



Utilizing UAV-based RGB and Multispectral Imagery to Predict Yield- Contributing Physiological Parameters of Cotton

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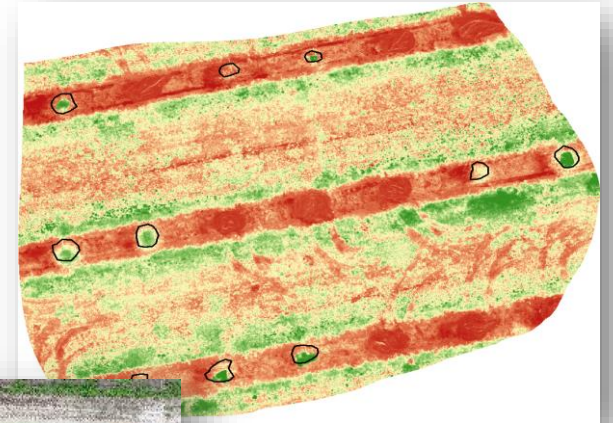
October 29-November 1 | St. Louis, MO



Remote Sensing

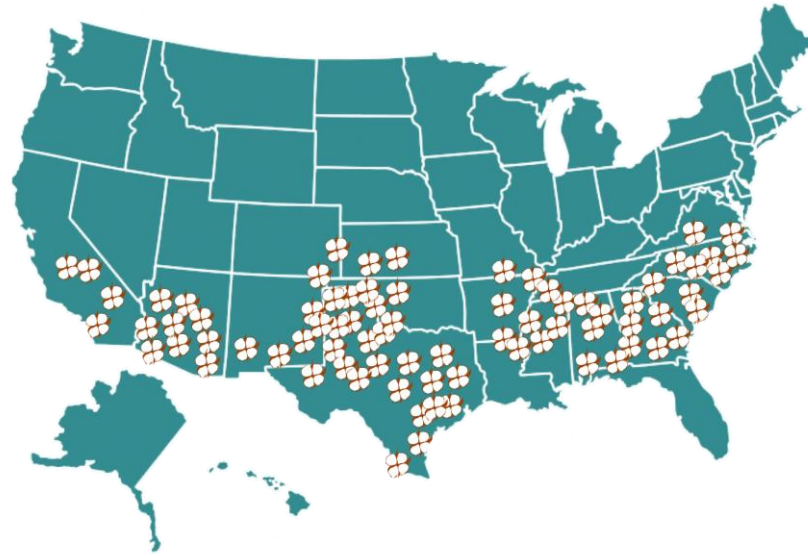
Unmanned Aerial Systems (UAS)
application in agriculture:

- ⌘ Mapping field variability
- ⌘ Crop species classification
- ⌘ Growth monitoring
- ⌘ Stress detection
- ⌘ Crop phenotyping
- ⌘ Yield prediction



Importance of Cotton

- Cotton has global importance as a commercial crop and substantial contribution to clothing and textile industry.



- Among top 3 cotton-producing countries
- Contribute 35% of global cotton export (USDA 2021)

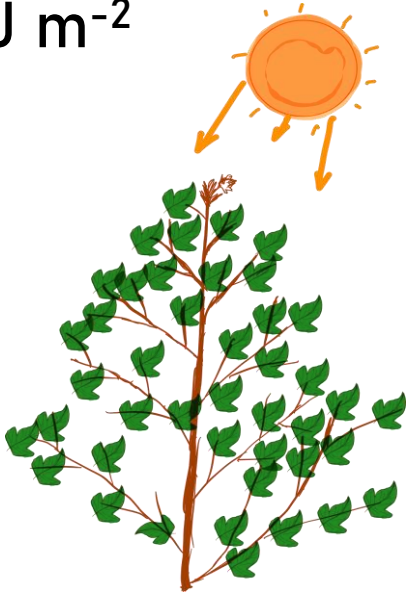
Yield Function

$$\text{Yield} = \text{IPAR} \times \text{RUE} \times \text{HI} \quad (\text{Monteith, 1972})$$

IPAR

⌘ Intercepted
Photosynthetically Active
Radiation

⌘ MJ m^{-2}



RUE

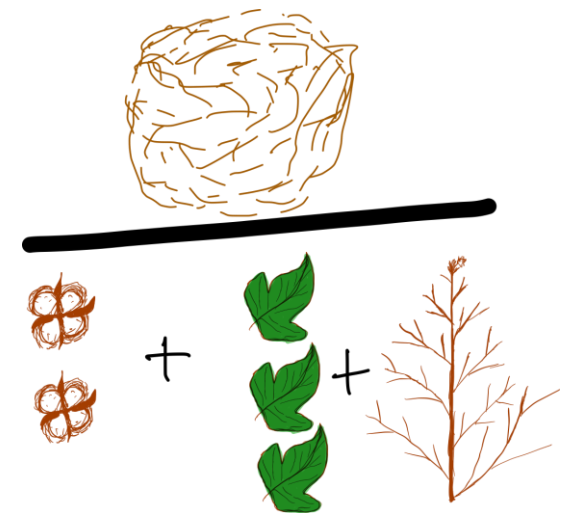
⌘ Radiation Use
Efficiency

⌘ g MJ^{-1}



HI

⌘ Harvest
Index



Hypothesis

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

Objectives

- ⌘ To develop and validate models to estimate $IPAR_f$, RUE, and HI throughout the season
- ⌘ To estimate cotton lint yield using cotton fiber index (CFI)
- ⌘ To investigate the potential of biomass and lint yield estimates to predict cotton harvest index (HI)

Experimental Layout

Study Year:

⌘ 2021, 2022

Cultivar:

