Estimating Leaf Area Index of Cassava Plantation using UAV Imagery

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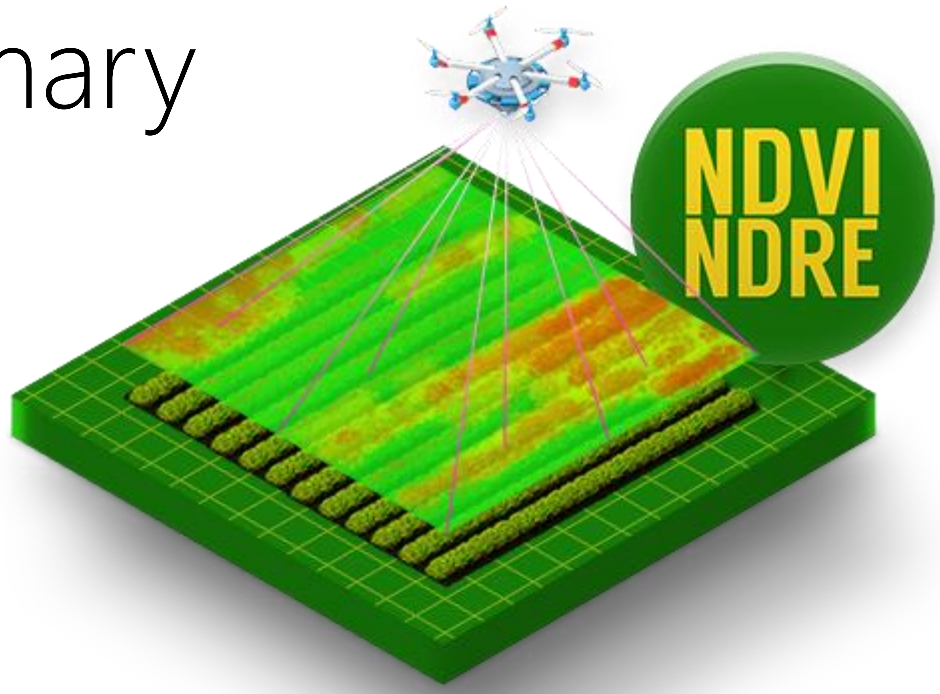
Outline

- Background
- Objectives
- Methods
- Preliminary Results
- Summary



Background

Background

- Cassava is a crucial cash crop for farmers and the planting, harvesting, processing, and export of this crop is essential to ensuring the livelihoods and employment of thousands of Cambodians. Fourth in Asia and tenth worldwide in terms of cassava production is Cambodia. (UNDP, 2021)
- In cassava, leaf area is a key indicator of crop growth rate and the storage bulking rate (Cock *et al.*, 1979).

Objectives

Objectives

The goal of this study is to use parrot sequoia pictures to generate a Leaf Area Index (LAI) layer for monitoring cassava farming in Battambang Province.

- Comparing different indices for estimating LAI from multispectral images
- Evaluating LAI estimation accuracy by using crossed validation method.

