*Research paper*

# Cotton yield prediction using drone derived LAI and chlorophyll content

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## ABSTRACT

The unmanned aerial vehicles (UAV) have become a better solution for agricultural growers due to advanced features such as minimal maintenance costs, quick set-up time, low acquisition costs, and live data capturing. Near-ground remote sensing (drone) has opened up new agronomic opportunities for better crop management. This study predicted the seed cotton yield for a cotton field area located at Tamil Nadu Agricultural University, Coimbatore. Pearson correlation analysis and regression analysis were done for ground truth data and vegetation indices for validation and accuracy and also to find the best-performing indices. It was concluded that the Wide Dynamic Range Vegetation Index (WDRVI) showed a better correlation coefficient (R=0.959) with LAI ground truth data ($R^2$=0.919). In contrast, the Modified Chlorophyll Absorption Ratio Index (MCARI) showed a better correlation coefficient (R=0.919) with SPAD chlorophyll ground truth data ($R^2$=0.845). Then the best performing indices WDRVI and MCARI were further used for generating the yield model. High spatial resolution drone imageries for determining LAI and chlorophyll are reliable and rapid, as per the study. It helps to determine the LAI and chlorophyll at a spatial scale and their influence on yield production. This yield prediction was technical support for the widespread adoption and application of unmanned aerial vehicle (UAV) remote sensing in large-scale precision agriculture.



***Keyword*:** Drone, LAI, Multispectral Imageries, SPAD, Vegetation Indices, Yield


Agriculture has prospered from the advancement of remote sensing technology, which has provided for acquiring data at both spatial and temporal scales. Because of its temporal coverage and ability to capture images in a range of spectral wavelengths, remote sensing of crop canopies has been promoted as a potentially useful tool for agricultural management. All of the key crop models, such as those for wheat, cotton, rice, and maize, were calibrated for yield estimation near to harvest time and during the early to peak growth season. Using satellite imageries for monitoring purposes has numerous limitations, including unpredictable weather conditions, and is unprofitable for small agricultural farms due to increased field maintenance expenses. Nowadays, smart farming is the need of the hour, and the next agricultural revolution will be data-oriented, so the advancements and implications of drones have great potential to transform our Indian agriculture.

Drones can cover hundreds of hectares in a single trip and are more effective for crop management and monitoring (Li *et al.*, 2019). Different sensors can be used in an agricultural drone depending on the crop characteristics that must be monitored (Yang *et al.*, 2019). These sensor data can be used to measure vegetative health, soil moisture, and other important agricultural characteristics at different stages of development (Tsouros *et al.*, 2019). Furthermore, UAV-based digital images could be a more cost-effective alternative to data gathered by manual fieldwork, which is time-consuming, involves destructive sampling, and can result in incorrect and subjective results. For intuitive visualization of crop growth status, agricultural remote sensing users use a variety of spectral vegetation indices (Ranjan *et al.*, 2012) of nominal reflectance values (Marang *et al.*, 2021). Because they can enhance spectral differences at specific wavelengths, these indices effectively assess crop growth status (De Castro *et al.*, 2021).

To optimize field management and crop production, it's essential to monitor crop development and accurately estimate crop yield. Accurate cotton yield estimation could aid farmers in making better decisions about harvest, transportation, and storage in the field (Moyer and Komm, 2015). UAV-based imaging systems were used to monitor cotton growth status (Duan *et al.*, 2017) and estimate cotton yield (Feng *et al.*, 2019). LAI (Chaudhari *et al.,* 2010) and chlorophyll are widely employed to define canopy structure and estimate yield (Guo *et al.*, 2020). However, traditional agricultural parameter estimation methods rely on destructive measurement, wasting time and energy and making it impossible to apply across a vast region. To accurately depict the diversity of foods, sources of income, and economic efficiency, yield predictions should be reliable at the individual crop level (Kumar *et al.*, 2022). This study aimed (1) to estimate cotton LAI and SPAD chlorophyll at the spatial level using drone derived multispectral vegetation indices and (2) to validate the derived spectral indices using measured ground truth data (3) to predict seed cotton yield through LAI and SPAD chlorophyll derived from spectral vegetation indices.