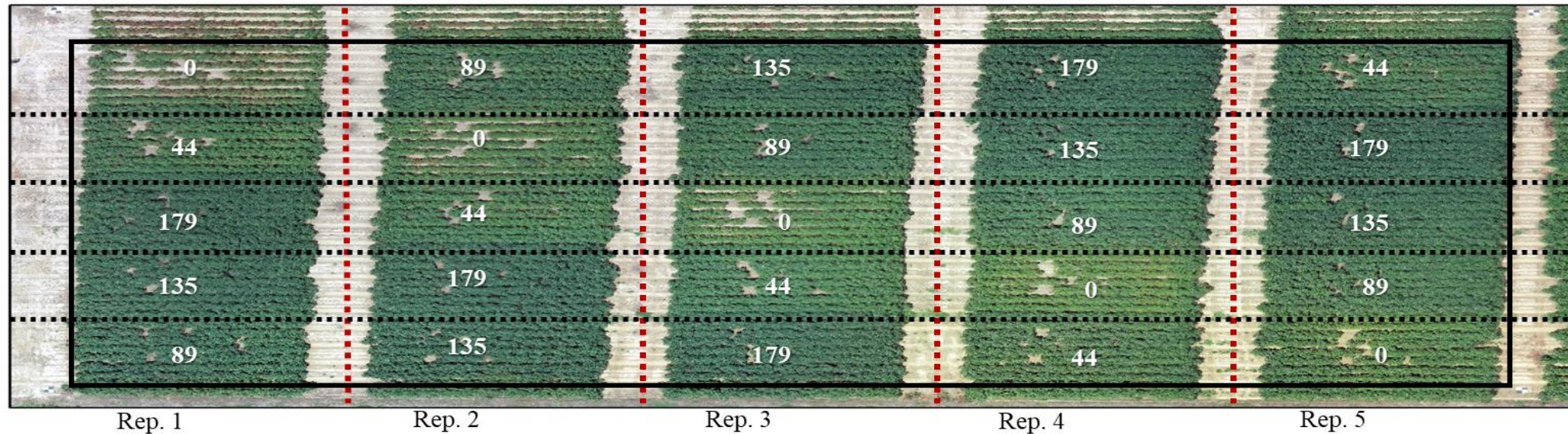
⌘ DP 1646

Nitrogen Treatments:

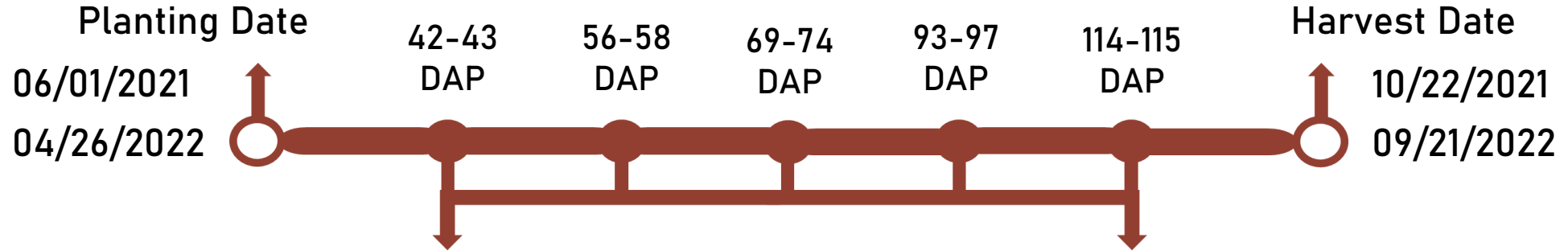
- ⌘ 0 kg N ha⁻¹
- ⌘ 44 kg N ha⁻¹
- ⌘ 89 kg N ha⁻¹
- ⌘ 134 kg N ha⁻¹
- ⌘ 179 kg N ha⁻¹

Design:

- ⌘ RCBD
- ⌘ 5 replications
- ⌘ 6 and 8 row plots



Measurements

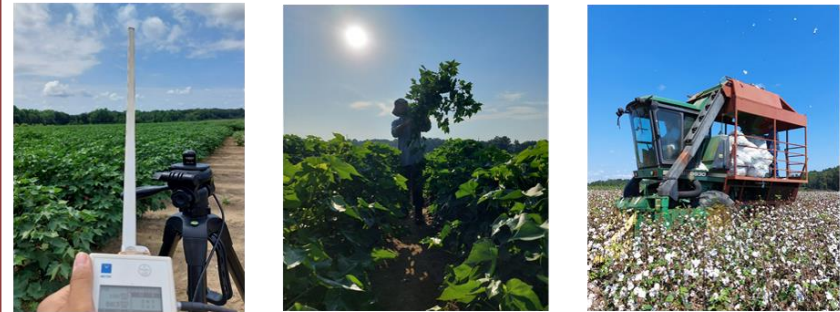


1. UAV Imagery



- Multispectral imagery using MicaSense RedEdge-MX™ Camera on DJI Inspire 2
- RGB imagery using DJI Phantom 4 Pro V2.0

