and sampling time.

Model application and evaluation

Our workflow to compare the predictive ability of RTMs, PLSR, and gPLSR to estimate leaf Chl, nitrogen, and V_{max} is illustrated in Fig. 1. We evaluated the performance of the PLSR, gPLSR, and RTMs to estimate leaf Chl and nitrogen. Then we conducted a comparison of various approaches to estimate V_{max}. The first approach utilized the leaf Chl or nitrogen to develop the linear regression models to estimate V_{max}. We conducted 4-fold cross-validation to evaluate the performance of these linear regression models. Then we tested the accuracy of using the leaf reflectance data to develop a PLSR model to estimate V_{max}. We also applied RTMs and gPLSR to estimate various leaf traits. Then through these 10 estimated traits (N, Chl, Car, Ant, Cs, Cw, Cdm, B, N_{mass}, and Ccl), we developed the trait-based PLSR model to predict V_{max}. Furthermore, as Chl and N_{mass} are two commonly used variables as a proxy for V_{max}, we also compared the performance of using only Chl, N_{mass}, and their multiplication to predict V_{max}. We used the comparison of spectra-based and trait-based PLSR models to identify the accurate and robust approaches to estimate V_{max}.

To comprehensively evaluate the estimated crop traits from leaf spectra, the Taylor diagram (Taylor, 2001) was used to present these three complementary statistics with a triangle–cosine–law relationship: the Pearson correlation coefficient (r), normalized standard deviation (NSTD, as in Equation 1), and normalized unbiased RMSD (NubRMSD; Equation 2). The radial distance stands for the NSTD, and the angle in the polar plot represents r. The reference point on the x-axis with r=1, NSTD=1, and

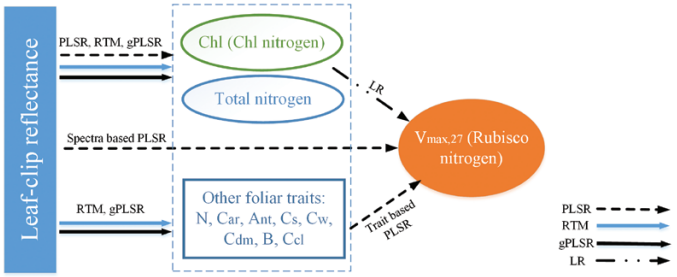

Fig. 1. Comparison of approaches to estimate leaf chlorophyll, nitrogen, and $V_{max,27}$. PLSR, partial least squares regression; gPLSR, generalized PLSR; RTM, radiative transfer model; LR, linear regression; Chl, leaf chlorophyll content; $V_{max,27}$, leaf maximum carboxylation rate standardized to 27 °C; N, leaf thickness parameter; Car, carotenoids; Ant, anthocyanins; Cs, senescent material fraction; Cw, leaf water content; Cdm, leaf dry matter content; B, the parameter to account for the leaf bidirectional reflectance; Ccl, leaf cellulose and lignin content; The dashed line indicates that methods require model training, while the solid lines are calibration-free approaches. This study compared three approaches to retrieve leaf chlorophyll and total nitrogen content, and four approaches to retrieve leaf $V_{max,27}$. (This figure is available in color at *JXB* online.)

NubRMSD=0 refers to the observation. The distance from the simulation point to the reference point represents NubRMSD of simulations and stands for the integrated performance for the simulation. The closer distance from simulation points to the reference point indicates better simulation performance.

$$NSTD_{sim} = STD_{sim}/STD_{obs} \quad (1)$$

$$NubRMSD^2_{obs,sim} = NSTD^2_{obs} + NSTD^2_{sim} 2NSTD_{obs} NSTD_{sim} cos r_{obs,sim} \quad (2)$$

where sim and obs represent the simulation results and the observations, respectively. $r_{obs,sim}$ refers to the correlation coefficient between simulations and observations, and NSTD is the normalized standard deviation.

Analysis of spectral signatures on predicting traits

To identify the contribution of spectral wavelengths to the prediction of Chl, nitrogen, and V_{max}, both physical model- and statistical method-based sensitivity approaches were applied. Through the comparison of these two approaches, this study can get a comprehensive understanding of the relationship between spectra wavelengths and the prediction of leaf traits.

In the physical model-based approach, we conducted a global sensitivity analysis of the PROSPECT-DyN-COSINE using the Sobol method (Sobol, 2001; Saltelli *et al.*, 2004), which is based on ANOVA decomposition to calculate the sensitivity of coupled inputs. The Sobol analysis can quantify the contribution of model parameters (leaf traits) to the wavelengths of leaf reflectance. The first-order Sobol sensitivity quantifies the independent contribution from each input to the output variables, while the second-order sensitivity quantifies interactions between every two inputs to the output variable. The Sobol analysis is sensitive to the configuration of the model parameter range and distribution. As this study focused on the maize photosynthetic traits, we utilized the 460 collected leaf spectra to invert RTMs to obtain the parameter distribution. Then, the kernel density sampling method was applied to generate the input data for sensitivity analysis. The kernel density sampling method has the advantage of resembling the distribution of the sampled dataset (S. Wang *et al.*, 2018). According to the kernel density distribution of model parameters, 20 000 samples were generated to assess the sensitivity of simulated leaf spectra to traits. Additionally, to the best of our knowledge, this study is the first one to integrate PROSPECT-DyN and COSINE for the retrieval of foliar traits. Such a sensitivity analysis can also provide insights into evaluating the impacts of incorporating COSINE for reflectance simulation.

