Predicting the Photosynthetic Capacity and Leaf Nitrogen of Woody Bioenergy Crops from Hyperspectral Reflectance Models

B35I-1525: Abstract ID 904542

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INTRODUCTION

Eastern cottonwood (*Populus deltoides*) and hybrid poplars are well-known bioenergy crops due to their high biomass productivity under short-rotation management.

Selection of *Populus* genotypes that can ensure promising biomass yield is usually needed as a pre-screening before tree breeding is continued.

Previous studies found that there was a relationship between spectral responses of leaves and growth-related parameters, such as photosynthetic capacity [1] and leaf nitrogen (N) content [2].

Therefore, hyperspectral leaf reflectance can potentially be used as a proxy to rapidly estimate the growth potential of selected *Populus* genotypes if robust statistical models can be developed.

OBJECTIVES

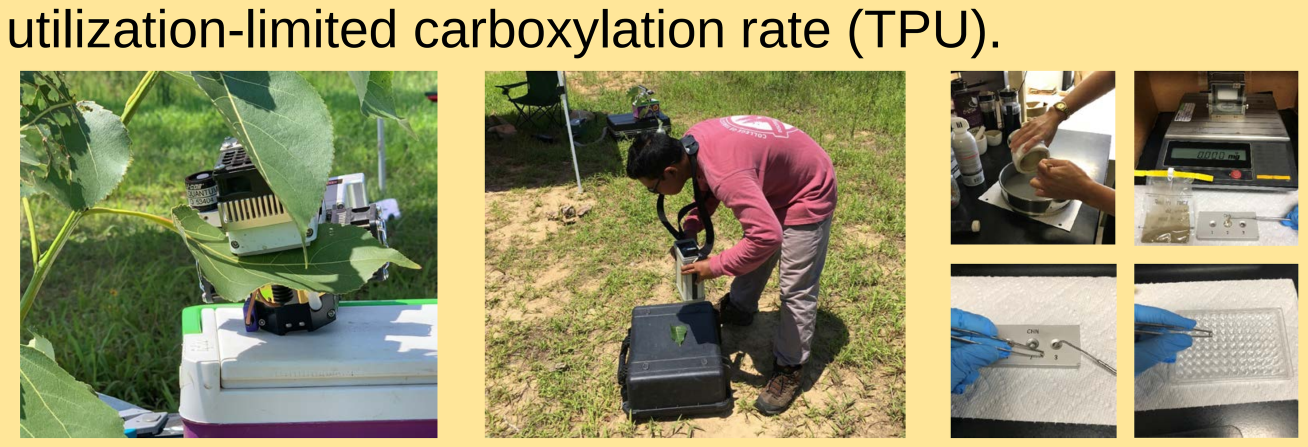
1) To assess whether hyperspectral leaf reflectance can model photosynthetic parameters and leaf N content of eastern cottonwood and hybrid poplar genotypes.
2) To identify critical wavelengths that are sensitive to these physicochemical parameters.

METHODS: Field and lab analysis

Two *Populus* bioenergy plantations were established in Monroe County and Pontotoc County, MS at 2.7×1.8 m spacing in 2018 and 2019, respectively.

In both plantations, CO_2 response curves, hyperspectral leaf reflectance, and leaf N content were measured from 105 leaves (n = 105), including 62 *Populus* genotypes under 7 taxa (Figure 1).

From CO_2 response curves, three photosynthetic parameters were calculated: 1) Rubisco-limited carboxylation rate (V_{cmax}), 2) electron transport-limited carboxylation rate (J_{max}), and 3) triose phosphate utilization-limited carboxylation rate (TPU).



(a) (b) (c)

Figure 1: Field and lab measurements.

(a) CO_2 response curves measurement using a LI-COR 6400.

(b) Leaf reflectance measurement using a GER 1500 field spectroradiometer.

(c) Analyzing N content in the leaves using an ECS 4010 CHNOS Elemental Analyzer.

METHODS: Statistical analysis

Least Absolute Shrinkage and Selection Operator (LASSO) and Principal Component Analysis (PCA) were used to develop the prediction models and to determine the wavelengths that were the most useful for capturing the variability in the photosynthetic parameters and leaf N data.