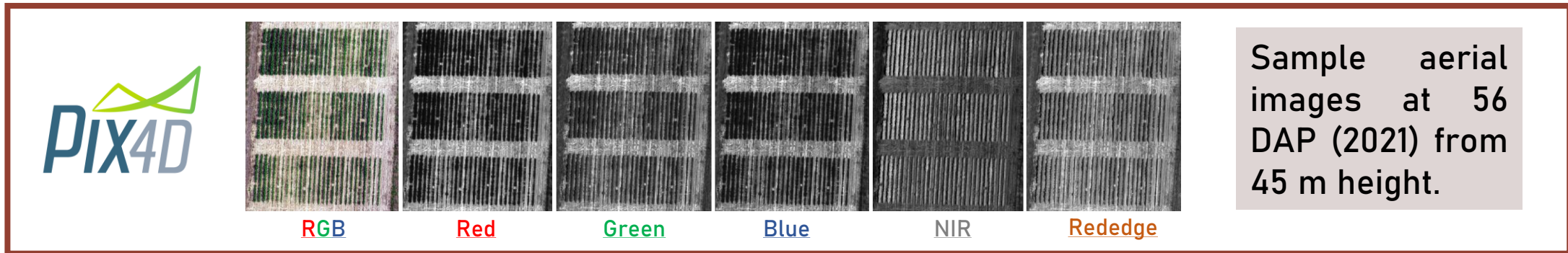
2. Physiological measurements



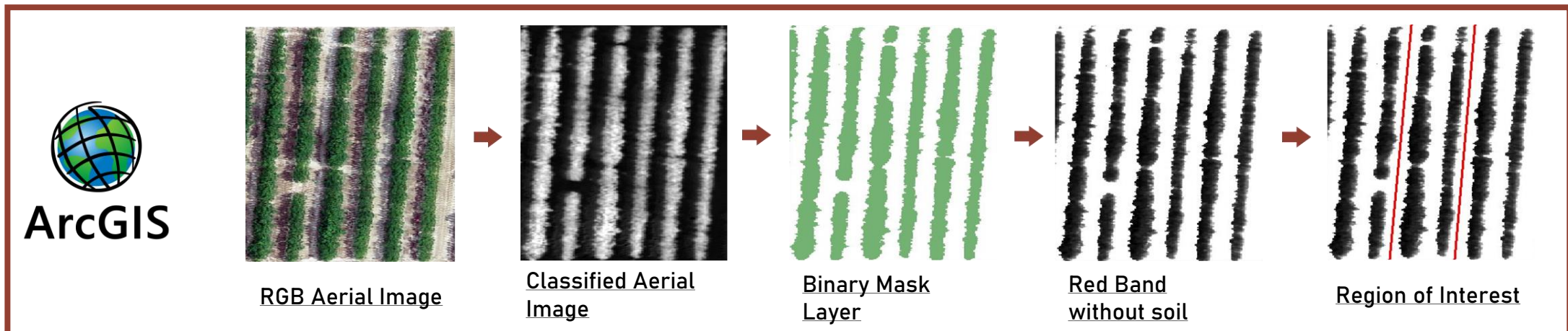
- Growing degree days and $IPAR_f$
- Above-ground biomass
- RUE
- Lint yield (Machine harvested) and HI

Image Processing and Analysis

- Image Processing: Pix4D[®] software was used to obtain mosaic images combining imagery for each sample date.



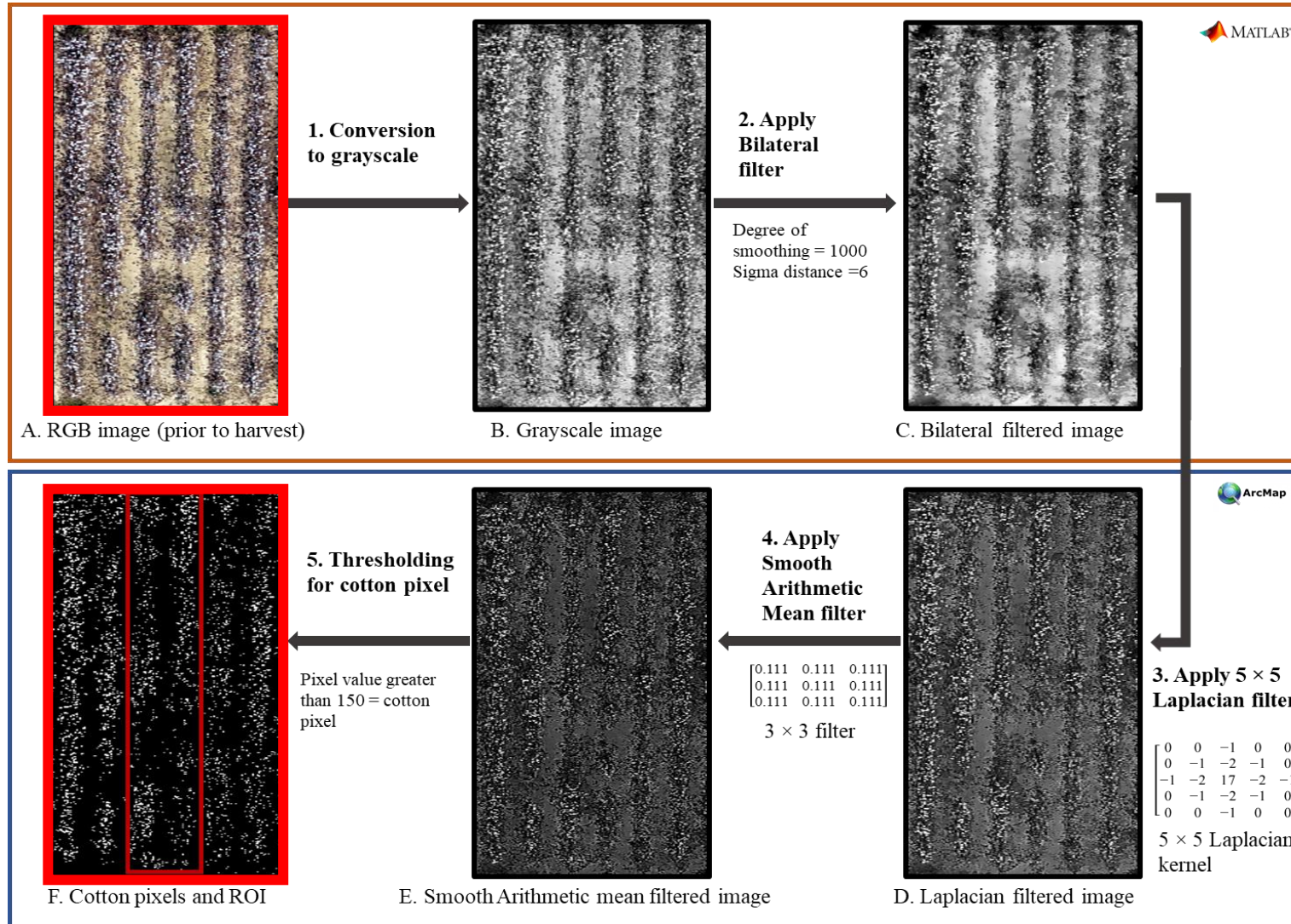
- Imagery Analysis: Arc Map 10.7.1[®] was used to extract reflectance index for vegetation indices (VI's) computation.