In the statistical approaches, the PLSR loading, coefficients, and variable influence on the projection (VIP) scores (Wold *et al.*, 2001) were computed. The wavelengths with high absolute values of loading, coefficients, and VIP scores indicate a high contribution to the leaf trait prediction. The similarity and difference of the model loadings, coefficients, and VIP scores of the PLSR models to predict Chl, N_{mass}, and V_{max} were compared to explore the spectral linkage among these key photosynthetic traits. Notably, this study did not employ RTMs to directly predict V_{max}. The sensitivity of spectral wavelength to V_{max} prediction focused on the PLSR approach. In addition, we also analyzed the PLSR loading using these 10 estimated traits (N, Chl, Car, Ant, Cs, Cw, Cdm, B, N_{mass}, and Ccl) to predict V_{max}. The VIP scores and loading analysis can show the linkages of these 10 traits to V_{max}.

Results

Measured leaf spectra and photosynthetic traits

The measured leaf spectra (Fig. 2A) followed a general pattern of low reflectance in the visible region (500–700 nm), high reflectance in the near-infrared region (700–1300 nm), and two water absorption features in the shortwave infrared region (1300–2400 nm). The coefficient of variation (CV) of the spectral data (Fig. 2B) indicated that the visible, red edge (700–750 nm), and shortwave infrared regions, which are strongly linked to leaf pigments and biochemical traits, have greater variability compared with the near-infrared, which reflects the structural parameters of leaves (e.g. leaf thickness and dry matter content).

After V_{max} was standardized to 27 °C using the fitting temperature response curve in Supplementary Fig. S2 ($V_{max,25}$=0.875 $V_{max,27}$), the measured leaf biochemical and photosynthetic traits, Chl, N_{mass}, N_{area}, and $V_{max,27}$, were all highly correlated (Fig. 3). Nonetheless, there were differences in the strength of trait correlations. Among all pairs, Chl and N_{area} had the highest linear correlation (r=0.89), and this high correlation indicated that maize tended to allocate leaf total nitrogen to Chl at a relatively constant rate. Both Chl and N_{mass} were highly correlated with $V_{max,27}$ (r=0.77 and 0.75, respectively), confirming previous findings showing that $V_{max,27}$ of maize is highly correlated with Chl (Houborg *et al.*, 2013; Croft *et al.*, 2017) and N_{mass} (Yendrek *et al.*, 2017). The large variabilities of measured photosynthetic traits can serve a robust dataset for testing the model performance to predict traits.

Predicted photosynthetic traits from leaf spectra

The results of comparing RTM, PLSR, and gPLSR (Fig. 1) to estimate leaf photosynthetic traits are shown in the Taylor diagram (Fig. 4). For leaf Chl, PLSR achieved the highest r of ~0.95, the lowest NubRMSD of ~0.33, and NSTD close to

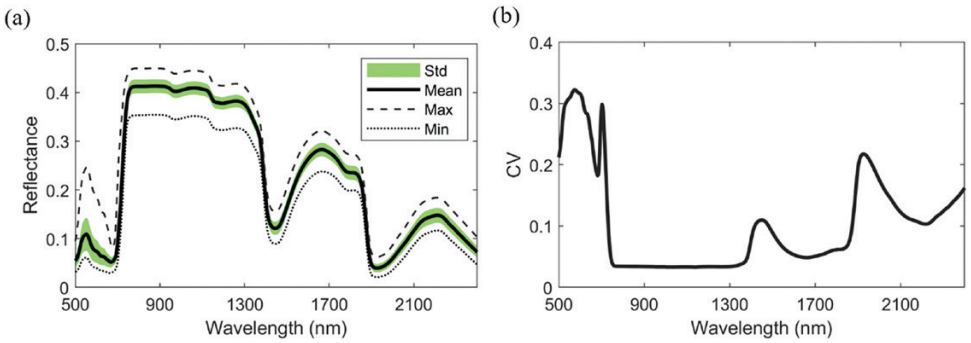

Fig. 2. Mean, maximum, minimum, standard deviation, and coefficient of variation (CV) of the measured leaf reflectance for maize. (This figure is available in color at *JXB* online.)

