Predicting Yield Contributing Physiological Parameters of Cotton using UAV-based Imagery

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Introduction

YIELD = IPAR × RUE × HI (Monteith, 1972)

• IPAR = Intercepted Photosynthetically Active Radiation (MJ m⁻²)
• RUE = Radiation Use Efficiency (g MJ⁻¹)
• HI = Harvest Index

• Yield improvement and decline can be attributed to alterations in any or all of the aforementioned physiological parameters.
• Nitrogen (N) is one of the most important yield-governing factors that influences cotton growth and development.
• It is important to understand the response of underlying physiological parameters (IPAR, RUE, and HI) to yield-altering N application rates.
• However, traditional methods of measuring these physiological parameters are time and labor intensive, and require destructive sampling.

Hypotheses

• UAV-based multispectral imagery can be utilized to predict in-season physiological parameters in cotton.

Objectives

• To develop and validate models to estimate fraction of IPAR and RUE throughout the season.

Materials and Methods

Location: Lang Rigdon Farm, University of Georgia, Tifton, GA

Cultivar: DP 1646 B2XF

Nitrogen treatments for variability: 0, 44, 89, 134, and 179 Kg N ha⁻¹

Measurements and Timeline: 2021 and 2022 growing seasons

<table>
<thead>
<tr>
<th>Planting Date</th>
<th>Harvest Date</th>
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<tbody>
<tr>
<td>06/01/2021</td>
<td>09/21/2022</td>
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<tr>
<td>04/26/2022</td>
<td>10/22/2022</td>
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UAV Imagery

1. UAV Imagery

a. RGB imagery
b. Multispectral bands: Red, Green, Blue, NIR, Rededge

2. Physiological measurements

Growing Degree Days (GDDs)= \[ \sum_{i=1}^{n} \frac{[\text{Daily avg. Temp.} - \text{base Temp.}]}{\text{C}} \]

where \( i \) signifies first day of planting and \( n \) each sampling date.

Fraction of IPAR (IPARf)\% = \[ \text{PAR above} - \text{PAR below} \]

RUE (g MJ⁻¹) = \[ (\text{Dry biomass} - \text{Dry biomass}) / (\text{Cumulative IPAR - Cumulative IPAR}) \]

IPARf = \[ (\text{NDVI} × 0.364 + 0.0287) \]

RUE = \[ (\text{MSAVI} × 0.04) - 0.8] \]

NDVI = \[ (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \]

MSAVI = \[ [(2 \times \text{NIR} + 1) / (\text{NIR} + 2)] - [(2 \times \text{NIR} - 1) / (\text{NIR} - 2)] \]

SAVI = \[ (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \]

R VI, OSAVI, SAVI = \[ (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \]

Figure 5: Graphs illustrating evolving linear relationship between IPAR, and biomass for few selected VIs at different growing degree days (GDDs). Different colors and symbols represent different GDDs. Solid lines represent linear regression functions.

Table 1: Nomenclature and Formula for the best performing VIs

<table>
<thead>
<tr>
<th>VIs</th>
<th>Abbreviations</th>
<th>Formula</th>
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<tbody>
<tr>
<td>RVI</td>
<td>Ratio Vegetation Index</td>
<td>NIR/R</td>
</tr>
<tr>
<td>RECI</td>
<td>Red-edge Chlorophyll Index</td>
<td>(NIR/RE)⁻¹</td>
</tr>
<tr>
<td>NDRE</td>
<td>Normalized Difference Red-edge Index</td>
<td>(NIR/RE)/(NIR+RE)</td>
</tr>
<tr>
<td>SCCCI</td>
<td>Simplified Canopy Chlorophyll Content Index</td>
<td>NIRD/NDVI</td>
</tr>
<tr>
<td>MSavi</td>
<td>Modified Soil Adjusted Vegetation Index</td>
<td>[(2NIR+1)/(2NIR+1/2)-0.8(NIR-R)]/2</td>
</tr>
<tr>
<td>OSAVI</td>
<td>Optimized Soil Adjusted Vegetation Index</td>
<td>(1+0.16)(NIR–R)/(NIR+R+0.16)</td>
</tr>
<tr>
<td>SAVI</td>
<td>Soil Adjusted Vegetation Index</td>
<td>(1+0.5)(NIR–R)/(NIR+R+0.5)</td>
</tr>
<tr>
<td>NIR/G</td>
<td>Near-infrared to Green Ratio</td>
<td>NIRD/NDVI</td>
</tr>
<tr>
<td>EVI2</td>
<td>Enhanced Vegetation Index</td>
<td>[(NIR-RED)/(NIR+RED)]</td>
</tr>
<tr>
<td>MSAVI</td>
<td>Multi-spectral Vegetation Index</td>
<td>[(2NIR+1)/(2NIR+1/2)-0.8(NIR-R)]/2</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
<td>(NIR–RED)/(NIR+RED)</td>
</tr>
<tr>
<td>SAVI</td>
<td>Soil Adjusted Vegetation Index</td>
<td>(1+0.5)(NIR–R)/(NIR+R+0.5)</td>
</tr>
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</table>

Figure 6: Predicted versus measured fit for the four models that performed the best in predicting (I) IPAR, (II) Biomass, and (III) RUE. Blue circles represent the training data, and red triangles represent the validation data. The diagonal line is a reference line with a slope equal to 1. RMSE and RMSEcv represent the coefficient of determination and root mean square sum error, respectively for cross-validation.

Conclusions

• IPAR -
  - Models based on RVI, RECI, NDRE, and SCCCI in integration with GDD were able to predict 93% of variation in IPAR.
  - RUE -
  - Average RECI, NIR/G, NDRE, and SCCCI were moderately related (R² = 0.40) with RUE.
  - Mechanistic model to predict RUE with actual biomass and RVI-based IPAR estimates had higher R² value (0.84).
  - Biomass -
  - Models based on MSAVI, OSAVI, RVI, and SAVI in integration with GDD explained 83–84% of variation in biomass.

Acknowledgements

References