## MATERIALS AND METHODS

### *Study location*

The experiment was carried out in a cotton research field at the Department of Cotton, Tamil Nadu Agricultural University, Coimbatore. The study area covers about 3.5 acres having the geo-coordinates from 11°01'13.99" N latitude and 76°55'44.69" E longitude to 11°01'11.98" N latitude and 76°55'49.82" E longitude at an altitude of 429m above MSL.

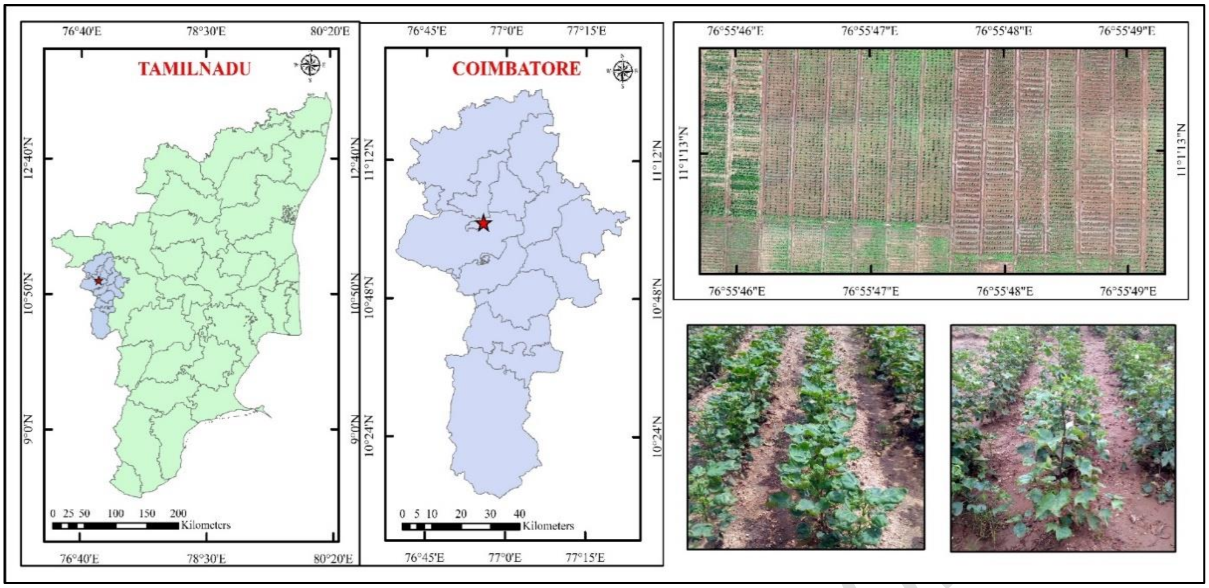


**Fig. 1**: Location of the study area

### *Image acquisition*

This study used a Quadcopter drone with a payload of MicaSense RedEdge multispectral camera. A flight mission was carried out on December, 2021, under a clear sky between 11 AM to 12 PM for 9 minutes for multispectral image collection. Geo-referencing was done using a ground control point (GCP). The camera captures the picture, stores it in memory, and sends it to the ground station through telemetry. In addition, MicaSense RedEdge calibration was done using a Calibrated Reflectance Panel (CRP). The calibration was immediately practiced before each flight according to the calibration manual. The harvest stage of the crop was chosen for this study as it will be very useful and was the most sensitive stage for yield prediction.

### *Ground data collection*

The ground data on LAI and SPAD chlorophyll were collected on the same day when drone images were captured to validate the vegetation index. The ten ground data was collected for the validation of the vegetation index. The seed cotton yield was recorded during each picking and final yield was recorded and expressed in g/plant.

### *Image processing*

Multispectral images obtained were processed using Pix4D mapper software. The raw data were processed, analyzed, and geo-referenced to produce ortho-mosaic. In addition, multiple overlapped images obtained were stitched together to create a large map for an accurate geo-referenced map.

### *Generated vegetation indices*

The vegetation indices are the primary tool for analyzing aerial images. First, post-processed photos were used to generate vegetation indices maps using ArcGIS 10.6 software. Then, the vegetation indices formula was applied to obtain information from the processed data. The vegetation indices like WDRVI, EVI, EVI2 and ARVI were very useful in predicting the LAI and CVI, EVI, EVI2, PVI, ARVI and MCARI were very useful in predicting the chlorophyll, respectively. Utilizing the ground data co-ordinates, the spectral information from the different vegetation indices was extracted using the pixel by value tool in ArcGIS 10.6 software. Finally, the extracted spectral information is subjected to statistical analysis.