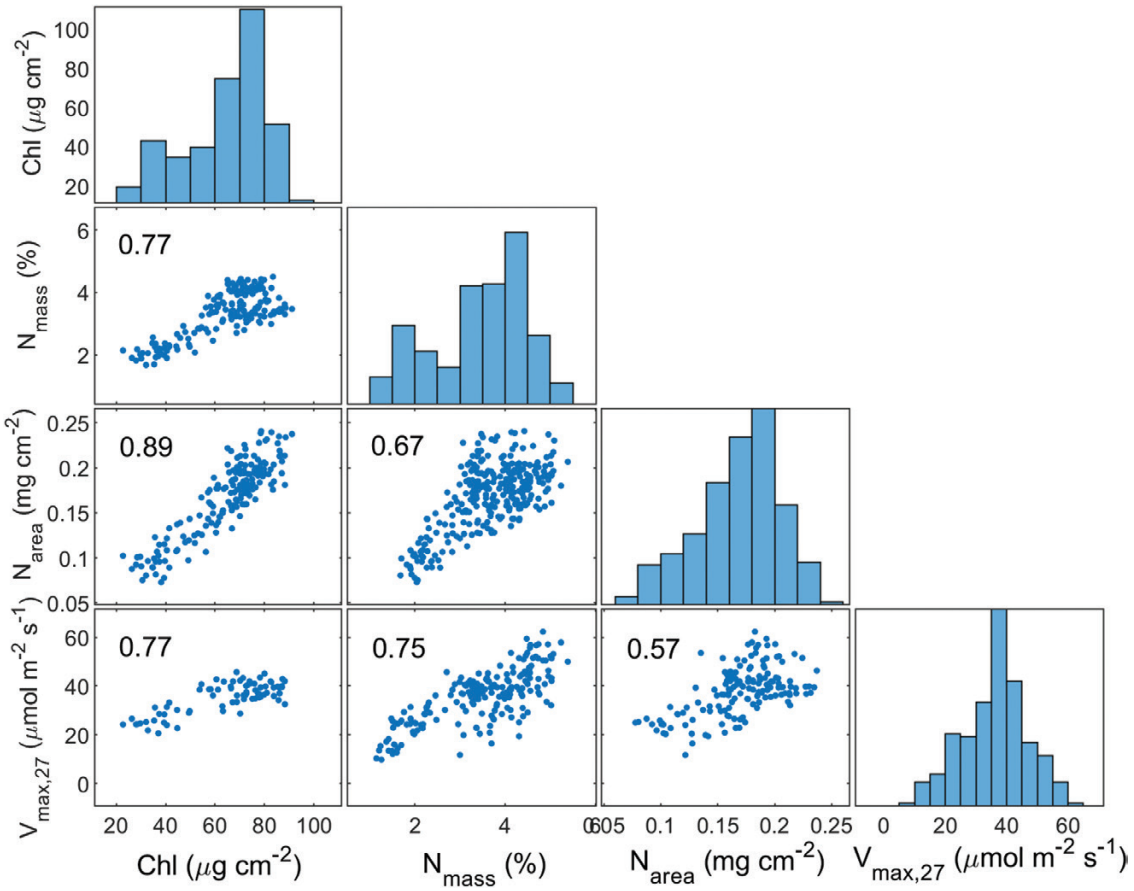

Fig. 3. Correlation matrix for measured leaf photosynthetic traits. $V_{max,27}$, the carboxylation rate at 27 °C (μmol m^{-2} s^{-1}); Chl, leaf chlorophyll content (μg cm^{-2}); N_{mass}, leaf nitrogen per mass (%); N_{area}, leaf nitrogen per area (mg cm^{-2}). The statistics in plots refer to the Pearson correlation coefficients. (This figure is available in color at *JXB* online.)

1. The RTM approach also achieved high performance with r ~0.95 and NubRMSD ~0.45. The gPLSR approach can obtain good performance with r of 0.88 and NubRMSD of 0.48. For N_{mass}, the PLSR method showed the highest r of ~0.96 and NubRMSD of 0.28. The gPLSR approach can also obtain a relatively good prediction of nitrogen with r of ~0.85 and NubRMSD of 0.56. The predictive power of the RTM (PROSPECT-DyN-COSINE) was weaker with r of ~0.60. Detailed scatterplots of predicting Chl and N_{mass} are illustrated in Supplementary Fig. S4.

For $V_{max,27}$ predictions, the best performance was achieved by the spectra-based PLSR model with r of 0.81, NubRMSD of ~0.61, and NSTD close to 1. The trait-based PLSR model utilizing 10 spectra-based traits (N, Chl, Car, Ant, Cs, Cw, Cdm,

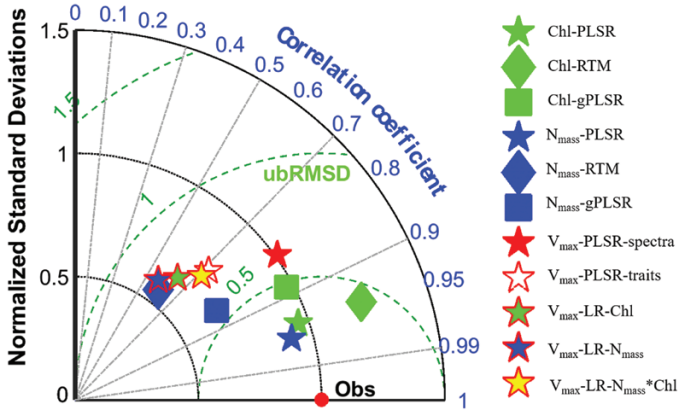

Fig. 4. Taylor diagram to present the performance of estimating leaf chlorophyll, nitrogen, and V_{max}. The pentagrams represent PLSR and LR (linear regression) methods. The diamonds are the RTM approaches, which refer to the PROSPECT-COSINE and PROSPECT-DyN-COSINE. The squares indicate the gPLSR method. The different markers represent chlorophyll-related, nitrogen-related, and V_{max}-related predictions. The radial coordinate represents the normalized standard deviation, which is equal to 1 for the observations. The angular coordinate indicates the correlation coefficient, which refers to 1 for the observations. The concentric dashed semi-circles represent the normalized unbiased RMSD. In the Taylor diagram, the points closer to the observation point refer to higher predictive ability for the models. (This figure is available in color at *JXB* online.)

B, N_{mass}, and Ccl) to predict $V_{max,27}$ also demonstrated a good predictive skill, with r of ~0.72 and NubRMSD of 0.70. These two PLSR models showed better performance than the linear regression models based on either Chl or N_{mass}. The linear regression models based on Chl or N_{mass} achieved a similar and moderate prediction performance with r of ~0.6. However, the predictive performance of the linear model significantly improved by using Chl×N_{mass}. The linear regression model between Chl×N_{mass} and V_{max} can achieve an r of ~0.71 and an NubRMSD of 0.70, which is close to the performance of the trait-based model (Supplementary Fig. S5). This result indicates that Chl and N_{mass} play a major role in the prediction of $V_{max,27}$ in the trait-based PLSR model.