Response variables = Photosynthetic parameters and leaf N content

Predictors = 512 spectral bands within the range of 287 to 1090 nm

RESULTS

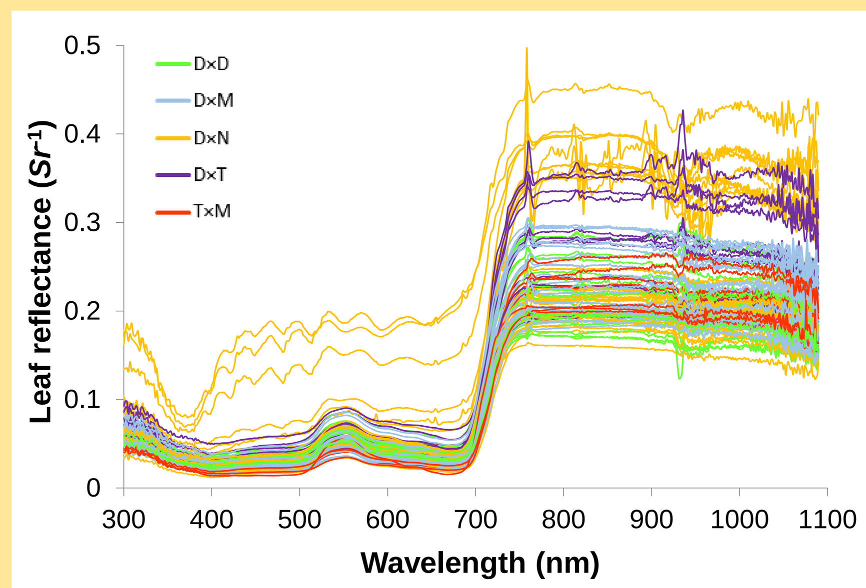


Figure 2. Leaf reflectance curves of *Populus* taxa. T×D (*P. trichocarpa* × *P. deltoides*) and (D×N)×M (*P. deltoides* × *P. nigra* × *P. maximowiczii*) were combined with D×T and D×N, respectively.

D×D = *P. deltoides* × *P. deltoides*
D×M = *P. deltoides* × *P. maximowiczii*
D×N = *P. deltoides* × *P. nigra*
D×T = *P. deltoides* × *P. trichocarpa*
T×M = *P. trichocarpa* × *P. maximowiczii*