Statistical analysis was done using SPSS 22 software for validation. First, Pearson correlation analysis was done to identify the best vegetation index with the highest correlation with ground truth data. Next, the coefficient of determination ($R^2$) and RMSE values was calculated to predict the model accuracy. Finally, regression ($R^2$) values were calculated for vegetation indices (independent variable) and ground truth data (dependent variable) to find out the best line of fit. A higher $R^2$ and lower RMSE value indicate that the independent variable is highly predictable from the dependent variable.

The ground data (LAI and SPAD chlorophyll) were correlated with seed cotton yield for predicting the yield model. The independent variables considered in the analysis were LAI and

SPAD chlorophyll, and the dependent variable was the seed cotton yield. The dependent variable was regressed with the independent variables at different combinations to find the best-fit regression equation for predicting the yield model.

## RESULTS AND DISCUSSION

The UAV collected high-resolution multispectral images for calculating LAI and chlorophyll, which yielded positive and negative, strongly correlated results. The study area generated different vegetation indices like ExG, GNDVI, EVI, EVI2, PVI, ARVI, WDRVI and MCARI. As each index uses different wavebands, the map outputs of the vegetation indices were different. By utilizing the ground data coordinates in ArcGIS 10.6 software, 10 points were selected from the indices map and extracted point values using the pixel by value tool (Table 1).

Statistical analysis was done to establish a relationship between UAV-derived vegetation indices value and ground truth data. Pearson correlation coefficient was done to identify the most sensitive vegetation index to the LAI and SPAD chlorophyll. The regression equation and RMSE values for the vegetation indices were calculated and given in Table 2.

**Table 1:** Vegetation indices value and Ground truth data for LAI, SPAD chlorophyll and seed cotton yield (g/plant)

| S.No. | Latitude | Longitude | ExG | GNDVI | EVI | EVI2 | PVI | ARVI | MCARI | WDRVI | LAI | SPAD | Yield |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 11.0202 | 76.9300 | 2.431 | 0.633 | 0.221 | 0.218 | 0.098 | 0.743 | 0.135 | 0.291 | 1.3 | 42.7 | 78 |
| 2 | 11.0201 | 76.9299 | 2.998 | 0.666 | 0.224 | 0.221 | 0.097 | 0.806 | 0.163 | 0.405 | 1.5 | 52.9 | 83 |
| 3 | 11.0202 | 76.9298 | 2.217 | 0.630 | 0.218 | 0.214 | 0.095 | 0.786 | 0.176 | 0.351 | 1.4 | 60.7 | 81 |
| 4 | 11.0201 | 76.9297 | 2.459 | 0.627 | 0.202 | 0.198 | 0.089 | 0.748 | 0.122 | 0.268 | 1.3 | 42.6 | 78 |
| 5 | 11.0202 | 76.9297 | 1.805 | 0.620 | 0.190 | 0.187 | 0.083 | 0.736 | 0.109 | 0.275 | 1.3 | 40.3 | 77 |
| 6 | 11.0200 | 76.9296 | 2.361 | 0.632 | 0.183 | 0.181 | 0.082 | 0.695 | 0.097 | 0.207 | 1.0 | 37.5 | 77 |
| 7 | 11.0201 | 76.9295 | 2.998 | 0.599 | 0.184 | 0.182 | 0.082 | 0.711 | 0.118 | 0.230 | 1.1 | 42.3 | 78 |
| 8 | 11.0200 | 76.9294 | 2.911 | 0.652 | 0.224 | 0.221 | 0.098 | 0.793 | 0.173 | 0.382 | 1.5 | 54.3 | 81 |
| 9 | 11.0201 | 76.9294 | 2.937 | 0.640 | 0.239 | 0.235 | 0.105 | 0.789 | 0.193 | 0.359 | 1.4 | 60.8 | 84 |
| 10 | 11.0201 | 76.9292 | 2.117 | 0.614 | 0.214 | 0.210 | 0.093 | 0.775 | 0.167 | 0.325 | 1.4 | 54.2 | 81 |