Contribution of spectral signatures on predicting traits

In the RTM-based spectra contribution analysis, this study retrieved parameter distribution (Supplementary Fig. S3) from the 460 collected leaf spectra. Then, the global sensitivity analyses of results of PROSPECT-COSINE and PROSPECT-DyN-COSINE for the case of simulating maize leaf-clip reflectance were conducted as shown in Fig. 5. In the visible region, pigments including Chl, Car, Ant, and Cs contributed to the reflectance variation (Fig. 5A), with red edge and green wavelengths (500–750 nm) influenced primarily by Chl. The leaf structural parameter N, which indicates the leaf thickness, and dry matter content (protein, cellulose, and lignin in PROSPECT-DyN, Fig. 5B) contributed to the variability of reflectance in near-infrared and shortwave infrared regions that was not explained by the parameter B. In particular, the shortwave infrared 1500–1900 nm and 2000–2400 nm are the main wavelengths exhibiting the nitrogen signal (Cp in Fig. 5B). The parameter B representing the bidirectional reflectance factor of leaves showed a significant contribution to the spectral variability across visible, near-infrared, and shortwave infrared, especially in blue and red wavelengths and the water absorption feature around 1900 nm. This high contribution indicated the importance of considering the bidirectional effects of leaf reflectance collected from a handheld leaf-clip spectroradiometer (Li *et al.*, 2019). In general, from the model-based contribution analysis, the visible information (500–750 nm) has strong implications for Chl estimation, while the shortwave infrared bands (1500–1900 nm and 2000–2400 nm) are important for nitrogen prediction.

In the statistical analysis, the VIP scores, loading, and coefficients of the spectra-based PLSR models were compared to analyze the similarity and difference of using spectra to predict $V_{max,27}$, Chl, and N_{mass} (Fig. 6A–C). In general, the visible wavelengths associated with green reflectance and red absorption (550 nm and 710 nm) contributed most significantly to the prediction of Chl, while the shortwave infrared wavelengths in the 1700–1900 nm and 2100–2200 nm shortwave infrared regions were most important to the prediction of nitrogen. These findings also agree with the model-based sensitivity analysis (Fig. 5) and confirm the robust performance of RTMs. The shaded gray regions in Fig. 6 correspond to the high absolute values of VIP scores for predicting $V_{max,27}$. In the visible part of the spectrum (500–750 nm), the VIP scores, loadings, and coefficients of $V_{max,27}$ and Chl were very similar. Specifically, the green and red edge (550 nm and 710 nm) largely contributed to the prediction of $V_{max,27}$. In the shortwave infrared region, the patterns of VIP scores, loadings, and coefficients for $V_{max,27}$ were close to those for N_{mass}. The PLSR models of $V_{max,27}$ and N_{mass} shared key wavelengths such as 1590, 1830, 1910, 2030, and 2110 nm. These results indicate that the spectra signals of Chl and N_{mass} have complementary contributions to the prediction of $V_{max,27}$. However, notably, there are also unique wavelengths such as 1500, 2200, and 2300 nm contributing to the prediction of $V_{max,27}$ that are not strongly related to Chl or N_{mass}.

Similar to the analysis of spectra-based PLSR models, the VIP scores and loading of the trait-based PLSR model also supported the findings on the large contribution of Chl and N_{mass} to $V_{max,27}$ predictions. In the VIP scores of the trait-based PLSR model (Fig. 7A), Chl and N_{mass} were the two strongest contributors to the prediction of $V_{max,27}$. The analysis of the components 1 and 2 of PLSR loading (Fig. 7B) showed that Chl largely contributed to the first component of PLSR loading. N_{mass} had a contribution to the first component but also provided unique information on the second component.

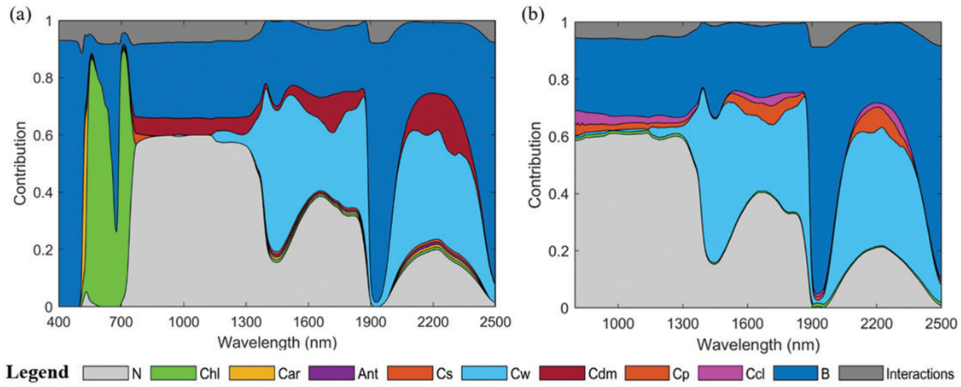

Fig. 5. Global sensitivity analysis of radiative transfer models. (A) PROSPECT-COSINE and (B) PROSPECT-DyN-COSINE. In the key, the variables N, Chl, Car, Ant, Cs, Cw, Cdm, Cp, Ccl, B, and Interactions refer to leaf thickness structure parameter, chlorophyll, carotenoids, anthocyanin, senescent materials, water content, dry matter content, protein, cellulose and lignin, leaf bidirectional reflectance factors, and interactions for the parameter sensitivities, respectively. (This figure is available in color at *JXB* online.)

