

Research Article

Comparative Analysis of Different Methods of Leaf Area Index Estimation of Strawberry under Egyptian Condition

Abdelraouf M. Ali, Mohamed Aboelghar

National Authority for Remote Sensing and Space Sciences (NARSS), Al-Nozha El-Gedida, Cairo, Egypt

Correspondence should be addressed to raouf.shoker@narss.sci.eg

Publication Date: 5 March 2019

DOI: <https://doi.org/10.23953/cloud.ijarsg.405>

Copyright © 2019. Abdelraouf M. Ali, Mohamed Aboelghar. This is an open access article distributed under the **Creative Commons Attribution License**, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract Leaf area index (LAI) is a factor for vegetative growth parameter. It is defined as leaf area per unit of ground area and could be used as a linkage between plant biophysical, biochemical and spectroscopic parameters. In this research, direct laboratory LAI measurements were tested versus different in situ field measurements for different parameters including LAI derived from LAI-2000 canopy analyzer and six hyperspectral vegetation indices (VIs) (normalized difference vegetation index (NDVI), chlorophyll index (CHI), photochemical reflectance index (PRI), triangular vegetation index (TVI), modified triangular vegetation index (MTVI)), that were generated from ASD-4 field spectroradiometer measurements. The objective is to calibrate the accuracy of LAI-2000 measurements and to examine hyperspectral vegetation indices as estimators of LAI through regression models. A strawberry cultivated area in the Nile delta of Egypt was selected as a study site. Linear regression models were used to calculate LAI through different variables with a high correlation coefficient (0.97, 0.93, 0.90, 0.90, 0.89 and 0.85) for $LA_{optical}$, PRI, TVI, NDVI, MTVI and Chl. Respectively. The correlation coefficient between actual and predicted models was used for validation assessment, the higher accuracy for validation showed high accuracy of all generated models, however, PRI index MTVI, TVI, $LA_{optical}$, NDVI and Chl. Index showed relative higher accuracy 0.941, 0.927, 0.927, 0.906, 0.902 and 0.806 respectively. High similarity was found between optical and actual LAI. Generated models are valid during the maximum phase of vegetative growth of strawberry under local conditions of Egyptian Nile delta.

Keywords *Hyperspectral remotely sensed data; LAI; VIs*

1. Introduction

Healthy plant canopy visually appears green because of the significant high absorption of leaf pigments to red and blue spectra with a strong reflectance of green spectrum. Red edge district has a solid retention because of the leaf chlorophyll, nitrogen fixation, and reflection due to mesophyll cells in developing plants (Datt, 1998). Spectral reflectance at the near infrared region is an indication to the vegetation cover and biomass and could be presented as leaf area index (LAI) (Watson, 1947). First defined LAI as the total one-sided area of the canopy per unit ground surface area (Chen and Black, 1992) It is a one-sided area of leaves per unit ground area. It mirrors the biochemical and physiological processes of vegetation; therefore, it is considered a perfect indicator of crop growth and productivity.

Observing the dynamics of LAI is significant for a wide range of agricultural studies including crop monitoring and crop yield estimation (Fang et al., 2011).

The traditional approach of measuring (LAI) includes removal of leaves from the plant and derivation of their cumulative area instrumentally. This approach is destructive, time-consuming and very labor intensive. The rapid and non-destructive method of measuring LAI could be performed using canopy analyzers, such as LAI 2000 Plant Canopy Analyzer (Li-Cor, Lincoln, NE). This device measures optical interference of the canopy by comparing simultaneous measures of light interception above and below the plant canopy and converting this to LAI using standard equations. As this method depends on the spectroscopic parameters of the investigated plants, it is closely related to spectral reflectance measures Qi et al. (2000). Spectroscopic parameters and spectral reflectance characteristics could be represented in forms of broadband and narrowband remotely sensed data. Using broadband data with satellite imagery is powerful in crop mapping and crop acreage estimation; however, it results in loss of detail of vegetative spectral response (Broge and Leblanc, 2001). Spectral reflectance characteristics of plant canopy could be analyzed through hyperspectral data that provides numerous narrow bands at high-resolution (Sahoo et al., 2015).

