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Pamuk Bitkisinde Yaprak Alan İndeksinin İzlenmesinde Bazı Uydu İndislerinin Kullanımının Araştırılması

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Öne Çıkanlar:

- LAI
- Vejetasyon İndisleri
- Optik Uydu Görüntüleri
- Google Earth Engine

Anahtar Kelimeler:

- Yaprak Alan İndeksi
- Vejetasyon İndeksleri
- Pamuk
- Sentinel-2
- Google Earth Engine

ÖZET:

Yaprak Alan İndeksi (LAI) bitki gelişiminin temel göstergelerinden kabul edilmektedir. Doğrudan LAI tahmin yöntemleri yoğun emek ve zaman gerektirmektedir. Bu çalışma; LAI tahminini, hasarsız, daha kısa zamanda ve daha az yoğun emek harcayarak gerçekleştirebilmek amacıyla; Mardin ili Artuklu ve Kızıltepe ilçelerine bağlı 8 köyde, pamuk tarımı yapılan toplam 27 adet parselde yapılmıştır. Çalışmada, yersel LAI gözlemi ile Sentinel-2 uydu verilerinden türetilen ARVI, GARI, EVI2, NDVI, WDRVI, MSI, NBR, NDMI, MTVI2, SIPI, OSAVI, SAVI indisleri arasındaki ilişkiler incelenmiştir. Tüm indisler 0.01 düzeyinde önemli bulunmuştur. Atmosferik düzeltme etkisine sahip ARVI ve GARI (sırasıyla $R^2 = 0.77-0.76$), temel indislerden EVI2, NDVI ve WDRVI (sırasıyla $R^2 = 0.74-0.74-0.75$), bitki nem içeriği hassasiyetli MSI, NBR ve NDMI (sırasıyla $R^2 = 0.77-0.79-0.77$) yüksek ilişki göstermişlerdir. Ayrıca pigment hassasiyetli MTVI2 ve SIPI ($R^2 = 0.73-0.74$), arka plan toprak etkisine karşı tasarlanan OSAVI ve SAVI ($R^2 = 0.74-0.74$) yüksek ilişki göstermişlerdir. İncelenen bu indislerin pamuk bitkisinde iyi bir LAI tahmin edicisi olarak kullanılması tavsiye edilmektedir. .

Investigation of the Use of Some Satellite Indices in Monitoring Leaf Area Index in Cotton Plants

Highlights:

- LAI
- Vegetation Index
- Optical Satellite Images
- Google Earth Engine

Keywords:

- Leaf Area Index
- Vegetation Indices
- Cotton
- Sentinel-2
- Google Earth Engine

ABSTRACT:

Leaf Area Index (LAI) is accepted as one of the basic indicators of plant development. Direct LAI estimation methods require intensive labor and time. This work; In order to realize the LAI estimation without damage, in a shorter time and with less labor-intensive effort, it was made on a total of 27 parcels where cotton cultivation is carried out in 8 villages in Artuklu and Kızıltepe districts of Mardin province. In the study, the relationships between terrestrial LAI observation and ARVI, GARI, EVI2, NDVI, WDRVI, MSI, NBR, NDMI, MTVI2, SIPI, OSAVI, SAVI indices derived from Sentinel-2 satellite data were examined. All indices were found significant at the 0.01 level. ARVI and GARI having atmospheric correction effect ($R^2 = 0.77-0.76$, respectively), basic indices EVI2, NDVI and WDRVI ($R^2 = 0.74-0.74-0.75$, respectively), MSI, NBR and NDMI with plant moisture content sensitivity ($R^2 = 0.77-0.79-0.77$, respectively) showed high relationships. In addition, pigment sensitivity MTVI2 and SIPI ($R^2 = 0.73-0.74$), OSAVI and SAVI designed against background soil effect ($R^2 = 0.74-0.74$) showed high relation. It is recommended that these indices be used as a good LAI estimator in cotton plant.