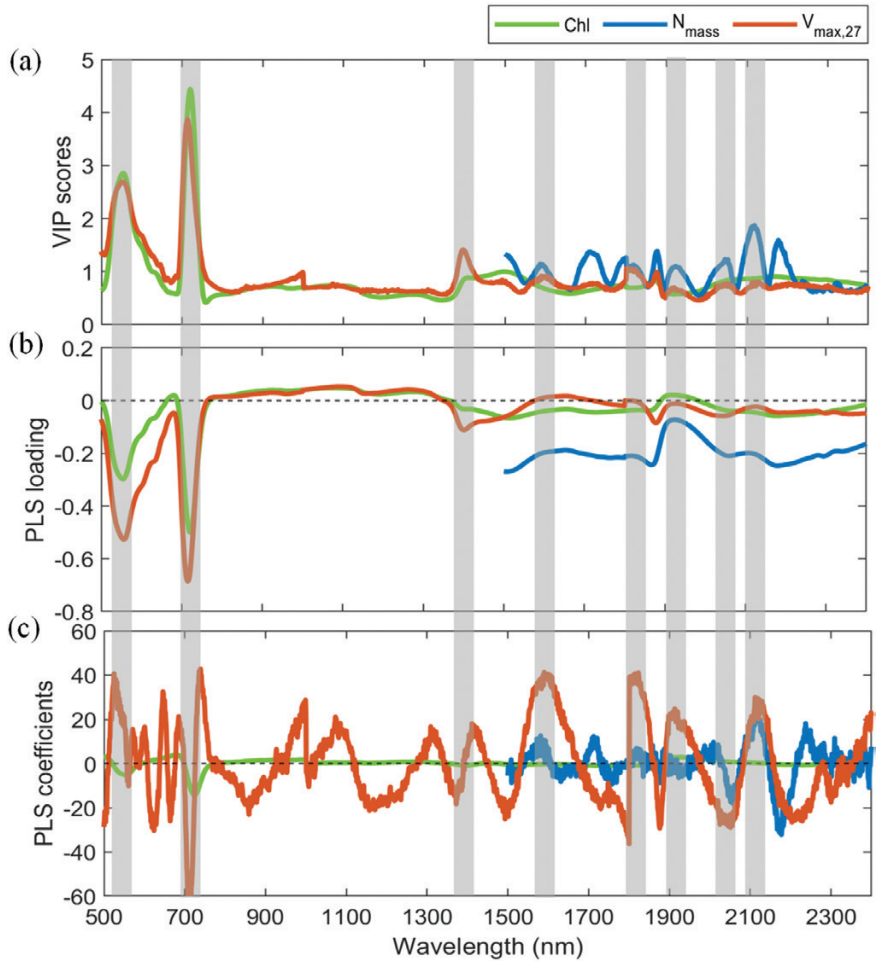

Fig. 6. (A) VIP scores, (B) loading, and (C) coefficients of the spectra-based PLSR model for $V_{max,27}$, chlorophyll, and nitrogen predictions. The orange curve shows leaf $V_{max,27}$ predictions. The green curve refers to the leaf chlorophyll content prediction. The blue curve represents leaf nitrogen per mass predictions. The shaded gray region indicates the key wavelengths for $V_{max,27}$ predictions. (This figure is available in color at *JXB* online.)

This analysis indicated that Chl and N_{mass} had shared but also unique contributions to the prediction of $V_{max,27}$. In the VIP scores for the trait-based PLSR model, Car and Cw showed a high contribution to the model prediction following Chl and N_{mass}. This contribution was probably due to the high correlation between Chl and Car (Kopsell *et al.*, 2004). Under

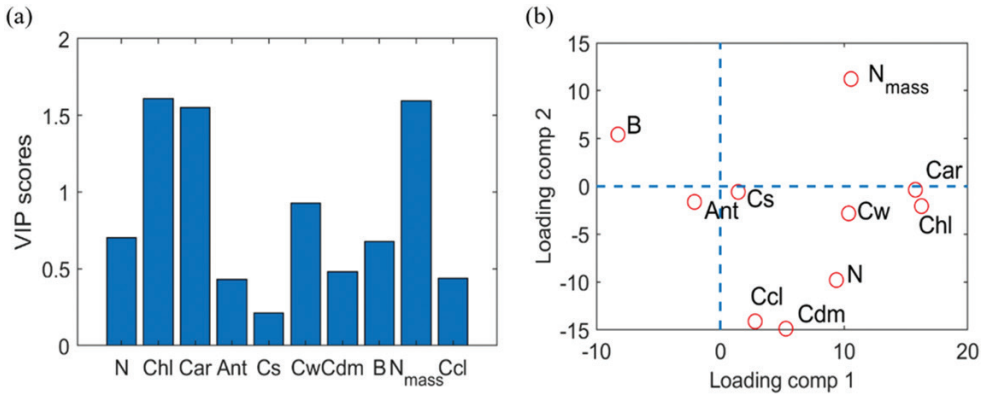

Fig. 7. (A) VIP scores and (B) loading components 1 and 2 of the trait-based PLSR model for the $V_{max,27}$ prediction. The traits N, Chl, Car, Ant, Cs, Cw, Cdm, B, N_{mass}, and Ccl refer to leaf thickness structure parameter, chlorophyll, carotenoids, anthocyanin, senescent materials, water content, dry matter content, leaf bidirectional reflectance factor, nitrogen per mass, and cellulose and lignin content, respectively. These foliar traits are from calibration-free approaches. The estimated N_{mass} is from gPLSR, due to its high accuracy. Other traits are from RTMs. (This figure is available in color at *JXB* online.)

drought conditions, low water availability can alter nitrogen uptake and thus results in a high correlation between leaf water content and V_{max} (Camino *et al.*, 2019).

Discussion

We provided a comprehensive evaluation of spectroscopy methods to retrieve Chl, N_{mass}, and V_{max}. These analyses could be helpful for the model selection to estimate leaf photosynthetic traits in high-throughput crop monitoring. First, for pre-trained approaches, the PROSPECT-D coupled with the COSINE model showed a strong ability to predict Chl, while gPLSR predicted leaf nitrogen better. With field measurements for model training, PLSR showed the best performance to predict foliar traits. Secondly, the spectra-based or trait-based PLSR models can provide accurate and effective means to predict V_{max}. We also found that Chl and N_{mass}, which are strongly linked to visible and shortwave infrared signals, respectively, showed shared and unique contributions to the prediction of V_{max}. Measurement and model uncertainties, implications on RTM and PLSR model selection, and mechanisms of controlling V_{max} based on these results are further discussed.

