

Using UAV to Improve Yield Estimation and Predict Maturity in Soybean Breeding

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Development of methods to improve soybean yield estimation and predict plant maturity with an unmanned aerial vehicle based platform

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Challenge



Opportunity





The efficiency of phenotyping in the field has not changed for decades while the genotyping is rapidly developing.

From Remote Sensing to Field Crop High Throughput Phenotyping

ECAT







Source: www.pbgworks.org, www.spltech.in, www. oceanoptics.com, blog.usi-inc.net

Breeding Improvement Potential







Objectives

- Measure the canopy geometric features and test the significance of plot row length as covariate in yield estimation model.
- Develop the machine learning model for binary soybean maturity classification using multispectral (NIR/R/G/B) data.

Methods: Field Setup

• Two breeding trials:

Trial A (GS): Genomic selection study containing 2980 plots from 26 breeding populations (~120 RILs), in single row 4 foot plots Trial B (NAM): Two sets of 60 selected soybean NAM lines, replicated twice with RCBD, in four-row 12 ft plots

- Twelve ground control points (GCPs) and a white-and-black calibration chessboard was used for spatial and radiation control
- GPS was recorded using survey grade Differential-GPS unit

Methods: HTP platform setup

UAV platform: Octocoptor + Dual-Camera System



3DRobotics X8, 850g payload, Autopilot and waypoint, 5 – 15 min duration



2×Canon S110, Lightweight, 12.1M Pixels, Raw format compatible



One S110 was converted into a pure NIR camera by Kolari Vision. Blue Channel to record NIR

Methods: Experiment Pipeline

Intermediate Results

Ground Control Points



Objectives

- Measure the canopy geometric features and test the significance of plot row length as covariate in yield estimation.
- Develop the machine learning model for binary maturity classification using multispectral (NIR/R/G/B) data.

Experiment on GS Field

1.1 Measuring Canopy Geometric

Features





Segmentation – Vector Design – Plot Basis Extraction – Feature Calculation

Canopy Size vs. Yield

1.1 Measuring Canopy Geometric

Features

Correlation between Canopy Size and Yield by Population



Canopy Size vs. Yield

1.1 Measuring Canopy Geometric

Features



Experiment on NAM Field

1.2 Plot Row Length Covariate

Test

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Can we address these issues to improve yield estimation model?

Yield Model Improvement

1.2 Plot Row Length Covariate

Test

Experiment Setup: Sixty genotypes, 4-row plots, center two row for yield, RCBD

Model 1: Yield = Genotype + Block + error Model 2: Yield = Genotype + Block + Row_Length + error

Model	Residual mean square	Genotypic variance	Standard error for genotype mean			H2	AIC
Model 1	78081	56385		238		0.33	895
Model 2	69919	52821		220		0.35	872

Discussion

1.2 Plot Row Length Covariate

Test

- Supervised classification model provided the information about canopy geometric features in the soybean growing season from HTP image data.
- Canopy size and plot row length highly correlate with yield up to *r* =0.82 and the correlation varied by populations.
- Traditional yield estimation model was improved by incorporating plot row length as covariate.

Objectives

- Measure the canopy geometric features and test the significance of plot row length as covariate in yield estimation.
- Develop the machine learning model for binary maturity classification using multispectral (NIR/R/G/B) data.

Image Selection

2 Development Maturity Prediction



Model Development

2 Development Maturity Prediction

Model

Multispectral information was extracted and averaged from the whole plot and center rows spatial polygons on normalized images.

Maturity Date	Image Date	Matured Plots
9/20	9/19	2
9/22, 9/24	9/23	13
9/26	9/26	24
9/28,9/30	9/30	525
10/2, 10/4, 10/6	10/6	901

Random Forest Model:

Maturity (yes/no) ~ NIR + R + G + B

Model Accuracy

2 Development Maturity Prediction

Model

GS Trial, single row 4 ft plot, Model Development

*								
		Matured	Not matured	Row total	User accuracy (%)			
	Matured	824	263	1087	75.80			
Predicted data	Not matured	255	6109	6364	95.99			
* NS in ac	Column total curacy between mod Producer accuracy (%)	1079 lels built on ce 76.37	6372 nter rows and 95.87	overall plot				
NAM Trial, four-row 12 ft plot, Model Validation								
		Matured	Not matured	Row total	User accuracy (%)			
	Matured	125	64	189	66.14			
Predicted data	Not matured	11	1000	1011	98.91			
	Column total	136	1064					
	Producer accuracy	Q1 Q1	03 08					

Model Validation

2 Development Maturity Prediction

Model



Discussion

2 Development Maturity Prediction

Model

- Binary random forest model achieved over 93% overall accuracy to predict soybean maturity from time-course HTP multispectral image data.
- The prediction ability of models developed from plot center rows data is not significantly different from the one from overall plot data.
- Blue and NIR bands are critical to make the soybean maturity prediction.
- The maturity prediction model retained similar high accuracy in an independent breeding trial with different plot type.

Final Thoughts (Opportunity)

- Data collected HTP platform could improve yield estimation accuracy, maturity recording efficiency, and enable yield prediction.
- Dynamic information during crop growing season would increase the scope of yield prediction.
- Convenience and throughput enable more applications in other field crop research.

Final Thoughts (Challenge)

- Stable platform and robust sensors are demanded for complicated experiments
- Weather / location limitation for UAV
- Compatible precision agriculture
- Multi-disciplinary collaboration (Crop Sciences, Engineering, GIS, Statistics, Computer Science)

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