Many studies have shown the effectiveness of hyperspectral data to improve LAI estimation (Pu et al., 2008; Verrelst et al., 2012; Duan et al., 2014). Hyperspectral data have been used for end-member extraction of mixed pixels Frank et al. (2009), atmospheric correction Perkins et al. (2012), improving the estimation of chlorophyll content and average leaf angle (Atzberger and Richter, 2012), spectroscopic identification of microorganisms (Aboelghar and Abdel Wahab, 2013) and for assessment of infected plants (Abdel Wahab et al., 2017).

Two main strategies have been addressed as methods to analyze the dynamic relation between LAI and spectral reflectance characteristics represented through hyperspectral data: 1) empirical relationship between vegetation indices (VIs) and biophysical parameter's (Xie et al., 2014) inversion of canopy radiative transfer models, such as the PROSAIL model (Jacquemoud et al., 2009). Estimation of (LAI) through empirical models could be applied in three main steps. The first step is the computation of spectral parameters that are significantly correlated with (LAI). This approach was used to estimate LAI of winter wheat (Xie et al., 2014) and to estimate (LAI) of rice at different growth stages under varying nitrogen rates Din et al. (2017).

In the current study, in situ hyperspectral remote sensing measurements in forms of Six hyperspectral vegetation indices (VIs): chlorophyll index (CHI), normalized difference vegetation index (NDVI), photochemical reflectance index (PRI), modified chlorophyll absorption ratio index (MCARI), triangular vegetation index (TVI), modified triangular vegetation index (MTVI) and test LAI-2000 canopy analyzer field measurements with LAI laboratory measurements for two seasons of strawberry were used to generate and validate empirical statistical regression models for LAI inversion in a case study in old strawberry cultivated lands in the Nile delta of Egypt.

2. Materials and Methods

2.1. Study Area and Sampling

The study site is located in El-Dair village, Egypt (latitude 30°22'10.56"N to 30°22'3.30"N, longitude 31°17'17.94"E to 31°17'16.53"E) with a total area of (933.8 m²) (Figure 1). Investigated samples (strawberry canopy) were cultivated in forty-eight lines with eight meters length for each line. These lines with different treatments of fertilizers and plastic mulches cover all possible treatments of strawberry in Egyptian Nile delta. Three randomly selected samples from each line were considered in the study to establish the dataset for one hundred forty-four samples for each season and total of two hundred eighty-eight samples for the two seasons from which randomly selected two-hundred sixteen (216) measures were considered for modeling and seventy-two (72) measures were considered for

validation process. A GPS (Global Positioning System) was used to locate each measurement in the field.