Uncertainty for photosynthetic capacity prediction

Compared with Chl and N_{mass} prediction, achieving high accuracy to predict V_{max} through spectroscopy has more challenges. These challenges are partially due to the limited amount and weak absorption features of Rubisco enzyme. Furthermore, uncertainties in field V_{max} measurements and models may also contribute to the performance of V_{max} prediction.

This study used commercial gas exchange systems to obtain the A/C_i curves to fit the horizontal asymptote of a four parameter non-rectangular hyperbolic function (Yendrek *et al.*, 2017) to quantify V_{max}. However, gas leakage, chamber edge effects, and lateral flux through leaf air space could bring uncertainties for A/C_i curves, when operating systems in the field (Long and Bernacchi, 2003). In addition, the Rubisco capacity V_{max} derived from gas exchange measurements is not always equal to the amount of Rubisco protein present (Crafts-Brandner and Salvucci, 2000). However, this study carefully screened all A/C_i curves to exclude the bad fitting of measurement curves as in Kauwe *et al.* (2016). As multiple machines were employed, we have also tested the reproducibility of machines to ensure similar A/C_i curves obtained from different machines for the same leaf. Furthermore, our V_{max} measurements are comparable with estimates reported in previous studies (Houborg *et al.*, 2013; Yendrek *et al.*, 2017; Miner and Bauerle *et al.*, 2019). All these strategies ensure the high accuracy of the measured V_{max} data for this study.

To diagnose the performance of the spectra–$V_{max,27}$ model, we further analyzed the relationships between model prediction residuals with leaf conditions, environmental stressors, experiment year, and genotypes (Fig. 8). The comparison between model residuals and leaf $V_{max,27}$ (Fig. 8A) shows model overestimation of $V_{max,27}$ when leaf $V_{max,27}$ is low, while the model underestimates $V_{max,27}$ when leaves have high $V_{max,27}$. We also found that the model residuals exhibit dependence on O_3 treatment (Fig. 8B), which indicates that O_3 can alter the leaf spectra and traits relationship (Yendrek *et al.*, 2017). Similarly, the spectra–trait model also shows a large difference when applied to different genotypes (Fig. 8D). However, we did not find a significant difference for model performances in different year data (Fig. 8C), which demonstrates the transferability of PLSR models for plants across growth stages (Wang *et al.*, 2019).

Selection of physically based and data-driven approaches

RTMs are developed based on physically based radiative transfer processes and thus have high accuracy to utilize the observed leaf spectra to accurately predict traits with strong

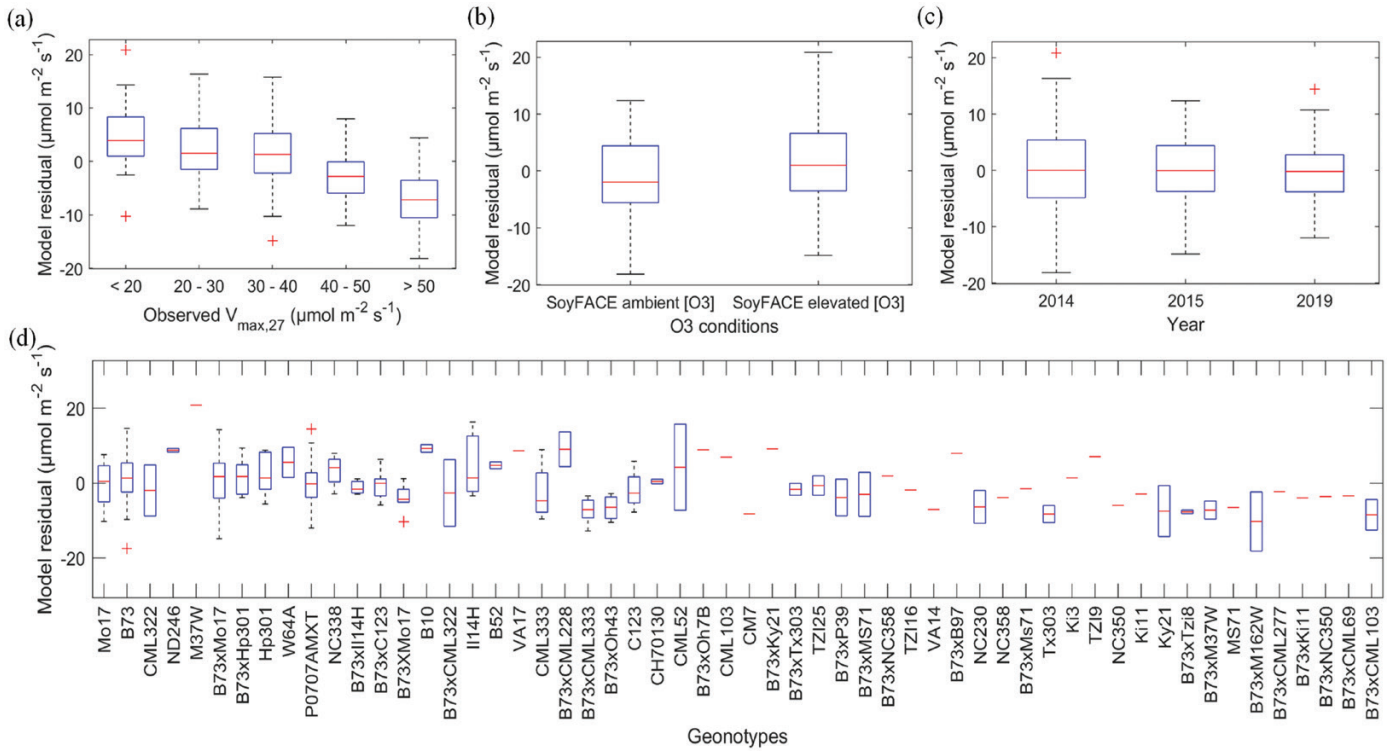

Fig. 8. Analysis of the performance of the spectra–$V_{max,27}$ model by (A) leaf condition, (B) environmental stressor, (C) experiment year, and (D) genotype. (This figure is available in color at *JXB* online.)