Vegetation Indices (20 total)

Abbreviated VI's	Nomenclature	Formula
ExG	Excessive Greenness	$2 \times G - R - B$
NDVI	Normalized Difference Vegetation Index	$\frac{NIR - R}{NIR + R}$
ExG*NDVI	ExG multiplied by NDVI (Classification Index)	$(2 \times G - R - B) \left(\frac{NIR - R}{NIR + R} \right)$
GNDVI	Green Normalized Difference Vegetation Index	$\frac{NIR - G}{NIR + G}$
NDRE	Normalized Difference Red Edge Index	$\frac{NIR - RE}{NIR + RE}$
RVI	Ratio Vegetation Index	$\frac{NIR}{R}$
SCCCI	Simplified Canopy Chlorophyll Content Index	$\frac{NDRE}{NDVI}$
RE/R	Red edge and Red Ratio	$\frac{RE}{R}$
GRVI	Green Ratio Vegetation Index	$\frac{NIR}{G}$

Cotton Fiber Index (CFI)



Cotton Fiber Index (Huang et al., 2016)

$$= \frac{\text{Number of white pixels in ROI}}{\text{Total number of pixels in ROI}}$$

Physiological Measurements

⌘ Growing Degree Days (GDDs) =

$$\sum_{i=1}^n \left[\frac{\text{Max. Temperature } ^\circ\text{C}_i + \text{Min. Temperature } ^\circ\text{C}_i}{2} - \text{Base Temperature } ^\circ\text{C} \right]$$

⌘ $\text{IPAR}_f = \frac{\text{PAR above} - \text{PAR below}}{\text{PAR above}}$

⌘ $\text{RUE (g MJ}^{-1}\text{)} = \frac{(\text{Dry biomass } _n - \text{Dry biomass } _1)}{(\text{Cumulative IPAR } _n - \text{Cumulative IPAR } _1)}$

⌘ $\text{HI} = \text{Lint yield} / \text{Maximum biomass}$



Model Development

⊗ $IPAR_f$ or Biomass = f (VI and GDD)

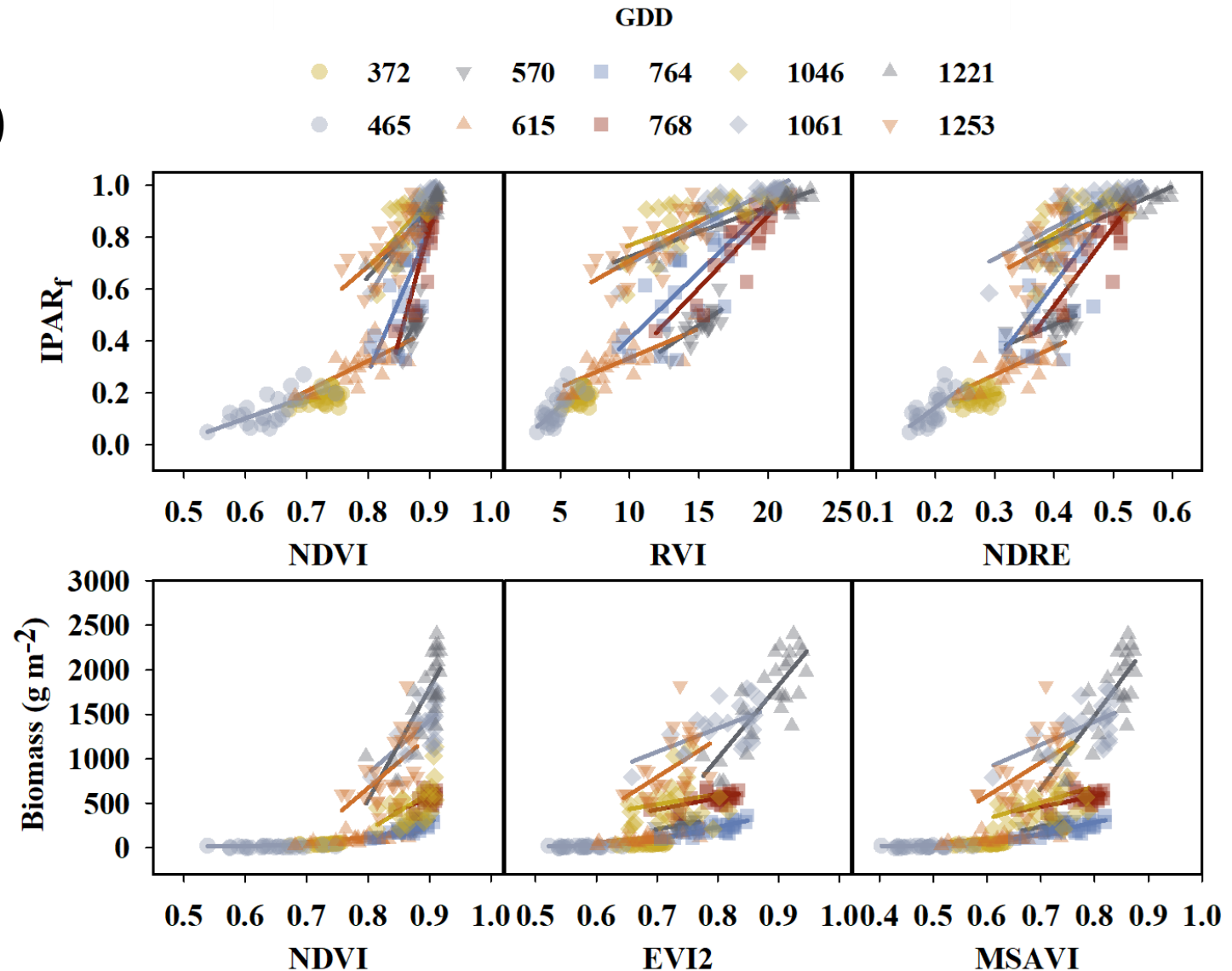
⊗ $IPAR_f$ always lies between 0 and 1

⊗ Biomass is strictly positive

⊗ $RUE = f$ (average VI)

⊗ Lint yield = f (CFI)

⊗ $HI = \frac{\text{CFI-based lint yield}}{\text{VI-based maximum biomass}}$



Statistical Analysis

Data Analysis:

- ⌘ Generalized Regression Models:
 - Beta regression for $IPAR_f$
 - Gamma regression for biomass
 - Standard linear regression for RUE
- ⌘ 60:40 ratio for training and independent validation dataset
- ⌘ Model Performance:
 - Generalized R^2 , AICc, and BIC for training data
- ⌘ Cross-validation: R^2 and RMSE

Software:

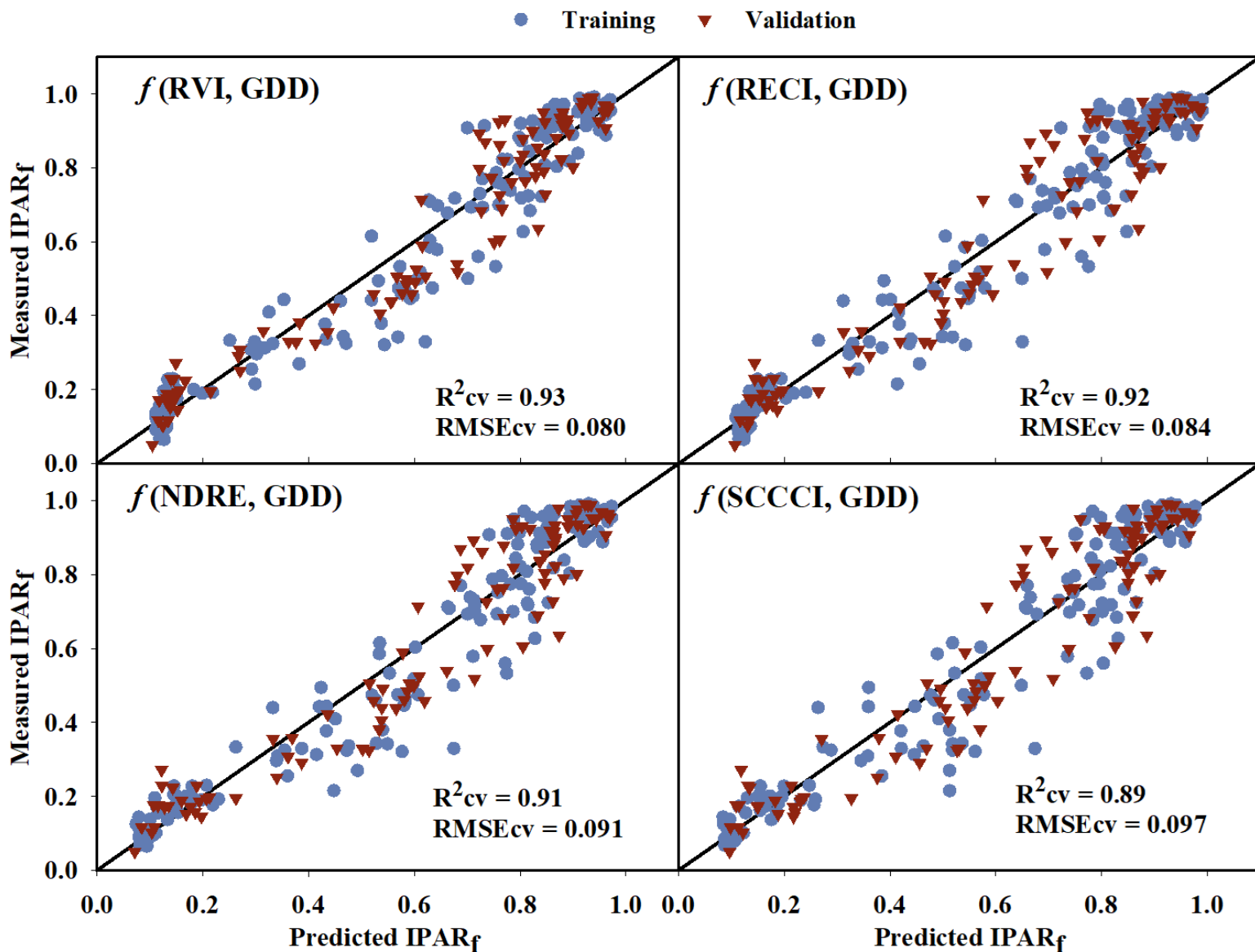
- ⌘ JMP[®] Pro 16.0.0 for training and cross-validation
- ⌘ Sigmaplot 15.0 (Systat Software Inc., San Jose, CA) for graphs