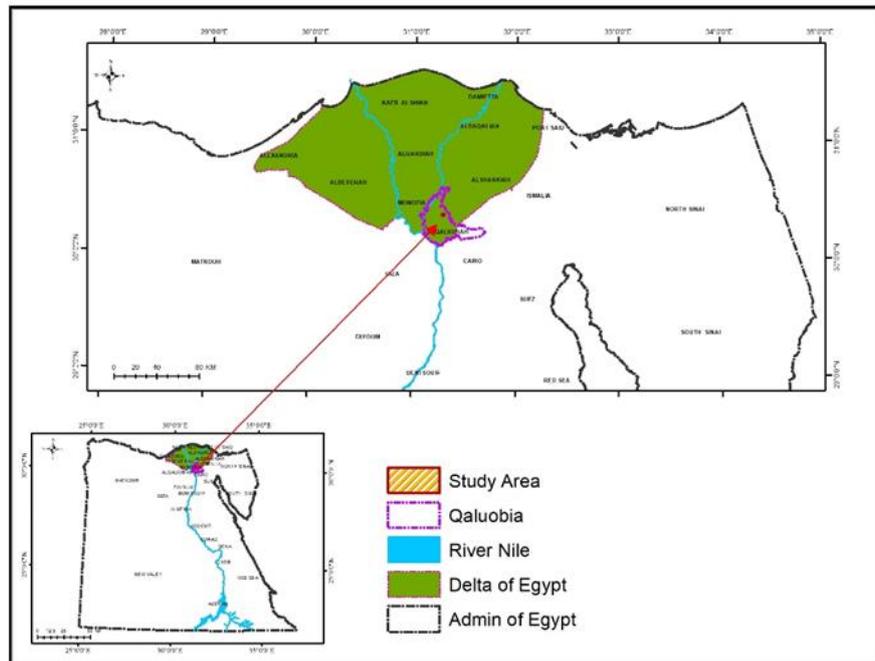


Figure 1: Location map of the study area

2.2. Canopy Spectral Reflectance

Measurements of Spectral reflectance were carried out through the day between the hours of 10:00 am and 24:00 pm under a clear and cloudless sky during Maximum vegetative crop growth through two seasons of 2015 and 2016. Canopy spectra were acquired with ASD-4 field spectroradiometer (an analytical spectral device (ASD, Boulder, CO, United States) that covers (350 - 2500 nm) spectral range (Pimstein et al., 2011). The radiometer sensor head was positioned 0.25 m above the canopy, with a nadir field of view. The reference panel (Baso₄) white panel was used to convert radiance from a Spectral acquired to derive the reflectance, which was used to calibrate the instrument at 5min intervals prior to each plot reflectance measurement Mahajan et al. (2014). The spectral data were exported to View Spec (ASD, Boulder, CO, United States) software and averaged for each treatment. For the analysis of the Field Spec measurements, six vegetation indices were calculated according to referenced and documented equations as shown in Table 1.

Table 1: Used vegetation indices

Vegetation index	Equation	Reference
NDVI	$(pNIR - pred) / (pNIR + pred)$	Rouse et al. (1974)
CARI	$(r700 - r670) - 0.2 * (r700 - r550)$	Kim et al. (1994)
PRI	$(p531 - p570) / (p531 + p570)$	Gamon et al. (1997)
MCARI	$[(P700 - P670) - 0.2(P700 - P550)] / (P700 / P670)$	Daughtry et al. (2000)
TVI	$0.5[120(p750 - p550) - 200(p670 - p550)]$	Broge and Leblanc (2001)
mTVI	$1.2[1.2(p800 - p550) - 2.5(p670 - p550)]$	Haboudane et al. (2004)

2.3. LAI Measurements

At the same time as the spectra were acquired, LAI was taken using a Plant Canopy Analyzer (LAI-2000, Li-Cor, Inc., Lincoln, NE, United States) for all investigated samples. The LAI-2000 is amid the most widely used advanced canopy LAI analyzers for many crops. The protocol of using LAI-2000

device was applied with each measure of each sample during the two seasons. This device calculates LAI depending on radiation measurements made with a fish-eye optical sensor of a 148° field of view. One Measurement was carried out above the canopy of the plant and 4 below the canopy are used to determine canopy light interception at 5 angles, LAI is calculated using a radioactive transfer model of in plant canopy. Measurements were made by positioning the optical sensor and pressing a button. The data were mechanically recorded into the control unit for storage and LAI calculations. Several below-canopy readings and the fish-eye view declare that LAI calculations are based on a large sample of the plant canopy. After collecting both above and below canopy measurements, the control unit performs all calculations and the results are available for immediate on-site-examination (LI-COR, Inc., 1992). Leaf samples from each point were collected and LAI was laboratory measured using a planimeter device. The planimetric approach was used for direct laboratory LAI measurements. This method is based on the principle of the correlation between the individual leaf area and the number of area units covered by that leaf in a horizontal plane. A leaf was horizontally fixed to a flat surface, its perimeter was measured with a planimeter, and its area was computed from this perimeter assessment. Planimeter consists of two identically perforated plates mounted in the top of an airtight drum, which is connected to a constant speed rotary pump. One plate, the specimen grid, is uncovered while the measuring grid is covered by an airtight slide. The pressure within the drum (the datum pressure) is noted before any leaves are mounted. Leaves are then mounted on the specimen plate and are held flat by suction pressure. When all leaves are mounted the pressure is brought back to the datum pressure by opening the slide which covers the measuring grid. The area of leaf is equal to the area of the exposed portion of the measuring plate. This area is recorded by a venire scale mounted on the slide.