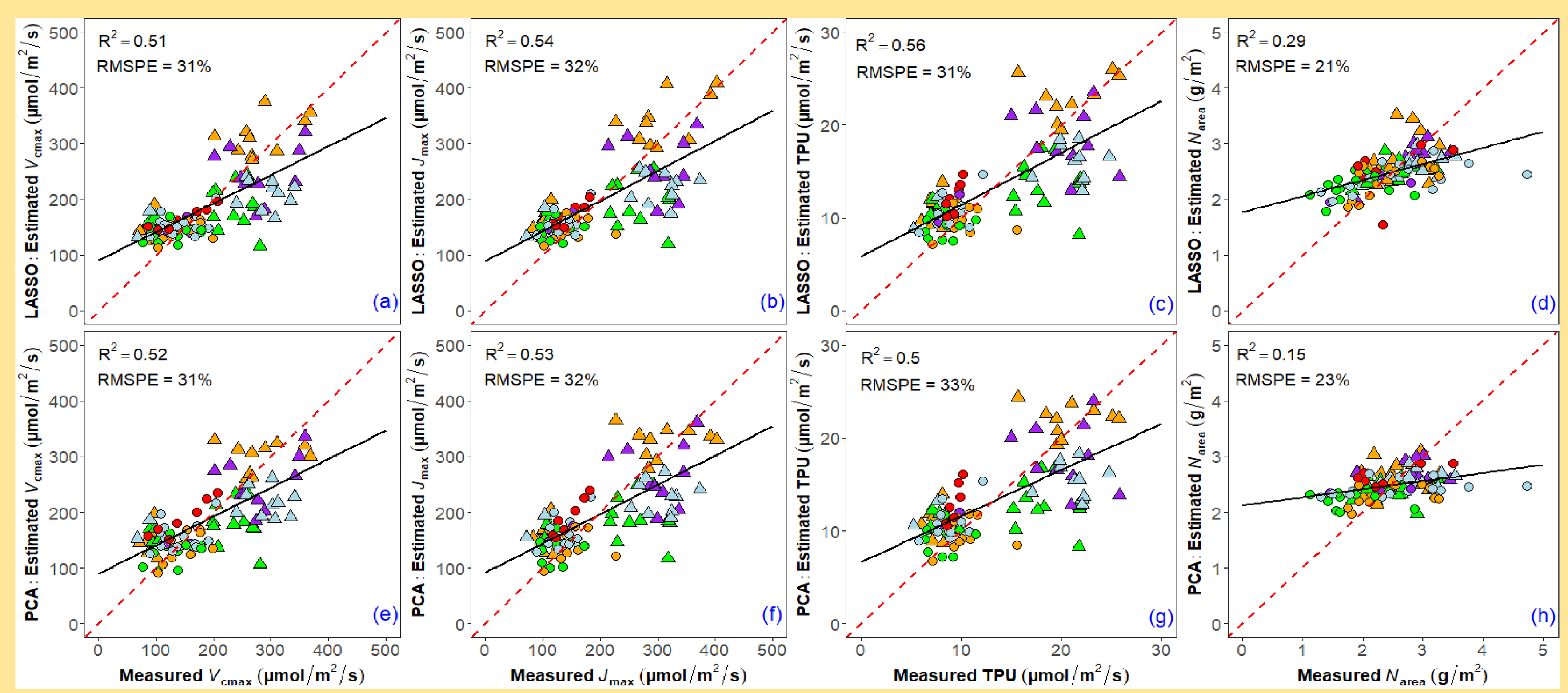


Figure 3. Scatterplots showing the linear relationship between measured and estimated V_{cmax}, J_{max}, TPU and leaf N for the LASSO: (a), (b), (c), and (d) and the PCA models: (e), (f), (g), and (h). The solid black line is the regression line, and the dotted red line is the 1:1 line.

Model	Model form	R^2	RMSPE	RMSE (Entire data)	Cross validated RMSE	
					Training data	Test data
LASSO: V_{cmax}	-30.2 + (601.1 × ρ758.29) + (302.7 × ρ935.71)	0.51	31%	57.20	59.07	57.37
LASSO: J_{max}	-44.6 + (796.2 × ρ758.29) + (200.57 × ρ935.71)	0.54	32%	60.98	61.68	60.64
LASSO: TPU	-6.4 + (-62.0 × ρ687.03) + (35.2 × ρ745.99) + (59.9 × ρ756.76)	0.56	31%	4.02	4.02	4.37
LASSO: Leaf N	2.0 + (28.3 × ρ303.51) + (-24.4 × ρ711.97) + (0.7 × ρ920.68) + (5.9 × ρ1021.44)	0.29	21%	0.51	0.53	0.51
PCA: V_{cmax}	184.4 + (-1.9 × PC1) + (-5.6 × PC2) + (-0.03 × PC1 × PC2)	0.52	31%	56.99	56.68	59.54
PCA: J_{max}	193.5 + (-2.4 × PC1) + (-5.3 × PC2) + (-0.01 × PC1 × PC2)	0.53	32%	61.92	62.46	64.72
PCA: TPU	13.2 + (-0.2 × PC1) + (-0.3 × PC2) + (-0.0007 × PC1 × PC2)	0.50	33%	4.30	4.20	4.65
PCA: Leaf N	2.5 + (0.0008 × PC1) + (-0.04 × PC2) + (-0.0005 × PC1 × PC2)	0.15	23%	0.56	0.60	0.55

Table 1. Selected wavelengths in the models and averaged 10-fold cross validation results. Training and testing data contained 70% and 30% of the entire data, respectively. ρ is spectral reflectance at the corresponding wavelengths, and PC is principal component.

DISCUSSION

Our results indicated that hyperspectral leaf reflectance could capture the variability in photosynthetic parameters (V_{cmax}, J_{max}, and TPU) and leaf N content across a diverse range of *Populus* genotypes.

According to other studies:

- 687 and 758 nm were solar-induced chlorophyll fluorescence retrieval bands [3].
- 935 nm was associated with plant stress [4].
- 746 nm was part of extended photosynthetically active radiation [5] and was correlated with carotenoid concentration [6].
- Due to its negative correlation with protective chemicals (resin and flavonoid content), 304 nm could be associated with leaf N content [7].
- 712 and 921 nm were correlated with leaf N [8,9], and 1021 nm was a N absorption feature [10].

CONCLUSION

1) The LASSO model outperformed the PCA model in model interpretability.
2) Due to its success in our single-leaf studies, chlorophyll fluorescence retrieval bands (687 and 758 nm) can potentially predict photosynthetic capacity of *Populus* plantations at the ecosystem level.
3) Hyperspectral leaf reflectance shows potential to be used as a cost-effective way to perform high throughput phenotyping and rapid clonal screening.

ACKNOWLEDGEMENTS

This publication is a contribution of the Forest and Wildlife Research Center, Mississippi State University.

We thank the National Institute of Food and Agriculture, USDA under award numbers 2018-67020-27934 and 2018-68005-27636 for funding this research.

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