**Table 2:** Relationship between vegetation indices with LAI and SPAD chlorophyll data

| Indices | Regression equation | $R^2$ | RMSE |
|---|---|---|---|
| **LAI** | | | |
| GNDVI | y = 5.4661x - 2.1406 | 0.418 | 0.130 |
| EVI | y = 7.1713x - 0.1955 | 0.730 | 0.088 |
| EVI2 | y = 7.4076x - 0.2197 | 0.729 | 0.089 |
| PVI | y = 16.07x - 0.1714 | 0.652 | 0.100 |
| ARVI | y = 4.1932x - 1.8687 | 0.944 | 0.040 |
| WDRVI | y = 2.3604x + 0.58 | 0.926 | 0.046 |
| **SPAD chlorophyll** | | | |
| ExG | y = 5.6854x + 34.484 | 0.075 | 8.862 |
| EVI | y = 371.47x - 29.157 | 0.674 | 5.256 |
| EVI2 | y = 380.69x - 29.786 | 0.662 | 5.351 |
| PVI | y = 841.3x - 28.723 | 0.615 | 5.714 |
| ARVI | y = 202.94x - 105.01 | 0.761 | 4.499 |
| MCARI | y = 256.14x + 11.624 | 0.949 | 2.072 |

Among the vegetation indices, the WDRVI and MCARI had a higher positive correlation coefficient (R=0.963 and R=0.974) with the LAI ground truth data than other vegetation indices. WDRVI and MCARI recorded an $R^2$ value of 0.926 and 0.949, RMSE of 0.046 and 2.072, respectively.

This shows that WDRVI and MCARI had higher accuracy for predicting the LAI and chlorophyll content. A higher correlation coefficient indicates healthy/dense vegetation with higher LAI and chlorophyll content, whereas lower values indicate stressed/sparse vegetation with lower LAI and chlorophyll content.

The highly correlated vegetation index WDRVI and MCARI were further used to generate the study area's LAI and SPAD chlorophyll map (Fig.2 and 3). This will be useful in predicting the crop's canopy coverage and chlorophyll content. The area covered by LAI with higher values recorded the higher SPAD chlorophyll content. This shows that the higher LAI will influence increased SPAD chlorophyll.

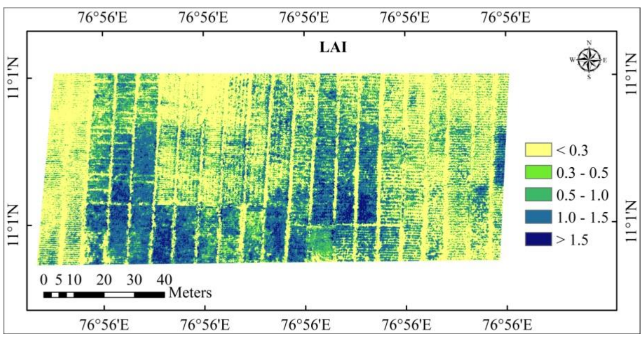


Fig 2: LAI map of the study area

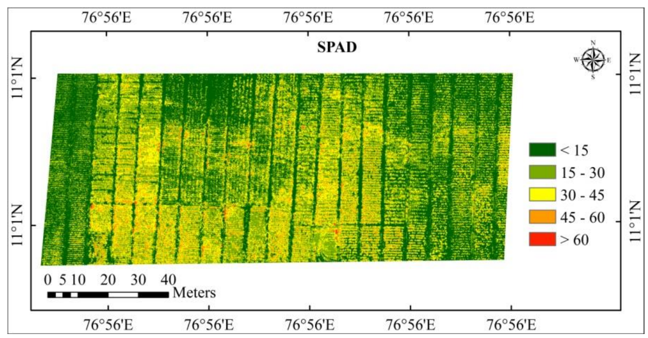


**Fig 3:** SPAD chlorophyll map of the study area

The stepwise multiple linear regression was calculated between the independent variables (LAI and SPAD chlorophyll) and dependent variable (seed cotton yield) in different combinations to find the best-fit regression equation (Table 3) for predicting the yield. The combined regression model (LAI and SPAD) showed a higher $R^2$ value of 0.836 with an RMSE of 1.158.