Research Methods

Case Study Location

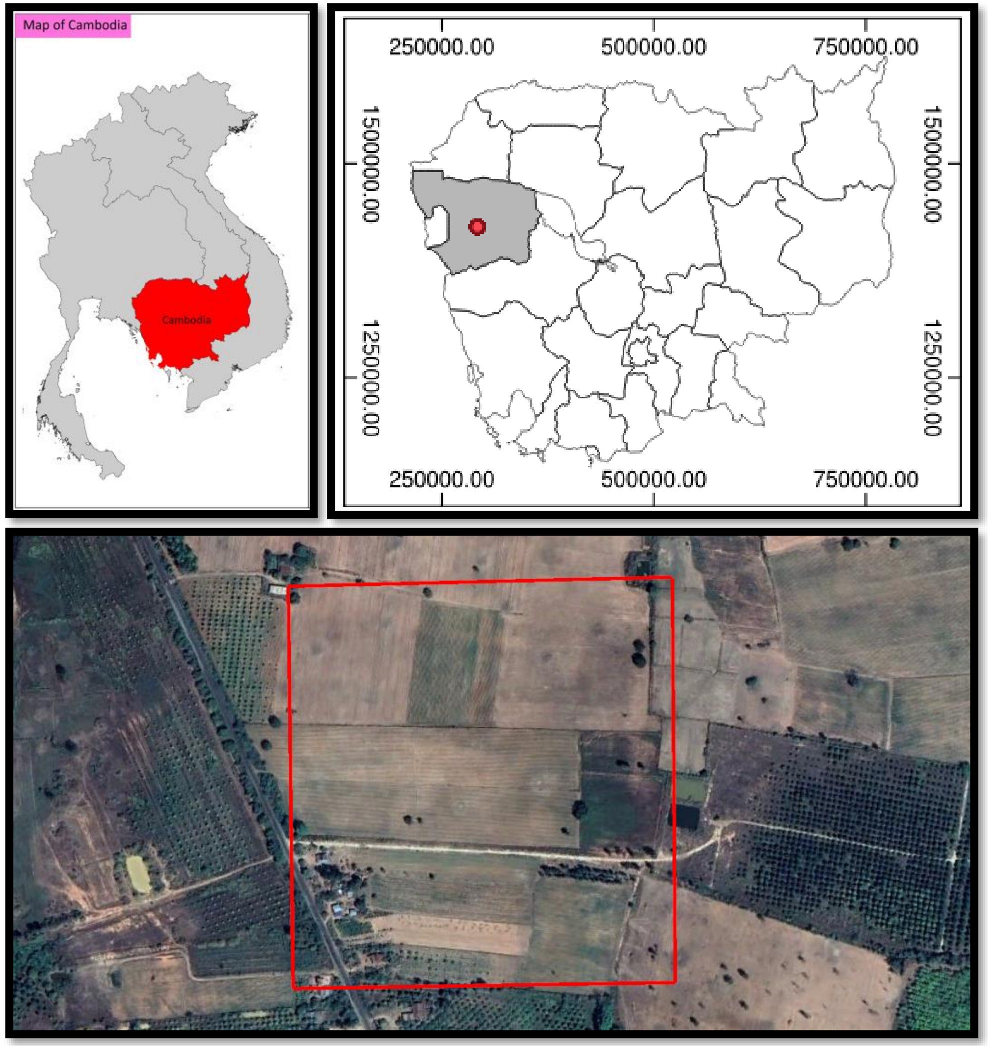


Figure 1. Selected site for the study

This study selected Battambang Province, located in northwestern Cambodia, where Battambang flourished with a diverse range of product beside rice.

In Battambang, the production of cassava was the second largest after rice (MAFF, 2023).

Aerial images collection

- Drone: DJI M100
- Software: DroneDeploy
- Plan: Grid-based in QGIS
- Altitude: 100m
- Overlap: 70%
- Calibration: Grey scale applied

Figure 2. UAV flight preparation

Figure 3. Cassava field from drone's point of views.

LAI data collection (in-situ information)

- Instrument: LAI-2200C
- Method: Row cropping, 270° cape
- Calibration: Diffuser cape applied
- Purpose: Data validation
- Data Extraction: Using FV2200 in lab to extract LAI into CSV format

Figure 4. Capture the above canopy

Figure 5. Capture the below canopy

Parrot sequoia camera

Multispectral images is collected using Parrot Sequoia which has one RGB camera and multispectral sensors;

- Green (530-570 nm)
- Red (640-680 nm)
- Red Edge Band (730-740 nm)
- Near Infrared (770-810 nm).

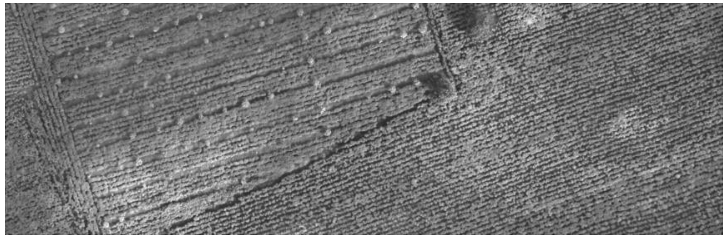


Figure 6. Green Band (530-570 nm)

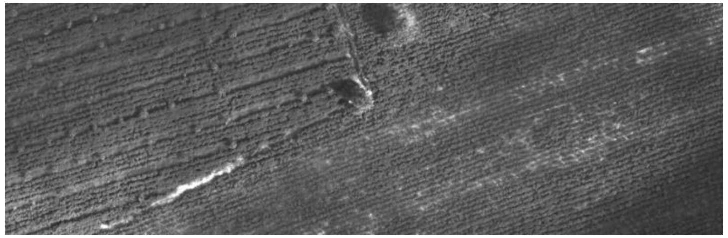


Figure 7. Red Band (640-680 nm)

