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

UNIVERSITY OF GEORGIA

Amrit Pokhrel, Simerjeet Virk, John L Snider, George Vellidis, Ved Parkash*

Department of Crop and Soil Science, College of Agriculture and Environmental Sciences, University of Georgia Tifton Campus, 2360 Rainwater Road, Tifton, GA 31793

**Email: amritpokhrel@uga.edu*

LinkedIn: Amrit Pokhrel

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 there 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 andRUE throughout the season.

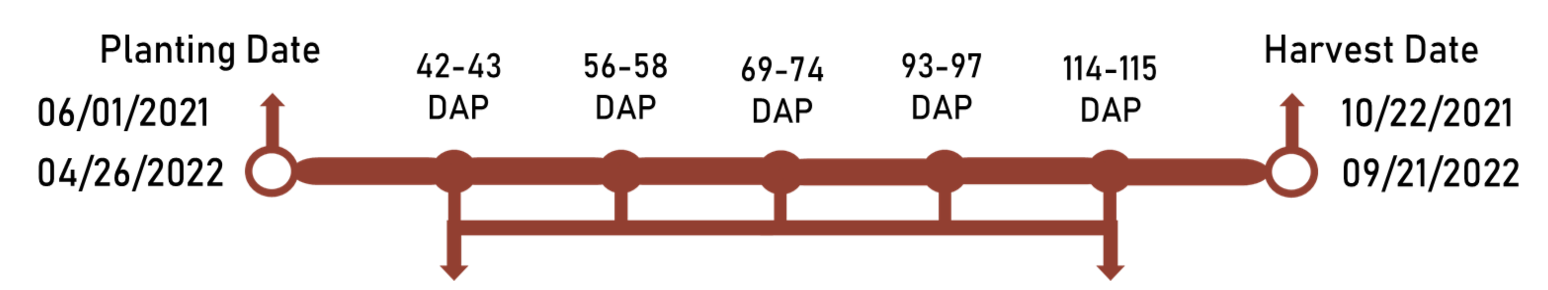
Materials and Methods

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



1. UAV Imagery

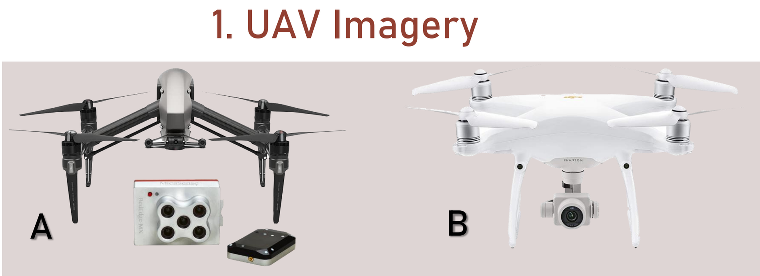


Figure 1: Images showing two UAVs used for imagery collection: Multispectral imagery using DJI Inspire 2 and MicaSense Rededge Camera (A), RGB imagery using DJI Phantom 4 Pro V2.0 (B)

2. Physiological measurements

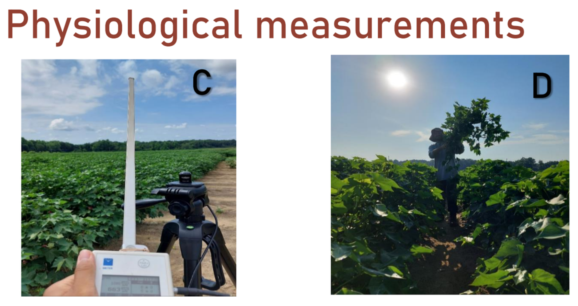


Figure 2: Images showing instruments used for physiological measurement: Light interception (C), Biomass collection(D)

Image Processing Obtained mosaic images combining imagery for each sample date.

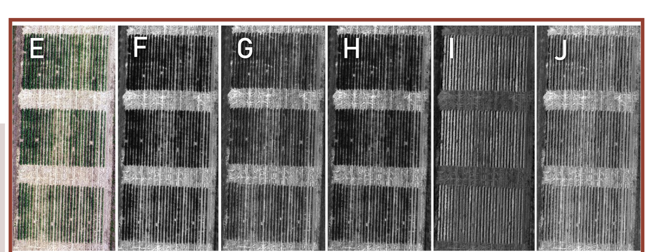


Figure 3: Images showing sample aerial image at 56 DAP from 45 m height. RGB imagery (E), Multispectral Bands: Red (F), Green (G), Blue (H), NIR (I), Rededge (J).

Image Analysis Extractes reflectance index value to calculate vegetation indices (VI's).