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INTRODUCTION

Cotton is an important industrial raw material worldwide and is used in many industrial sectors such as textiles, oil, feed and chemicals. It is used in many industrial sectors. While the demand for cotton products increases with rapid population growth, it is observed that cotton production has not increased sufficiently (Anonymous 2012; Johnson et al., 2020). Trade has decreased and stocking has increased due to reasons such as the Covid-19 crisis, climate change, excessive and irregular rainfall, as well as regional drought disasters that have become more frequent in recent years. According to the 2021/2022 data of the International Cotton Advisory Board (ICAC), the cotton cultivation area in the world is 33.18 million ha, production amount is 25.73 million tons, consumption is 25.62 million tons, stock amount is 20.45 million tons has been observed. In Turkey, the cotton cultivation area was 480000 ha, production was 833,000 tons, consumption was 1.61 million tons, and the stock amount was 1.54 million tons (Anonymous 2022).

Leaf Area Index (LAI) is an important biophysical parameter and is defined as the unilateral leaf area per unit ground area (Kaplan & Rozenstein, 2021). LAI is considered one of the basic indicators of plant development due to its significant relationship with leaf chlorophyll content and Photosynthetic Active Radiation Fraction (FAPAR). It is an indicator that can be constantly observed during growth stages and has been used to estimate plant development status in early periods and yield in later periods (Sharma et al., 2017).

LAI can be estimated by two methods: direct and indirect. (Küßner & Mosandl, 2000). Although direct prediction methods are quite accurate, they are not very suitable for monitoring large areas as they require intensive labor, work force and time (Siegmann & Jarmer, 2015). One of the indirect ways is remote sensing methods (Biudes et al., 2014). Studies have been conducted on many different plant species using vegetation indices to estimate LAI with remote sensing data (Carlson & Ripley, 1997; Ray et al., 2006; Wang et al., 2007; Darvishzadeh et al., 2009; Vina et al., 2011; Delegido et al., 2013; Jin et al., 2013; Ali et al., 2017; Zhen-wang et al., 2017; Srivastava et al., 2019; Prananda et al., 2020; Solgi et al., 2023).

It has been found that LAI is an important indicator of plant yield estimation (Dabrowska-Zielinska et al., 2018; Mokhtari et al., 2018; Ji et al., 2021; Zhu et al., 2021), cotton population growth and canopy surface energy exchange (Peng et al., 2022), canopy spectral characteristics are closely related to LAI (Liang FengChao, 2014) and distinctly reflect changes in LAI (Thenkabail et al., 2000). Especially in recent years, various indices have been tried to be created in order to monitor LAI changes in cotton plants more accurately (Li et al., 2021; Li et al., 2022; Huang et al., 2023;) and it has been shown that many models can be used in this regard, and as a result, spectral data are used to monitor LAI values in cotton. It has been reported that it is appropriate to use the indices such as NDVI, TVI, RVI, EVI2, SAVI, WEVI, DVI (Kaplan & Rozenstein, 2021; Ma et al., 2022; Fan et al., 2023).

This study was conducted to estimate LAI without damage, in a shorter time and with less intensive effort. For this purpose, LAI values obtained from ground measurements were compared with 12 multispectral indices in the literature and the LAI estimation power of the indices was evaluated. Additionally, the study aims to contribute to the widespread use of remote sensing in agriculture by utilizing technological development tools in remote sensing, such as open-access satellite imagery and cloud platforms, thereby providing ease of access and application in predicting LAI and similar plant biophysical parameters.

MATERIALS AND METHODS

Study Area

The research was conducted in 27 different plots of cotton crops in 8 villages of Artuklu and Kızıltepe districts of Mardin. Information about the parcels is given in Figure 1 and Table 1.