Figure 8. Red Edge Band (730-740 nm)

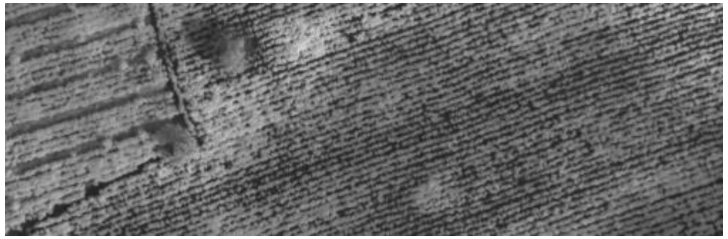


Figure 9. Near Infrared Band (770-810 nm)

Figure 10. RGB image

Aerial Image Processing Workflow

RGB Images:

- Key Points Processing
- Point Cloud Generation
- Ortho-Mosaicking to GeoTIFF Files

Multispectral Images:

- Same Workflow Plus Radiometric Calibration for Each Band

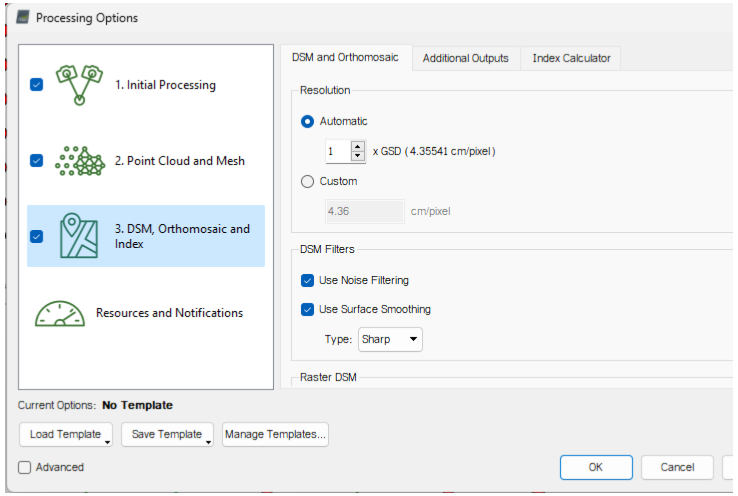


Figure 11. UAV imagery processing steps

Figure 12. Radiometric Reflectance Panel

Vegetation Indices

Table 1. Vegetation indices and its equation

Index	Formula	Source
NDVI	(NIR - Red) / (NIR + Red)	Tucker, C. J. (1979)
EVI2	2.5 * (NIR - RED) / (NIR + 2.4 * RED + 1.0)	Jiang, Z. et al. (2006)
OSAVI	1 + 0.16 * ((NIR - RED) / (NIR + RED + 0.16))	Rondeaux, G. et al. (1996)
GCI	(Green - NIR) / NIR	Gitelson, M. Y. et al. (2003)
REGCI	(Red-edge - NIR) / (Red-edge + NIR)	Woebbecke, D. E. et al. (1993) or Gitelson, M. Y. et al. (2003)

Machine Learning

- Generated five vegetation indices.
- Applied Random Forest model:
- Training: 70% in-situ LAI data.
- Validation: 30% in-situ LAI data.
- Evaluated using R-square (R^2) and RMSE.
- Goal: Enhance LAI precision and vegetation analysis accuracy.