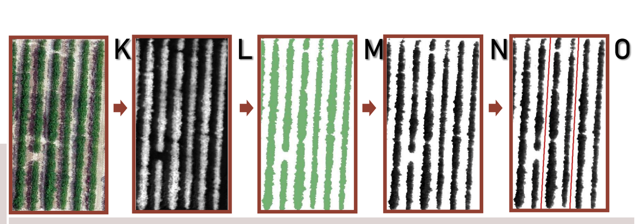


Figure 4: RGB aerial image of cotton rows (K), Classified aerial image for soil and plant using ExG*NDVI index (L), Binary mask layer (M), Red reflectance index with soil removed (N), Multispectral band's reflectance index extracted from middle two row (O)

Physiological measurements:

- Growing Degree Days (GDDs)= $\sum_{i=1}^{n}$[Daily avg. Temp.°C$_i$ – Base Temp. °C]

where *i =1* signifies first day of planting and *n* is each sampling date.

- Fraction of IPAR ($IPAR_f$)= $\dfrac{\text{PAR above} - \text{PAR below}}{\text{PAR above}}$

- RUE (g MJ^{-1}) =

$$\frac{(\text{Dry biomass}_{n} - \text{Dry biomass}_{1})}{(\text{Cumulative IPAR}_{n} - \text{Cumulative IPAR}_{1})}$$

where, dry biomass $_1$ and cumulative IPAR $_1$ are the reference measurements of the first sampling date, and *n* represents each subsequent sampling date in the season.

Vegetation Indices (VIs): 20 different VIs were calculated in Microsoft Excel using the extracted reflectance index value from ArcMap for the 5 spectral bands.

Statistical Analysis: Generalized linear regression analysis was performed, where 60% of data was used for training model and remaining 40% for cross-validation.

$IPAR_f$ or above-ground biomass = *f* (instantaneous VI and GDD)

RUE_n = *f* (average of VI within the RUE calculation period)

Models were ranked based on their AICc, and BIC values for training models and R^2cv and RMSEcv during cross validation.