absorption features, such as pigments. For instance, this study demonstrated the high accuracy of PROSPECT-COSINE to estimate Chl (r=0.94) in maize. Compared with pigments, protein has relatively weaker absorption features in shortwave infrared, and RTM showed moderate accuracy to estimate N_{mass} (Fig. 4). Data-driven methods such as PLSR have the advantage of exploiting spectral signatures to link reflectance with *in situ* measurements to accurately predict traits such as N_{mass} (r=0.96). However, the development of PLSR models requires collecting a large dataset of foliar traits for model training, and models may not be applicable outside the conditions of *in situ* collections. In practical applications, the pre-trained gPLSR models, which can be implemented without field-measured traits, have high flexibility and accuracy to predict traits such as N_{mass} (r=0.85).

Regarding V_{max} prediction, the spectra-based PLSR model in this study achieved the highest accuracy (r=0.81). The trait-based PLSR model achieved slightly worse but still reasonably good performance (r=0.72). The integration of Chl and N_{mass} can also achieve good predictive performance (r=0.71). For leaf-scale applications, the spectra-based models show great potential. However, such leaf spectra models have challenges to be directly applied to the canopy scale, as spectra vary significantly across leaf and canopy scales. The upscaling of reflectance from leaf to canopy is also highly non-linear, due to light scattering throughout the canopy profile, sensor viewing angles, solar radiation angles, and the fraction of sunlit and shaded leaves (Verhoef, 1984). The upscaling of V_{max} from leaf to canopy is also highly non-linear, but the process is influenced by nitrogen allocation throughout the canopy profile and within leaves (Hammer and Wright, 1994; Evans and Clarke, 2019). Thus, the leaf-scale spectra–V_{max} relationship could hardly be used for the canopy spectra, as different mechanisms are involved in the upscaling of spectra and V_{max} from leaf to canopy.

To predict V_{max} across leaf, canopy, regional, or global scales, the trait-based V_{max} model has more flexibility (Houborg *et al.*, 2013; Luo *et al.*, 2019). For instance, Houborg *et al.* (2013) showed that using the leaf Chl–V_{max} relationship along with satellite-derived Chl content, the community land model achieved an improved estimation of canopy gross primary production. Similarly, Luo *et al.* (2019) applied such a leaf Chl–V_{max} relationship to the global scale to derive terrestrial photosynthesis. In these studies, leaf traits were retrieved from the canopy reflectance through RTMs (Jacquemoud *et al.*, 2009) and then the trait–V_{max} relationship was applied to derive photosynthetic capacity.

Foliar nitrogen allocation and photosynthetic capacity prediction

Photosynthesis requires a large number of proteins, such as Rubisco and the light-harvesting complex, which account for 69–75% of the nitrogen in leaves (Makino and Osmond, 1991;

Onoda *et al.*, 2017). Around 25–31% nitrogen is allocated to the non-photosynthetic components such as cell walls, mitochondria, peroxisomes, and the cytosol, as shown in Fig. 9 (Mu *et al.*, 2016; Evans and Clarke, 2019). The nitrogen allocation to Rubisco and other components shows strong variability depending on species, growth stages, and environmental conditions (Evans and Clarke, 2019). For instance, Onoda *et al.* (2017) found that when leaves increased leaf dry mass per area, the fraction of leaf nitrogen allocated to Rubisco declined to compensate for the increased allocation to the cell wall materials. Due to the greater photosynthetic rate per unit leaf nitrogen in young leaves, V_{max} showed strong variations with leaf ages (Albert *et al.*, 2018; Wu *et al.*, 2019). The proportion of photosynthetic proteins in maize showed large variations with treatments with nitrogen fertilizers (Mu *et al.*, 2016). Understanding leaf nitrogen allocation is important for V_{max} prediction.

The proposed approach in this study (Fig. 9), which estimates Chl and total nitrogen through the visible and shortwave infrared spectra, respectively, can integrate Chl and nitrogen information to infer nitrogen allocation to predict V_{max}. Compared with the remote sensing approaches utilizing either Chl or total nitrogen to approximate V_{max} (Houborg *et al.*, 2013; Dechant *et al.*, 2017), this proposed approach has greater potential for V_{max} retrieval. For instance, Chl-deficient tobaccos have a much lower Chl to V_{max} ratio than normal species (Meacham-Hensold *et al.*, 2019). Using a universal Chl and V_{max} relationship may underestimate V_{max} in such species. However, with additional nitrogen information, the prediction of V_{max} could be improved. Likewise, use of total nitrogen to predict V_{max} may result in low correlations for species such as soybean (Koester *et al.*, 2016) due to excessive nitrogen storage. The additional information of Chl could thus be vital to improving the prediction of soybean V_{max}. Moreover, the sensing techniques provide estimates of the pool sizes for leaf nitrogen components, such as Chl or total nitrogen. To further constrain V_{max} prediction, the optimality theories on plant resource allocation (Smith *et al.*, 2019) can be leveraged to combine with the retrieved nitrogen components from sensing techniques. For natural ecosystems or nitrogen deficit crops, plants tend to maximize carbon gains with improving nitrogen allocation among leaf nitrogen pools (Quebbeman and Ramirez, 2016). With such information about nitrogen allocation, the prediction of V_{max} could be further improved. Towards operational prediction of V_{max} from hyperspectral reflectance with less dependency on model training, the integration of RTM-derived Chl and gPLSR-derived N_{mass} to develop the generalized model for V_{max} prediction shows great potential.