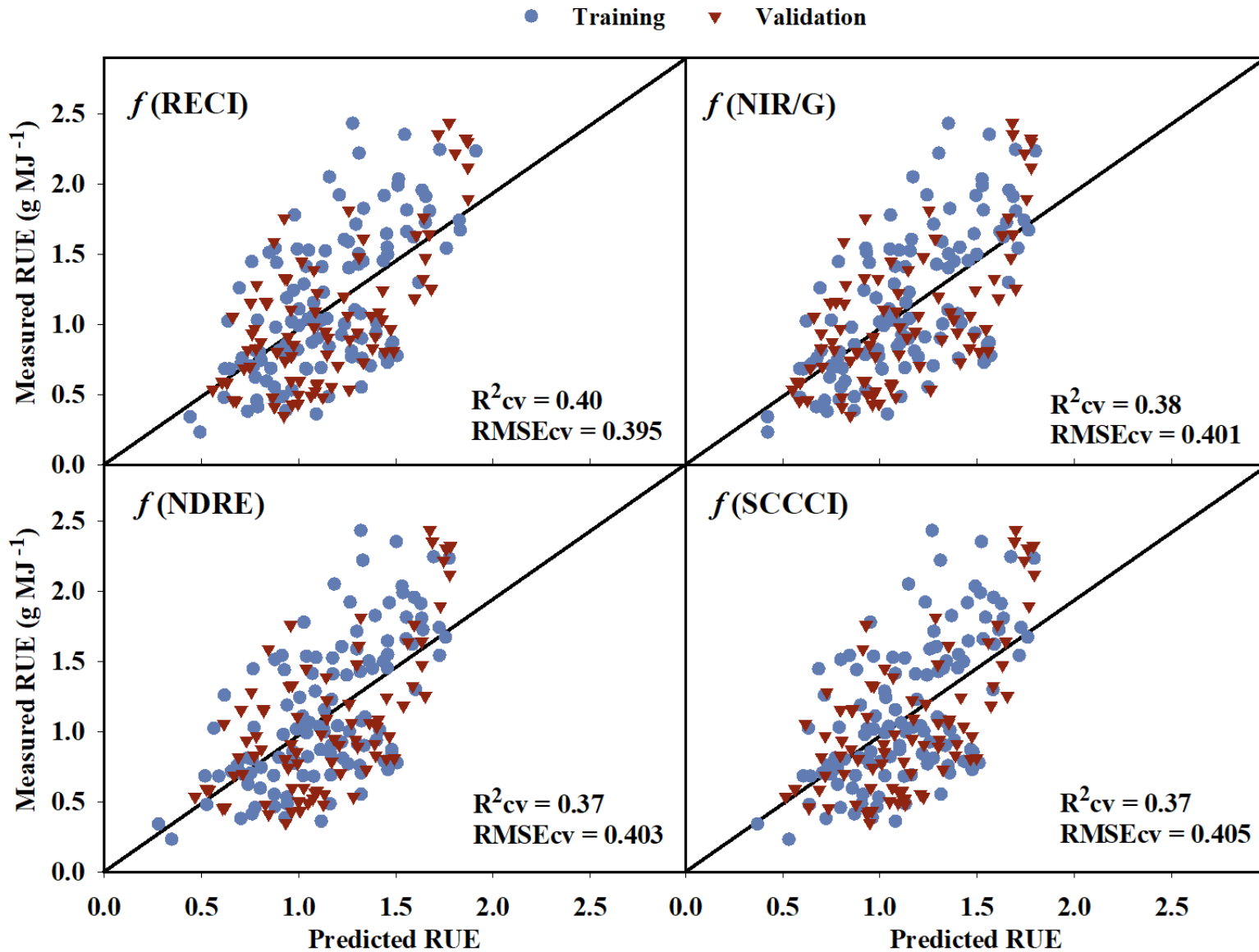
Results

Fraction of IPAR



- ⊗ Ratio Vegetation Index (RVI)
- ⊗ Red-edge Chlorophyll Index (RECI)
- ⊗ Normalized Differences Red-edge Index (NDRE)
- ⊗ Simple Canopy Chlorophyll Content Index (SCCCI)

RUE



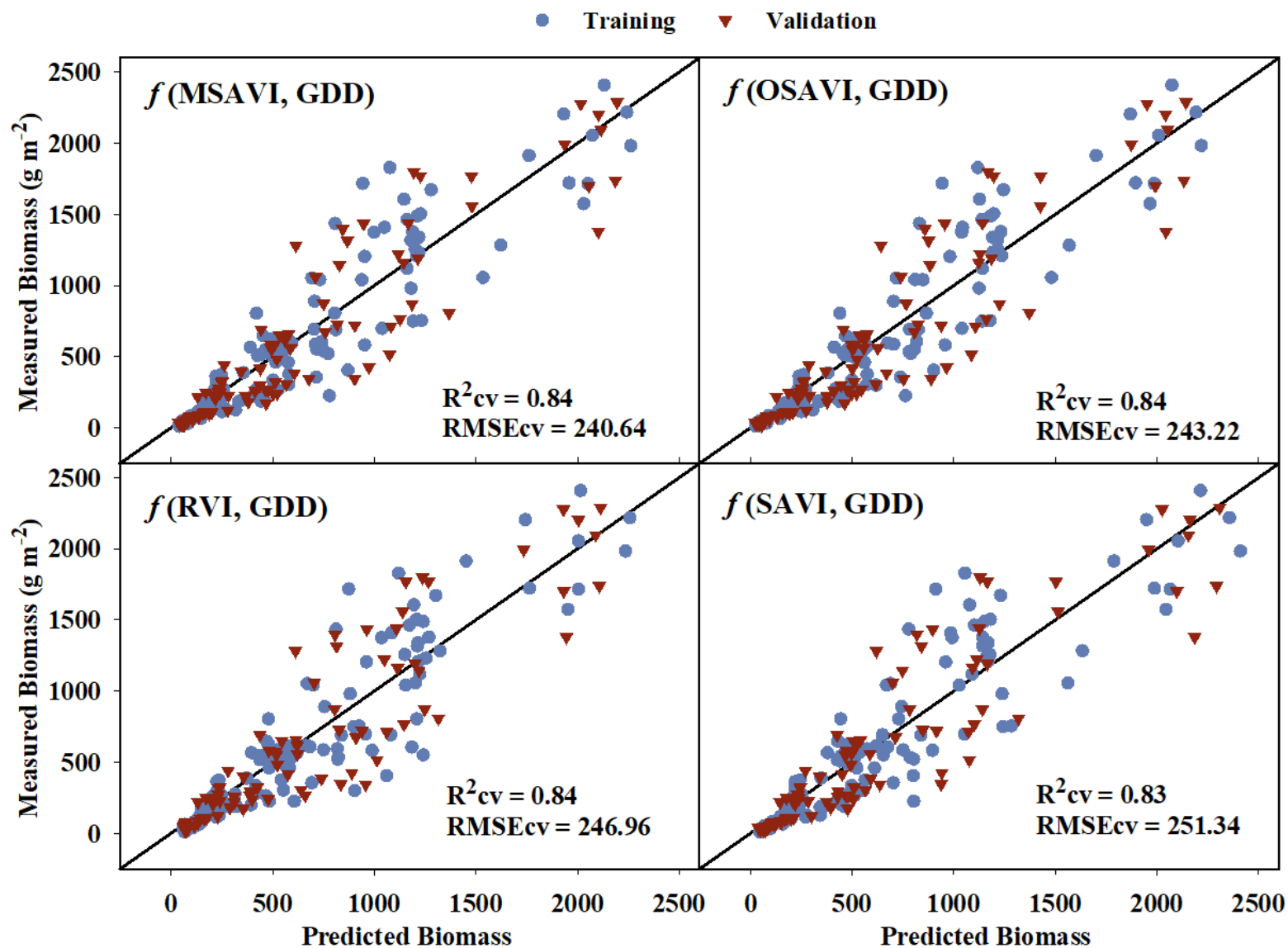
⊗ Red-edge Chlorophyll Index (RECI)

⊗ NIR to Green Ratio (NIR/G)

⊗ Normalized Differences Red-edge Index (NDRE)

⊗ Simple Canopy Chlorophyll Content Index (SCCCI)