Results

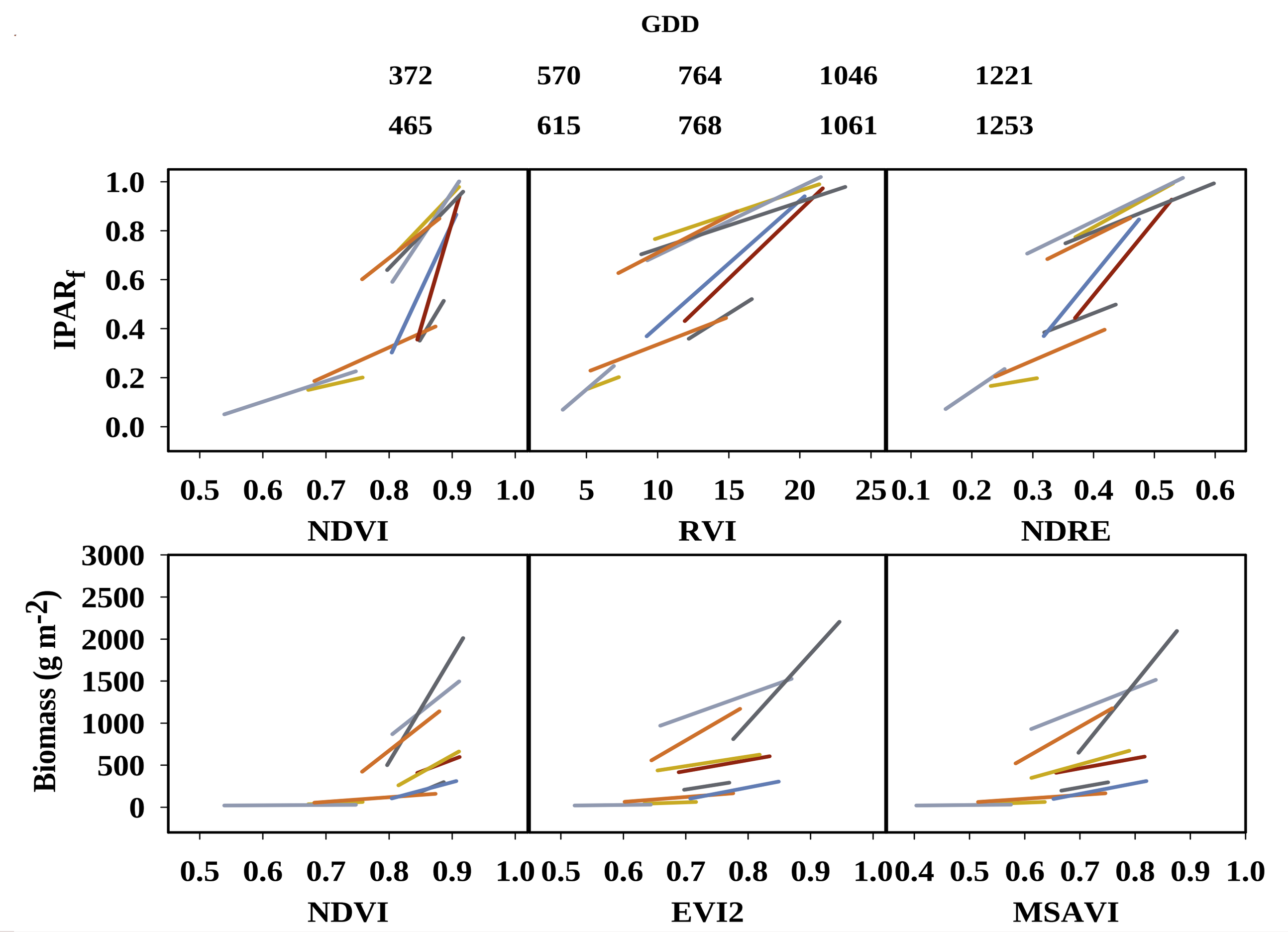


Figure 5: Graphs illustrating evolving linear relationship between $IPAR_f$ and biomass for few selected VIs at different growing degree days (GDDs). Different colors and symbols represent different GDDs. Solid lines represent linear regression functions.

Table 1: Nomenclature and Formula for the best performing VIs

VIs	Abbreviations	Formula
RVI	Ratio Vegetation Index	NIR/R
RECI	Red-edge Chlorophyll Index	(NIR/RE)-1
NDRE	Normalized Difference Red-edge Index	(NIR–RE)/(NIR+RE)
SCCCI	Simplified Canopy Chlorophyll Content Index	NDRE/NDVI
MSAVI	Modified Soil Adjusted Vegetation Index	[(2NIR+1)–√((2NIR+1)2–8(NIR–R))]/2
OSAVI	Optimized Soil Adjusted Vegetation Index	(1+0.16)[(NIR–R)/(NIR+R+0.16)]
SAVI	Soil Adjusted Vegetation Index	(1+0.5)((NIR–R)/(NIR+R+0.5))
NIR/G	Near-infrared to Green Ratio	NIR/G

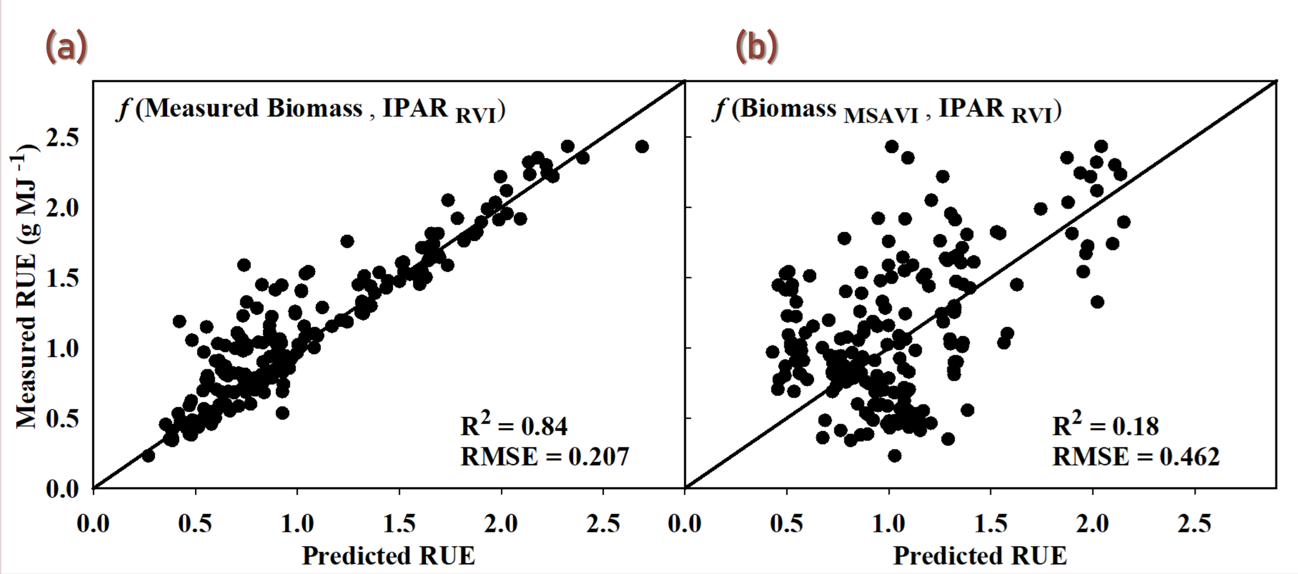


Figure 7: Predicted versus measured plot for RUE values obtained using (a) measured biomass/RVI-based IPAR model, and (b) MSAVI-based biomass model/RVI-based IPAR model. R^2 and RMSE represent the coefficient of determination and root mean sum square error. The diagonal line is a reference line with a slope equal to 1.