2.4. Data Analysis

Laboratory measured LA_{Direct} was statistically correlated with each individual field measured factor. Working in this study could be divided into three parts: laboratory LAI measurements, in situ field measurements and regression analysis between laboratory LA_{Direct} versus optical $LA_{Optical}$ and between LA_{Actual} and each individual vegetation index. Modeling and validation should be process were carried out through cross-validation approach. In cross-validation approach, the data were divided into four subsets. For each modeling trial, seventy-two (72) measures were used as the validation set while the other subsets were put together to form a training set. Then, error estimation was averaged over the four trials to get the total effectiveness of the proposed model. In this approach, each measure was used twice, once in a validation set and ones in the training set.

3. Results and Discussion

Generally, the direct method is assumed to be the most correct for estimating LAI. This method serves as a reference for the performance of the indirect methods. In order to be able to use the indirect methods to determine the LAI, regression equations have been calculated between the results of the indirect and the direct method.

Regression analysis between laboratory measured LA_{Direct} as the dependent variable and each field measured factor as independent variable showed that all factors were highly correlated with laboratory measured LA_{Direct} as the correlation coefficient ranged from (0.85) to (0.97). This is clear evidence that spectral vegetation variables could be considered realistic indicators for canopy phonological, physiological and production parameters. The high statistical similarity between optical field measured $LA_{Optical}$ and laboratory LA_{Direct} is also an evidence for the high accuracy of the optical LAI measurements by LAI-2000 canopy analyzer. Similarly, (Mussche et al., 2001) reported high similarity between $LA_{Optical}$ and LA_{Direct} as long as no changes in the canopy structure are made (Jonckheere et al., 2005) also reported that no significant difference was found between LA_{Direct} and $LA_{Optical}$, however, correction for blue light scattering, clumping, and the non-leafy material is necessary when measuring LAI for tree cover.

All tested vegetation indices were highly correlated with LAI; however, the relatively high accuracy was found with PRI with (0.93) correlation coefficient. The generated models to retrieve LAI from spectral vegetation indices and the model that identify the correlation between LA_{Direct} and LA_{Optical} along with the correlation coefficient for each generated model. Regression models between LA_{Direct} and each factor with the highest correlation coefficient were considered and shown in Table 2.

Validation process was applied using the correlation coefficient between LAI_{Actual} and LAI_{Predicted}. It was performed four times according to cross-validation approach and the average of the four trials was registered as shown in Figure 2.