**Table 3:** Seed cotton yield prediction equation using LAI and SPAD chlorophyll

| Attributes | Regression equation | $R^2$ | RMSE |
|---|---|---|---|
| LAI | Y = 64.47 + 11.61 LAI | 0.552 | 1.795 |
| SPAD | Y = 66.86 + 0.2651 SPAD | 0.829 | 1.109 |
| LAI and SPAD | Y = 65.54 + 0.2359 SPAD + 2.08 LAI | 0.836 | 1.158 |

Therefore, the area with higher LAI and SPAD chlorophyll predicted more yield, indicating the crop's healthy condition at harvest stage. Conversely, the area with lower LAI and SPAD chlorophyll area defines the stressed condition of the crop with a lower yield. This lower yield prediction may also due to the crop loss at later growth stages as the crop coincides the heavy rainfall in December month (harvest stage) of crop. The yield equation model having a higher $R^2$ value was further used to generate the seed cotton yield map (Fig. 4, 5 and 6) for the study area.

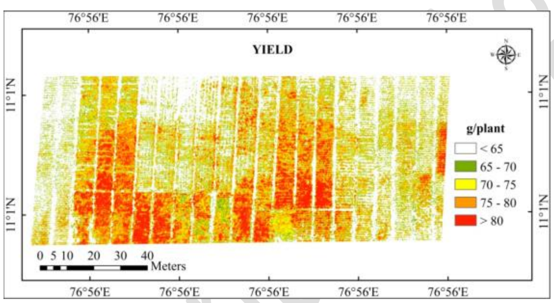


**Fig 4:** Predicted yield map using LAI

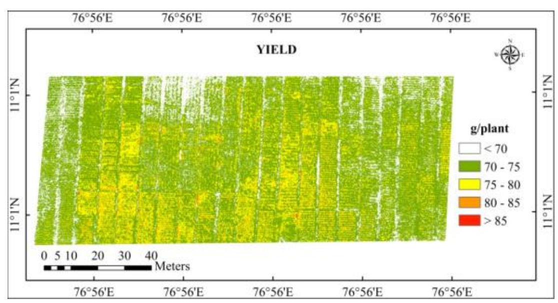


**Fig 5:** Predicted yield map using SPAD

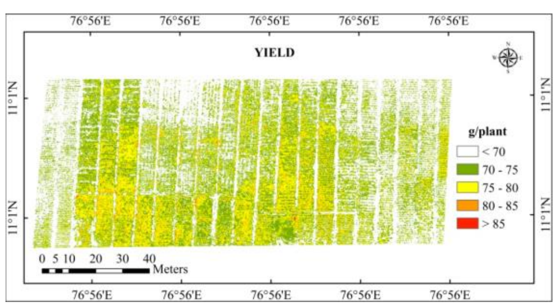


**Fig 6:** Predicted yield map using LAI and SPAD

The predicted LAI and SPAD chlorophyll maps were tested for their accuracy using regression analysis (Table 4) between the ground truth observed values and predicted values. The predicted yield maps using LAI, SPAD chlorophyll, and a combination of LAI and SPAD chlorophyll were tested for accuracy by using regression analysis (Table 5) between the observed yield and predicted yield from the maps. The yield predicted by using LAI and SPAD chlorophyll had a higher positive correlation with the observed yield with an $R^2$ value of 0.822 confirming that yield will be influence by LAI and chlorophyll content.

**Table 4:** Accuracy assessment between observed and predicted LAI and SPAD chlorophyll

| Predicted values | Regression Equation | $R^2$ | RMSE |
|---|---|---|---|
| LAI | y = 0.8682x + 0.0152 | 0.645 | 0.077 |
| SPAD | y = 0.7206x + 11.63 | 0.688 | 2.735 |

**Table 5:** Accuracy assessment between observed yield and predicted using LAI, SPAD chlorophyll, combination of LAI and SPAD chlorophyll yield

| Predicted yield | Regression Equation | $R^2$ |
|---|---|---|
| LAI | y = 0.8106x + 14.173 | 0.635 |
| SPAD | y = 1.0238x - 1.8129 | 0.703 |
| LAI and SPAD | y = 0.8417x + 12.097 | 0.822 |

Furthermore, the changes in crop growth status, which can be successfully, tracked using spectral measurements, directly impact the final yield. Therefore, this yield prediction will be useful for the farmers in estimating the yield loss or gain for fixing the market value of the produce.