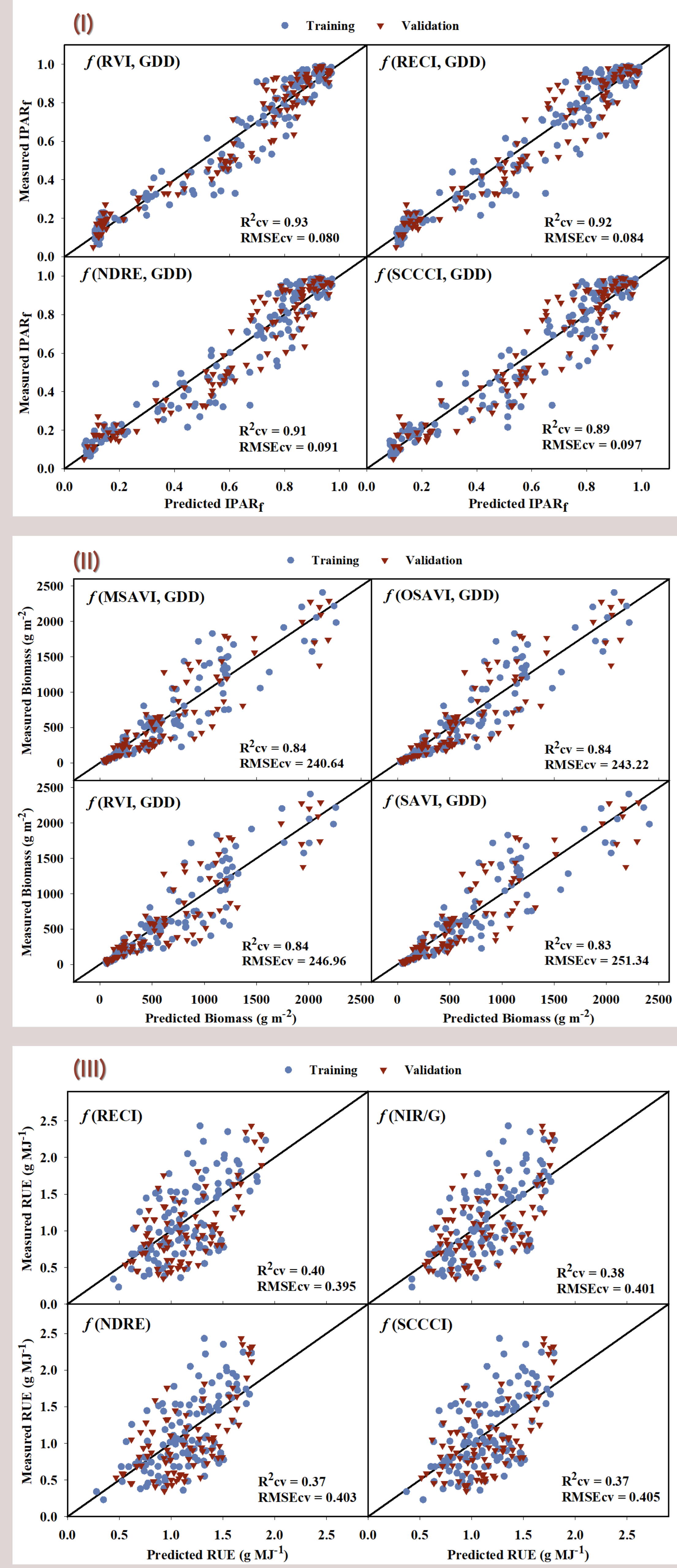


Figure 6: Predicted versus measured fit for the four models that performed the best in predicting (I) $IPAR_f$, (II) Biomass, and (III) RUE. Blue circles represent the training data, and red traingles represents the validation data. The diagonal line is a reference line with a slope equal to 1. R^2cv and RMSEcv represent the coefficient of determination and root mean sum square error, respectively for cross-validation.

Conclusions

- $IPAR_f$ -
  - Models based on RVI, RECI, NDRE, and SCCCI in integration with GDD were able to predict 93% 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).
- Biomass-
  - Models based on MSAVI, OSAVI, RVI, and SAVI in integration with GDD explained 83-84% of variation in biomass.

Acknowledgements

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References

- Monteith, J.L. 1972. Solar radiation and productivity in tropical ecosystems. J. Appl. Ecol. 9: 747–766.