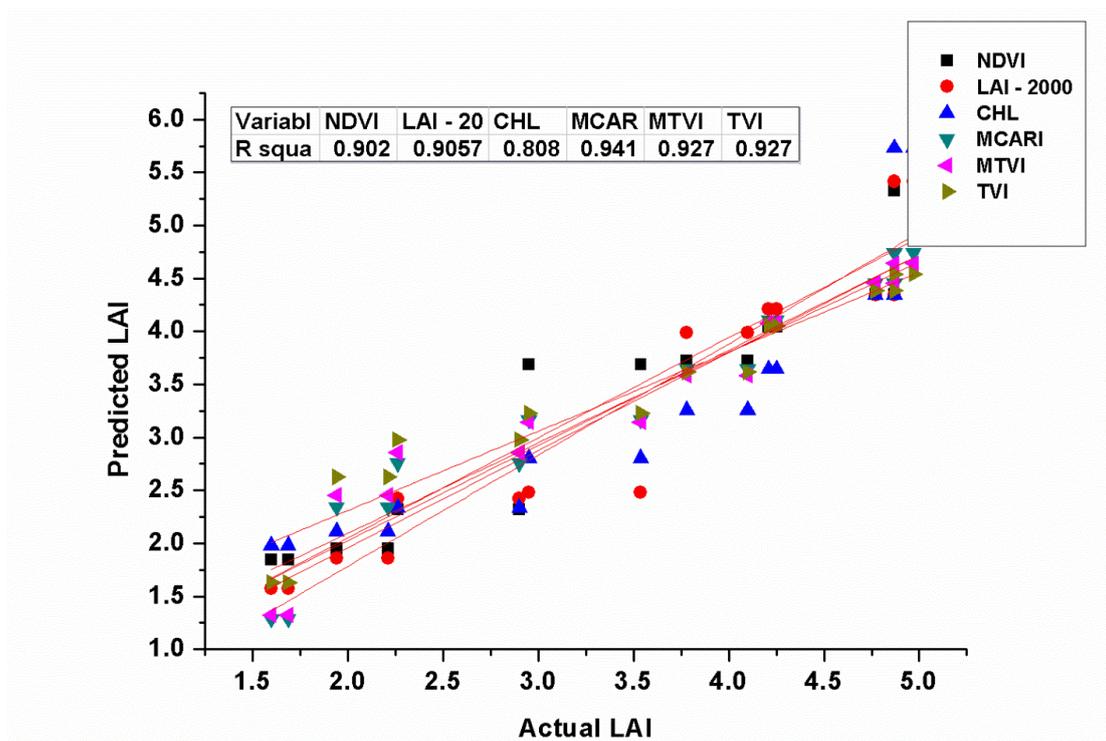


Figure 2: Correlation coefficient between actual and predicted LAI through different generated models

Table 2. Regression analysis between the dependent variable (Laboratory measured LAI) and each field measured factor

Independent variable	Slope	Intercept	R ²	SE	Model
LAI _{Optical}	0.53	3.19	0.97	0.02	LAI _{lab} = 0.53LAI _{field} + 3.19
NDVI	9.90	-3.53	0.90	0.67	LAI _{lab} = 9.9NDVI - 3.53
PRI	41.83	3.68	0.93	2.90	LAI _{lab} = 41.83PRI + 3.68
Chl	2.09	2.96	0.85	0.18	LAI _{lab} = 2.09Chl + 2.96
TVI	0.14	0.46	0.90	0.01	LAI _{lab} = 0.14TVI + 0.46
MTVI	5.81	0.20	0.89	0.42	LAI _{lab} = 5.81MTVI + 0.2

The direct method to estimate LAI quantifies the change of the needle area itself rather than measuring other variables that are influenced by canopy structure, e.g. radiation transmission and gap size, as in optical methods. At the same time, the direct methods to estimate LAI are more laborious and time-consuming than optical methods. Therefore, the main objectives of the current study were to propose a non-destructive method to estimate LAI and to compare optical and direct methods for LAI estimation of Strawberry plants. Basically, optical approach of LAI measurements depends on measuring light interception of a vegetation canopy. Comparative analysis was carried out between optical and direct LAI. Six regression models to retrieve LAI from spectral variables were generated with adequate accuracy ranged from (0.808) to (0.941). Generated models are site-specific limited to the conditions of observation including (site, crop phenology and meteorological conditions). These models could be applied regularly to predict LAI during the phase of the maximum vegetative growth. These regular monitoring of LAI could be the basis of early yield prediction system as canopy vigor is an accurate indicator for expected yield.

Our analysis is consistent with several studies that also compared optical non destructive LAI measures to direct destructive LAI estimates for different crops. Wihelm et al. (2000) found that the percentage of underestimation of LAI of Corn (*Zea mays* L.) was higher in case of direct methods than optical method. Oppositely, Hunt et al. (1999) found that the LAI 2000 overestimated LAI in soybean and the bean leaf beetle (*C. trifurcate*). They suggested that the optical instruments should overestimate LAI since instruments do not discriminate between leaf and stem; therefore, all plant parts are counted as leaf area in proportion to the amount of light they intercept. In contrast, destructive sampling measured only the area of leaf blades. We assume that the difference in the two trends of results is dependent on the differences between the crops being investigated. Grass stems (as the case of strawberry) are very thin and occupy a small area in proportion to total leaf area.