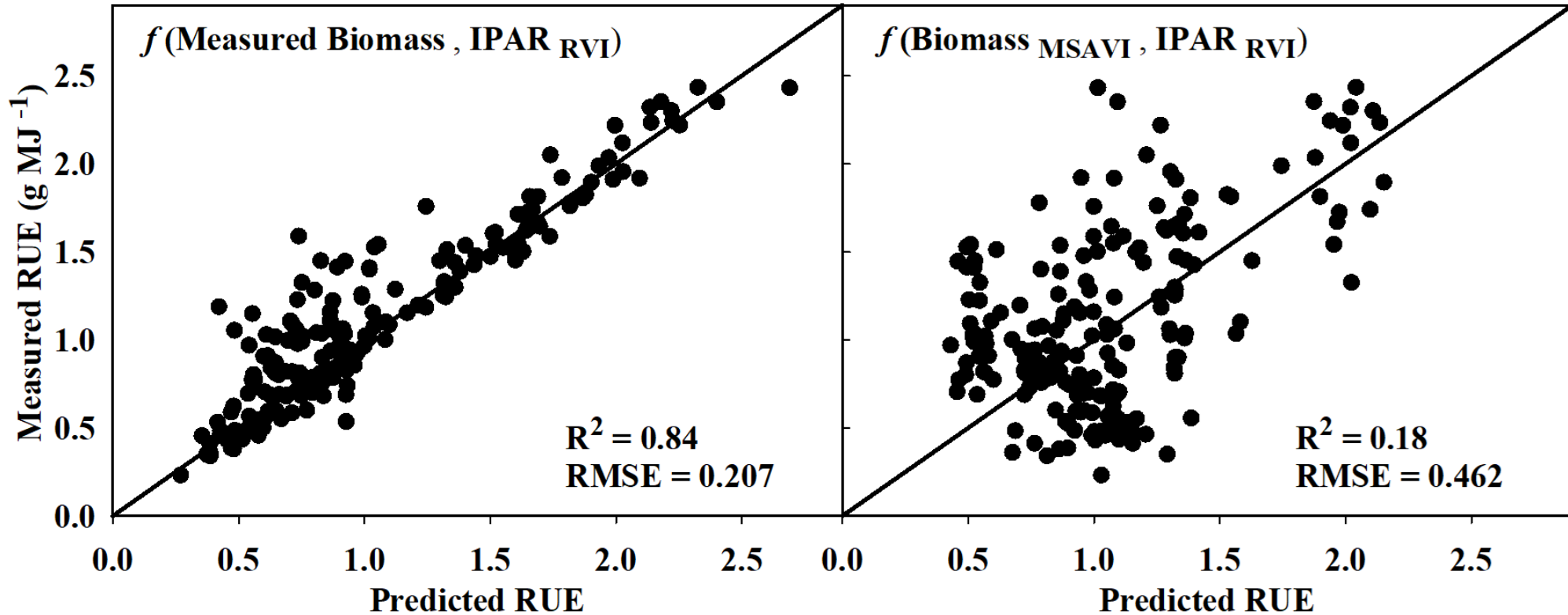
Biomass



- ⊗ Modified Soil Adjusted Vegetation Index (MSAVI)
- ⊗ Optimized Soil Adjusted Vegetation Index (OSAVI)
- ⊗ Ratio Vegetation Index (RVI)
- ⊗ Soil Adjusted Vegetation Index (SAVI)

RUE

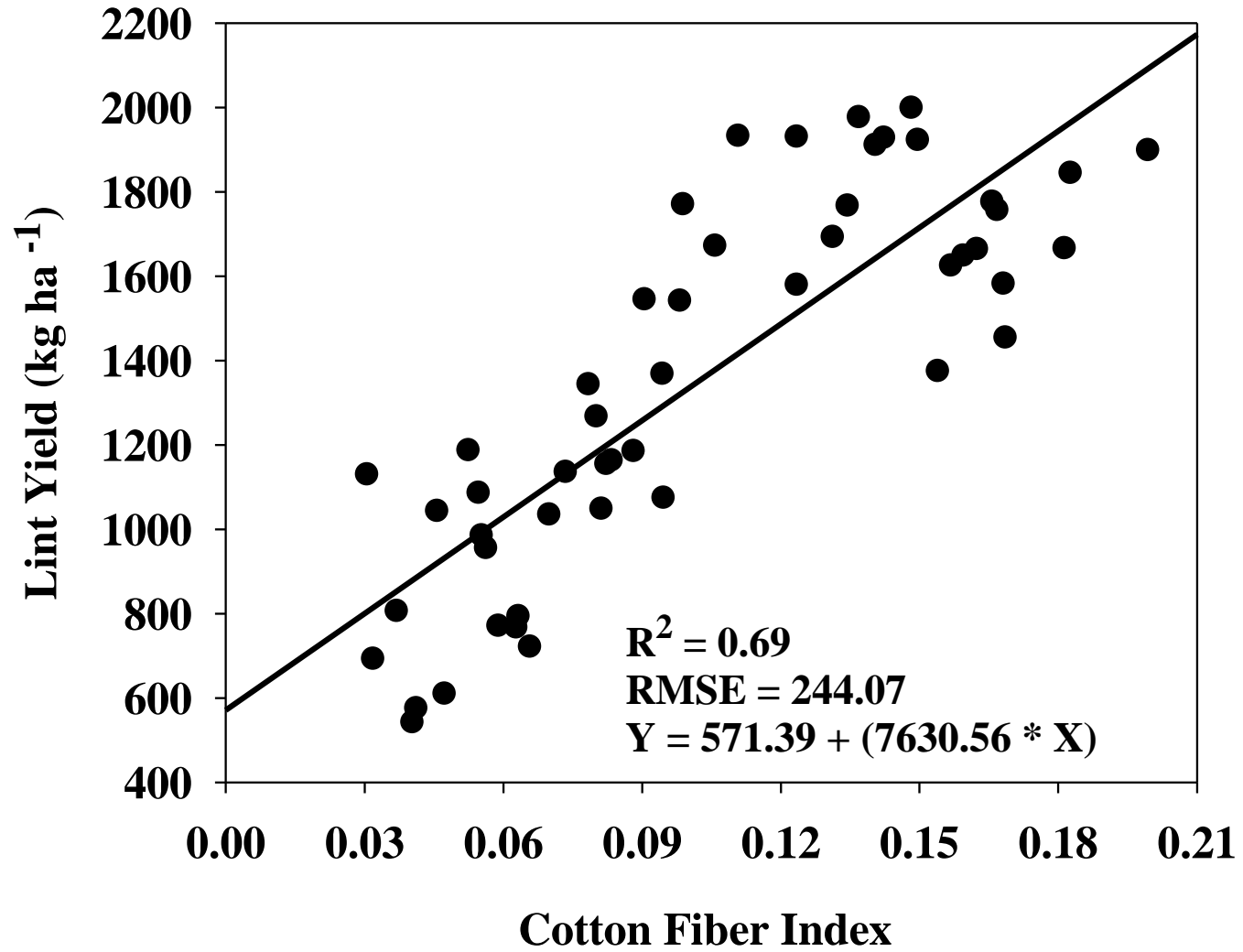
$$\text{Biomass} = \text{IPAR} \times \text{RUE}$$