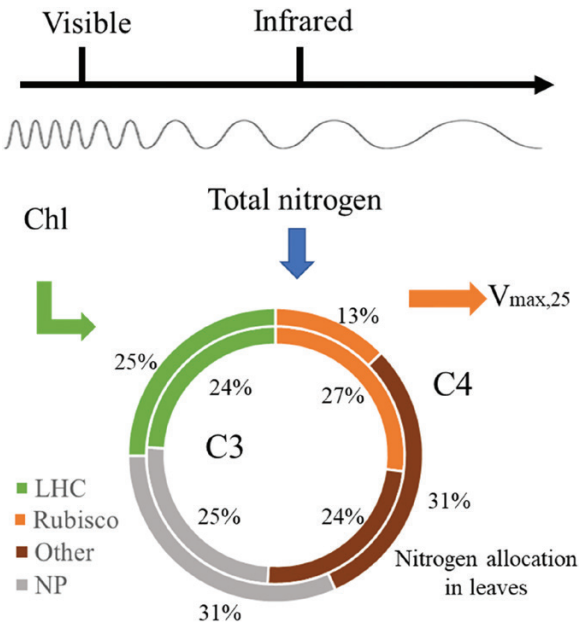

Fig. 9. Methodology to integrate the visible and infrared hyperspectral reflectance to quantify nitrogen allocation to estimate V_{max}. The inner and outer circles refer to the typical nitrogen allocation in C_3 leaves and C_4 leaves, respectively. The data for nitrogen allocation for C_3 and C_4 leaves are from Evans and Clarke (2019) and Mu *et al.* (2016), respectively. Notably, the allocation rates vary with environmental conditions, species, and growth stages. LHC refers to nitrogen in the light-harvesting complex. Rubisco represents nitrogen in the Rubisco protein. Other stands for nitrogen in other photosynthetic proteins. NP means non-photosynthetic proteins, such as cell wall, mitochondria, and cytosol. (This figure is available in color at *JXB* online.)

Conclusion

The accurate, fast, non-destructive, and cost-effective approaches to estimate photosynthetic traits, such as CO_2-saturated photosynthesis rate (V_{max}), chlorophyll, and nitrogen, are greatly needed for crop monitoring. This study comprehensively evaluated radiative transfer models (RTMs), partial least squares regression (PLSR), and generalized PLSR (gPLSR) to retrieve photosynthetic traits from leaf-clip reflectance collected in diverse maize plots with different genotypes, growth stages, treatments with nitrogen fertilizers, and ozone pollution in three growing seasons. This study led to the following conclusions. (i) Both pre-trained RTM and gPLSR methods have great potential to estimate photosynthetic traits. RTMs can achieve a high performance to retrieve foliar pigments such as Chl content (r=0.95). gPLSR can be used to estimate foliar nitrogen concentration (r=0.85). (ii) With model training, PLSR methods can exploit leaf reflectance in conjunction with field samples to achieve high accuracy to predict traits. The PLSR models based on spectra (r=0.81) or the spectra-retrieved traits (r=0.72) can provide good predictions of V_{max}. In particular, the trait-based V_{max} model has the ability to be applied across spatial scales—using either leaf or canopy level data. (iii) We found that leaf Chl content and nitrogen concentration showed complementary contributions to the prediction of V_{max}. The integration of leaf Chl and total nitrogen information, which indicates leaf Chl nitrogen and total nitrogen pool

sizes, respectively, can significantly improve V_{max} prediction (r=0.71) compared with that using only Chl or nitrogen. The information on nitrogen allocation among nitrogen pools is vital for V_{max} predictions.

This study provided new insights into improving V_{max} prediction by sensing both Chl and nitrogen for maize. Such approaches could also be applied to other crops, such as perennial bioenergy C_4 grasses. Further, applying estimated photosynthetic traits from spectroscopy into the terrestrial ecosystem models could significantly improve the ability to predict crop yields and carbon cycles. Leveraging the advanced imaging spectroscopy approaches on towers, unmanned or manned airborne systems, or satellites such as PRISMA (launched in 2019), HISUI (launched in 2019), EnMAP (expected launch in 2021), and NASA SBG and ESA CHIME (expected launches in the late 2020s), we can extend the leaf retrieval to the canopy and regional scale for high-throughput and large-scale agricultural monitoring.

Supplementary data

The following supplementary data are available at *JXB* online.

Fig. S1. Overview of the study site.

Fig. S2. Fitted V_{max} temperature correction curve for maize.

Fig. S3. Retrieved distribution of the PRO-COSINE and PRODyN-COSINE parameters from the 470 measured maize leaf reflectance.

Fig. S4. Scatterplots of predicting (a–c) leaf chlorophyll content and (d–f) nitrogen concentration from leaf-clip reflectance.

Fig. S5. Scatterplots of predicting V_{max} from leaf spectra or spectra-based traits.

Dataset S1. Measured leaf traits, measured reflectance, and generated spectra–trait PLSR models.

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Author contributions

SW, KG, ZW, EAA, and PT conceived the project. KG, EAA, and PT contributed to funding acquisition. SW, ZW, TZ, KL, CM, and GW performed the experiments and data collection. SW conducted data processing and analysis. SW, KG, ZW, EAA, PT, and CJ contributed to data interpretation and discussion. SW wrote the original draft of the manuscript. All authors have revised and approved the final manuscript.

Conflict of interest

The authors declare that they have no conflicts of interest.

Data availability

All data supporting the findings of this study are available within the paper and within its supplementary data published online.

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