4. Conclusion

Six spectrally based regression models to retrieve LAI for strawberry cultivations in Egyptian Nile delta were generated in this study. All models showed high accuracy ranged from (0.808) to (0.941) as the correlation coefficient between actual and predicted LAI. Spectral variables were used in form of spectral vegetation indices. Among these (VIs), PRI showed a relatively higher accuracy than the rest of (VIs). The study confirmed the high accuracy of the optical field measured LAI as high correlation coefficient was found between LA_{Actual} and $LA_{Optical}$. Generated models are easy to be applied, however, they are site-specific models limited to the conditions of the observation. Proposed models could be used for early estimation of strawberry yield as vegetation health is an indicator for expected yield under the assumption of the absence of any up normal conditions (unexpected climatic conditions, epidemic infection etc.).

References

- Abdel Wahab, H., Aboelghar, M., Ali, A. and Yones, M. 2017. Spectral and molecular studies on gray mold in strawberry. *Asian Journal of Plant Pathology*, 11, pp.167-173.
- Aboelghar, M. and Abdel Wahab, H. 2013. Spectral footprint of *Botrytis cinerea*, a novel way for fungal characterization. *Advances in Bioscience and Biotechnology*, 4, pp.374-382.
- Aboelghar, M., Arafat, S., Abo Yousef, M., El-Shirbeny, M., Naeem, S., Massoud, A. and Saleh, N. 2011. Using SPOT data and leaf area index for rice yield estimation in Egyptian Nile delta. *Egyptian Journal of Remote Sensing and Space Science*, 14(2), pp.81-89.
- Atzberger, C. and Richter, K. 2012. Spatially constrained inversion of radiative transfer models for improved LAI mapping from future Sentinel-2 imagery. *Remote Sensing of Environment*, 120, pp.208-218

- Broge, H. and Leblanc, E. 2001. Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. *Remote Sensing of Environment*, 76, pp.156-172.
- Chen, J. and Black, T., 1992. Defining leaf area index for non-flat leaves. *Plant Cell & Environment*, 15(4), pp.421-429.
- Datt, B. 1998. Remote sensing of chlorophyll a, chlorophyll b, chlorophyll a+b, and total carotenoid content in eucalyptus leaves. *Remote Sensing of Environment*, 66(2), pp.111-121.
- Daughtry, C.S.T., Walthall, C.L., Kim, M.S., Brown de Colstoun, E. and McMurtrey III, J.E. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sensing of Environment*, 74, pp.229-239.
- Duan, S.B., Li, Z.L., Wu, H., Tang, B.H., Ma, L., Zhao, E. and Li, C. 2014. Inversion of the PROSAIL model to estimate leaf area index of maize, potato, and sunflower fields from unmanned aerial vehicle hyperspectral data. *International Journal of Applied Earth Observation and Geoinformation*, 26, pp.12-20.
- Fang, H., Liang, S. and Hoogenboom, G. 2011. Integration of MODIS LAI and vegetation index products with the CSM-CERES-Maize model for corn yield estimation. *International Journal of Remote Sensing*, 32(4), pp.1039-1065.
- Franke, J., Roberts, D., Halligan, K. and Menz, G. 2009. Hierarchical Multiple Endmember Spectral Mixture Analysis (MESMA) of hyperspectral imagery for urban environments. *Remote Sensing for Environment*, 113, pp.1712-1723.
- Gamon, J.A., Serrano, L. and Surfus, J.S. 1997. The photochemical reflectance index: an optical indicator of photosynthetic radiation use efficiency across species, functional types and nutrient levels. *Oecologia*, 112, pp.492-501.
- Haboudane, D., Miller, J.R., Pattey, E., Zarco-Tejada, P.J. and Strachan, I.B. 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: modeling and validation in the context of precision agriculture. *Remote Sensing of Environment*, 90, pp.337-352.
- Hunt, T.E., Haile, F.J., Hoback, W.W. and Higley, L.G. 1999. Indirect measurement of insect defoliation. *Environ. Entomol.*, 28, pp.1136-1139.
- Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P.J., Asner, G.P., Franc, C. and Ustin, S.L. 2009. PROSPECT + SAIL models: a review of use for vegetation characterization. *Remote Sensing of Environment*, 113, pp.56-66.
- Jonckheere, I., Muys, B. and Coppin, P. 2005. Allometry and evaluation of in situ optical LAI determination in Scots pine: a case study in Belgium. *Tree Physiology*, 25, pp.723-732
- Kim, M.S., Daughtry, C.S.T., Chappelle, E.W. and McMurtrey, J.E. 1994. *The use of high spectral resolution bands for estimating absorbed photosynthetically active radiation (Apar)*. In: Proceedings of the Sixth Symposium on Physical Measurements and Signatures in Remote Sensing, Val D'Isere, France. pp.299-306.
- LI-COR. 1992. *LAI-2000 Plant Canopy Analyzer*. Instruction Manual. Lincoln, NE, USA.