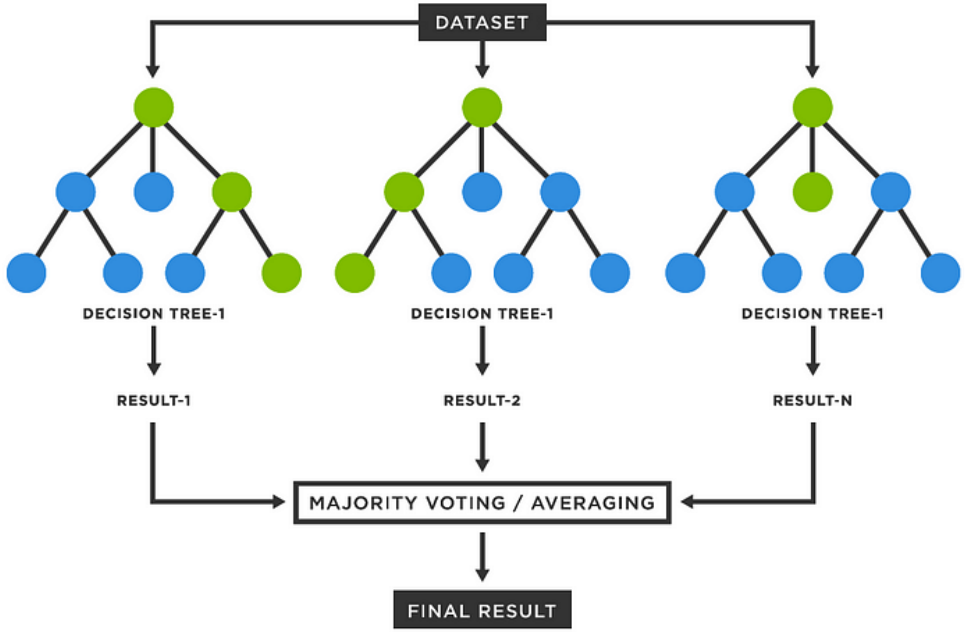


Figure 13. Random Forest Algorithm

Validation method

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (1)$$

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

(Yan *et al.*, 2022)

Where y_i and $\hat{y}_i$ are estimated, measured cassava LAI, $\bar{\mathbf{y}}$ is the average values of field LAI measured and n is the numbers of samples measured at a specific field.