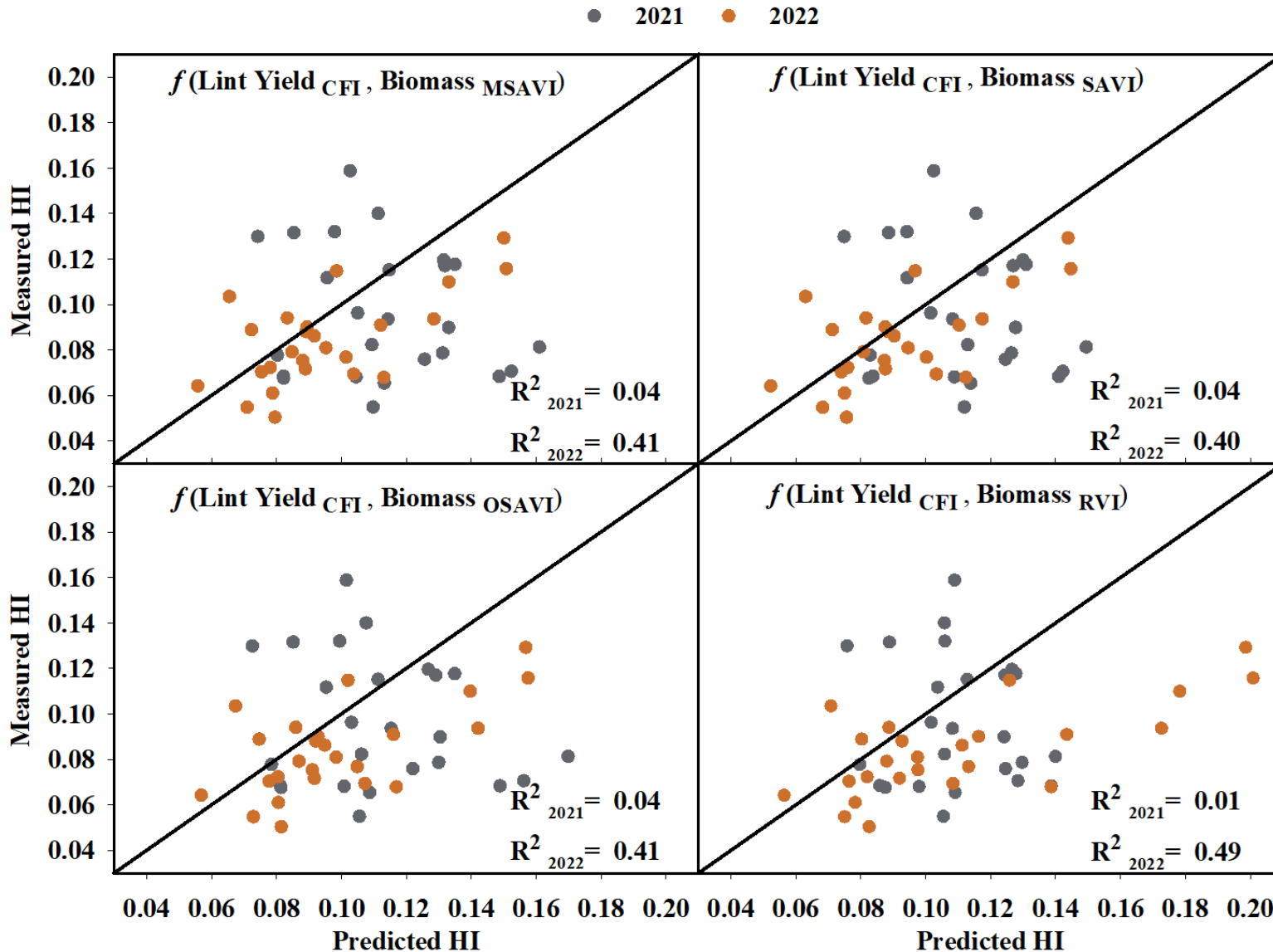
⊗ $\frac{\text{Actual biomass}}{\text{RVI-based IPAR}}$

⊗ $\frac{\text{MSAVI-based biomass}}{\text{RVI-based IPAR}}$

Lint Yield



Harvest Index



- ⊗ HI estimates = $\frac{\text{CFI-based Lint yield}}{\text{VI-based max. biomass}}$
- ⊗ Not a significant relationship for both years combined
- ⊗ Significant for 2022 growing season.

Conclusions

⌘ IPAR_f -

- RVI, RECI, NDRE, and SCCCI in integration with GDD were able to predict 94% of variation in IPAR_f.

⌘ RUE -

- Average RECI, NIR/G, NDRE, and SCCCI were moderately ($R^2 = 0.40$) related with RUE.
- Mechanistic model to predict RUE with actual biomass and RVI-based IPAR estimates had higher R^2 value (0.84).

⌘ Lint yield- Cotton Fiber Index (CFI) explained 69% of variation in lint yield.

⌘ HI -

- Prediction of HI is possible with more accurate estimation of lint yield and above-ground biomass.

Applications, Limitations, and Future research

⌘ Applications -

- Agronomic decision making to prevent significant yield loss during limited nitrogen and excessive irrigation circumstances.
- High-throughput phenotyping of cotton genotypes for yield determining physiological parameters.

⌘ Limitations -

- Single cotton cultivar and data within GDD range of 372 to 1253 GDD.
- Flight height from 45m may not fully capture cotton bolls present in middle section of canopy.

⌘ Future research -

- Inclusion of training data from different cotton cultivars across multiple production environment.
- Investigate the influence of flight height and sensor resolution for accurate estimation in cotton lint yield.

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UGA Digital Ag

THANK YOU!!

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Estimating yield-contributing physiological parameters of cotton using UAV-based imagery

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FULL ARTICLE