- Mairaj, D., Wen, Z., Rashid, M., Wang, S. and Zhihua S. 2017. Evaluating hyperspectral vegetation indices for leaf area estimation of *Oryzastiva* L. at diverse phenological stages. *Frontiers in Plant Science*, 8, p.820.
- Mahajan, G.R., Sahoo, R.N., Pandey, R.N., Gupta, V.K. and Kumar, D. 2014. Using hyperspectral remote sensing techniques to monitor nitrogen, phosphorus, Sulphur, and potassium in wheat (*Triticumaestivum* L.). *Precision Agriculture*, 15(2), pp.227-240.
- Mussche, S., Samson, R., Nachtergale, L., De Schrijver, A., Lemeur, R. and Lust, N. 2001. A comparison of optical and direct methods for monitoring the seasonal dynamics of leaf area index in deciduous forests. *Silva Fennica*, 35(4): 373-384.
- Perkins, T., Adler-Golden, S., Matthew, M.W., Berk, A., Bernstein, L.S., Lee, J. and Fox, M. 2012. Speed and accuracy improvements in FLAASH atmospheric correction of hyperspectral imagery. *Optical Engineering*, 51(11), pp.111707-111711.
- Pimstein, A., Karnieli, A., Bansal, S.K. and Bonfil, D.J. 2011. Exploring remotely sensed technologies for monitoring wheat potassium and phosphorus using field spectroscopy. *Field Crops Research*, 121(1), pp.125-135.
- Pu, R., Gong, P. and Yu, Q. 2008. Comparative analysis of EO-1 ALI and hyperion, and Landsat ETM+ Data for mapping forest crown closure and leaf area index. *Sensors*, 8, pp.3744-3766.
- Qi, J., Kerr, Y.H., Moran, M.S., Wertz, M., Huete, A.R., Sorooshian, S. and Bryant, R. 2000. Leaf area index estimates using remotely sensed data and BRDF models in a semiarid region. *Remote Sensing of Environment*, 73, pp.18-30.
- Xie, Q., Huang, W., Dong L., Chen, P., Wu, C., Yang, G., Zhang, J., Huang, L. and Zhang, D. 2014. Leaf area index estimation using vegetation indices derived from airborne hyperspectral images in winter wheat. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(8), pp.3586-3594.
- Rouse, J.W., Haas, R.H., Schell, J.A. and Deering, D.W. 1974. *Monitoring vegetation systems in the Great Plains with ERTS*. In: Freden, S.C., Mercanti, E.P. and Becker, M. (eds) Third Earth Resources Technology Satellite-1 Symposium. Technical Presentations, NASA SP-351, NASA, Washington, D.C. Volume I, pp.309-317.
- Sahoo, R.N., Ray, S.S. and Manjunath, K.R. 2015. *Hyperspectral remote sensing of agriculture*. CRC Press, Boca Raton, FL.
- Verrelst, J., Romijn, E. and Kooistra, L. 2012. Mapping vegetation density in a heterogeneous river floodplain ecosystem using paintable CHRIS/PROBA data. *Remote Sensing*, 4, p.2866-2889.
- Watson, D.J. 1947. Comparative physiological studies in the growth of field crops. I. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. *Annals of Botany*, 11, pp.41-76.
- Wilhelm, W.W., Ruwe, K. and Schlemmer, M.R. 2000. Comparison of three leaf area index meters in a corn canopy. *Crop Sci.*, 40, pp.1179-1183.