## CONCLUSION

Developing efficient tools for precise yield estimation before harvest is crucial in cotton cultivation. The UAV multispectral remote sensing system has considerable application potential in rapidly, accurately, and economically assessing agricultural crop characteristics and yields. Crop growth indicators like LAI and chlorophyll were more connected to canopy spectral reflectance. Due to the correlation between crop yield and the amount of photosynthetic tissue, spectral indices collected during the growing season can also be used to estimate the crop yield. Therefore, they could be done on a wide scale in contrast to the traditional measurement of agronomic parameters, such as LAI and chlorophyll.

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***Conflict of Interests***

The authors declare that there is no conflict of interest related to this article.

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***Data availability:***

## REFERENCES

Chaudhari, K.N., Tripathy, R. and Patel, N.K. (2010). Spatial wheat yield prediction using crop simulation model, GIS, remote sensing and ground observed data. *J. Agrometeorol.*, 12 (2): 174-180. http://doi.org/10.54386/jam.v12i2.1300

De Castro, A.I., Shi, Y., Maja, J.M. and Pena, J.M. (2021). UAVs for Vegetation Monitoring: Overview and Recent Scientific Contributions. *Remote Sens.*, 13: pp. 2139. https://doi.org/10.3390/rs13112139

Duan, T., Zheng, B., Guo, W., Ninomiya, S., Guo, Y. and Chapman, S.C. (2017). Comparison of ground cover estimates from experiment plots in cotton, sorghum and sugarcane based on images and ortho-mosaics captured by UAV. *Functional Plant Biol.*, 44 (1): pp. 169e183. https://doi.org/10.1071/fp16123

Feng, A., Zhang, M., Sudduth, K.A., Vories, E.D. and Zhou, J. (2019). Cotton yield estimation from UAV-based plant height. *Trans. ASABE (American Soc. Agric. Biol. Engg.)*, 62 (2): pp. 393e404. https://doi.org/10.13031/trans.13067

Guo, Y., Wang, H., Wu, Z., Wang, S. and Fu, Y. (2020). Modified Red Blue Vegetation Index for Chlorophyll Estimation and Yield Prediction of Maize from Visible Images Captured by UAV. *Sensors*, 20: pp. 5055. http://dx.doi.org/10.3390/s20185055

Kumar, D.A., Neelima, T., Srikanth, P., Devi, M.U., Suresh, K. and Murthy, C. (2022). Maize yield prediction using NDVI derived from Sentinal 2 data in Siddipet district of Telangana state. *J. Agrometeorol.*, 24 (2): 165-168. http://doi.org/10.54386/jam.v24i2.1635

Li, M., Wu, J., Song, C., He, Y., Niu, B. and Fu, G. *et al.* (2019). Temporal Variability of Precipitation and Biomass of Alpine Grasslands on the Northern Tibetan Plateau. *Remote Sens.*, 11: pp. 360. https://doi.org/10.3390/rs11030360

Marang, I.J., Filippi, P., Weaver, T.B., Evans, B.J., Whelan, B.M., Bishop, T.F.A., Murad, M.O.F., Al-Shammari, D. and Roth, G. (2021). Machine Learning Optimised Hyperspectral Remote Sensing Retrieves Cotton Nitrogen Status. *Remote Sens.*, 13: pp. 1428. http://dx.doi.org/10.3390/rs13081428

Moyer, M. and Komm, B. (2015). Vineyard Yield Estimation. *Washington State University Extension*, pp. 0-11.

Ranjan, R., Nain, A.S. and Panwar, R. (2012). Predicting yield of wheat with remote sensing and weather data. *J. Agrometeorol.*, 14 (special issue): 390-392.

Tsouros, D.C., Triantafyllou, A., Bibi, S. and Sarigannidis, P.G. (2019). Data acquisition and analysis methods in UAV-based applications for Precision Agriculture. In "15th International Conference on Distributed Computing in Sensor Systems (DCOSS) IEEE". pp. 377-384. http://dx.doi.org/10.1109/DCOSS.2019.00080

Yang, G., Liu, J., Zhao, C., Li, Z., Huang, Y., Yu, H., Xu, B., Yang, X., Zhu, D., Zhang, X., Zhang, R., Feng, H., Zhao, X., Li, Z., Li, H. and Yang, H. (2019). Unmanned Aerial

Vehicle Remote Sensing for Field-Based Crop Phenotyping: Current Status and Perspectives. *Front. Plant Sci.*, 8: 1111. https://doi.org/10.3389/fpls.2017.01111