Preliminary Results

Preliminary Result

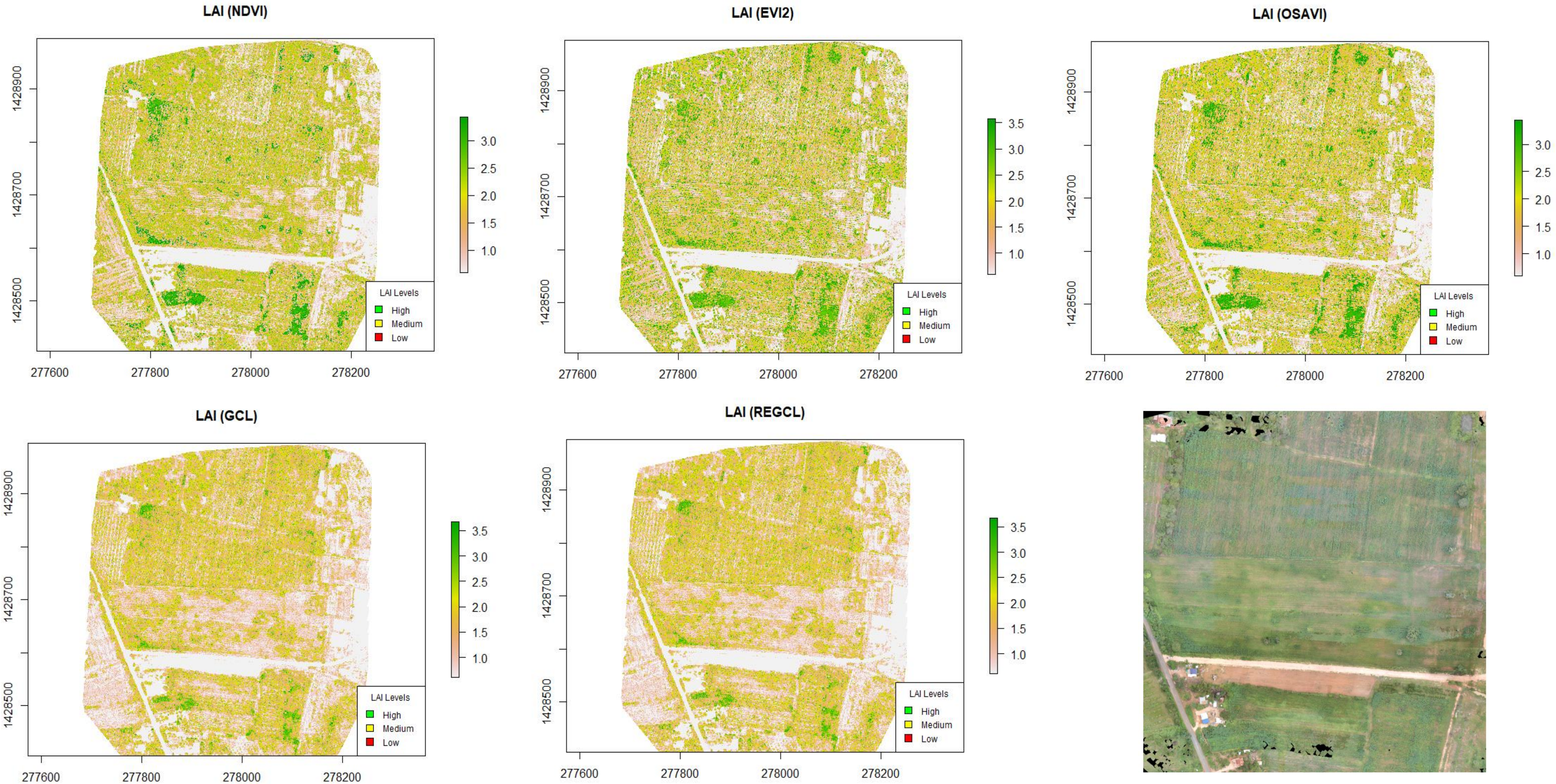


Figure 14. Estimated leaf area index Maps of every indices and a referenced RGB aerial image.

LAI Equation Result

Table 2. Leaf area index equation from 5 different vegetation indices and its effectiveness (R Square)

Indices	Regression Equation	R^2	df
NDVI	LAI = 1.0211*NDVI - 0.0847	0.55***	49
EVI2	LAI = 0.85898*EVI2 + 0.08915	0.48***	49
OSAVI	LAI = 0.94861*OSAVI + 0.01047	0.54***	49
GCI	LAI = 1.0920*GCL - 0.1427	0.65***	49
REGCI	LAI = 0.99577*REGCL - 0.01808	0.52***	49

-- Signif. codes '***' indicated that $P \leq 0.001$

Summary

The analysis of Leaf Area Index (LAI) estimation using vegetation indices (NDVI, EVI2, OSAVI, GCI, and REGCI) through linear regression models demonstrates that all indices can predict LAI with varying effectiveness.

- NDVI and REGCL are highly effective across various conditions
- while EVI2 and OSAVI offer benefits in reducing atmospheric and soil background noise
- GCL shows the greatest sensitivity to LAI changes, making it ideal for detailed vegetation studies.

Conclusion

Conclusion

"Drones + Vegetation Indices = Efficient Plant Monitoring"

This Powerful Combination Enables Efficient Monitoring of Crops, Forests, and Ecosystems. By Tracking Plant Health and Productivity Over Large Areas, We Gain Valuable Insights for Sustainable Resource Management.

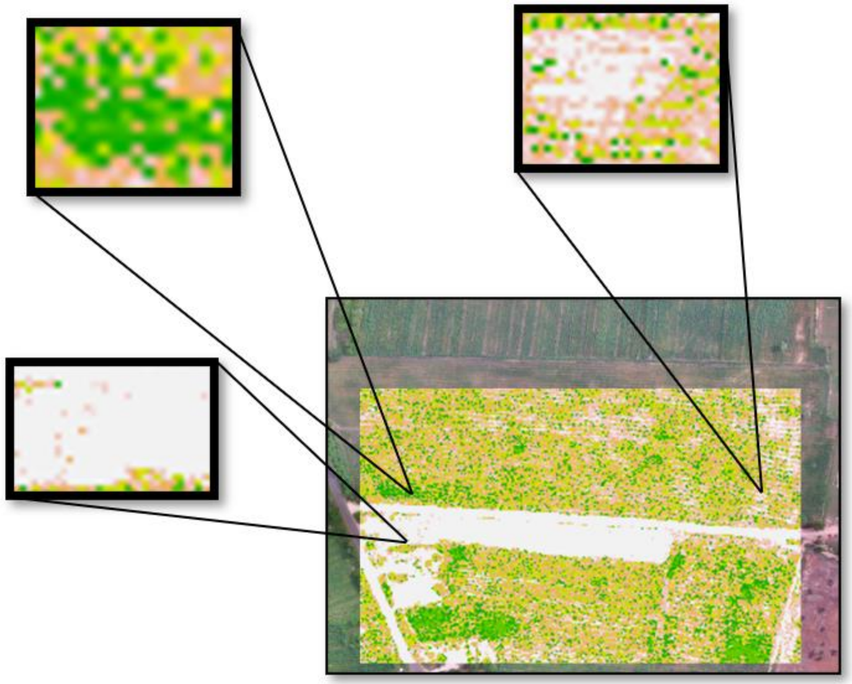


Figure 15. Leaf area index Maps from processed aerial image.

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