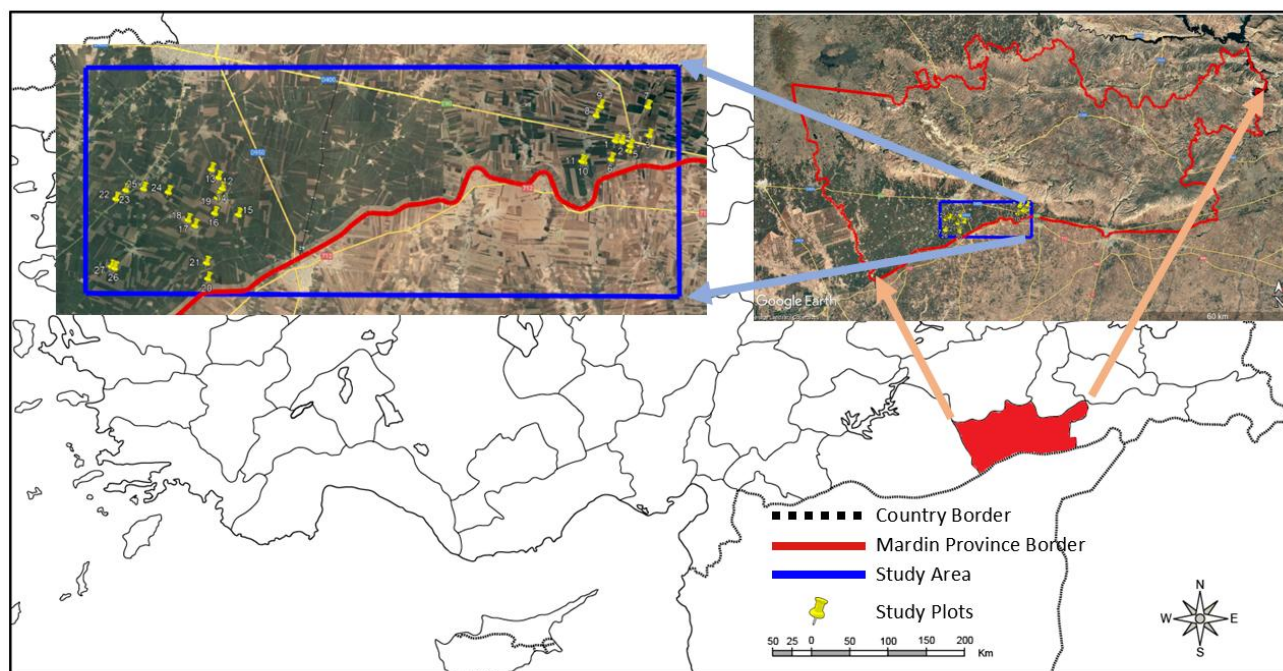


Figure 1. Working area

Table 1. Information and coordinates of the parcels

NO	X	Y	NO	X	Y
S01	40.856	37.139	S15	40.611	37.100
S02	40.860	37.138	S16	40.596	37.101
S03	40.878	37.142	S17	40.583	37.094
S04	40.866	37.136	S18	40.578	37.097
S05	40.865	37.134	S19	40.597	37.109
S06	40.853	37.129	S20	40.591	37.067
S07	40.877	37.157	S21	40.590	37.075
S08	40.843	37.152	S22	40.531	37.108
S09	40.846	37.157	S23	40.538	37.113
S10	40.836	37.128	S24	40.565	37.112
S11	40.834	37.128	S25	40.549	37.114
S12	40.598	37.119	S26	40.531	37.072
S13	40.593	37.124	S27	40.528	37.073
S14	40.600	37.114			

In the study areas, cotton was planted in 2021 and in-field cultural operations, care-feeding and irrigation were carried out under farm conditions and no additional practices were applied. There was no rainfall in the region during the June-September period when the study was conducted.

Leaf Area Index (LAI)

Delta-T brand SS1 Sunscan Canopy Analysis System device was used to measure leaf area index. The measurement was carried out in the middle of the field and in the parts with homogenous vegetation cover during cloudless hours when the sun was clearly visible and between 9-15 hours of the day. The dome sensor is positioned to receive direct sunlight, the measurement probe has been placed on the ground under the vegetation and 10 measurements were taken from each plot and the average was

determined (Figure 2). Taking into account plant growth and satellite image acquisition dates, a total of 5 measurements were taken in the field (Figure 3).



Figure 2. LAI measurement device and use case

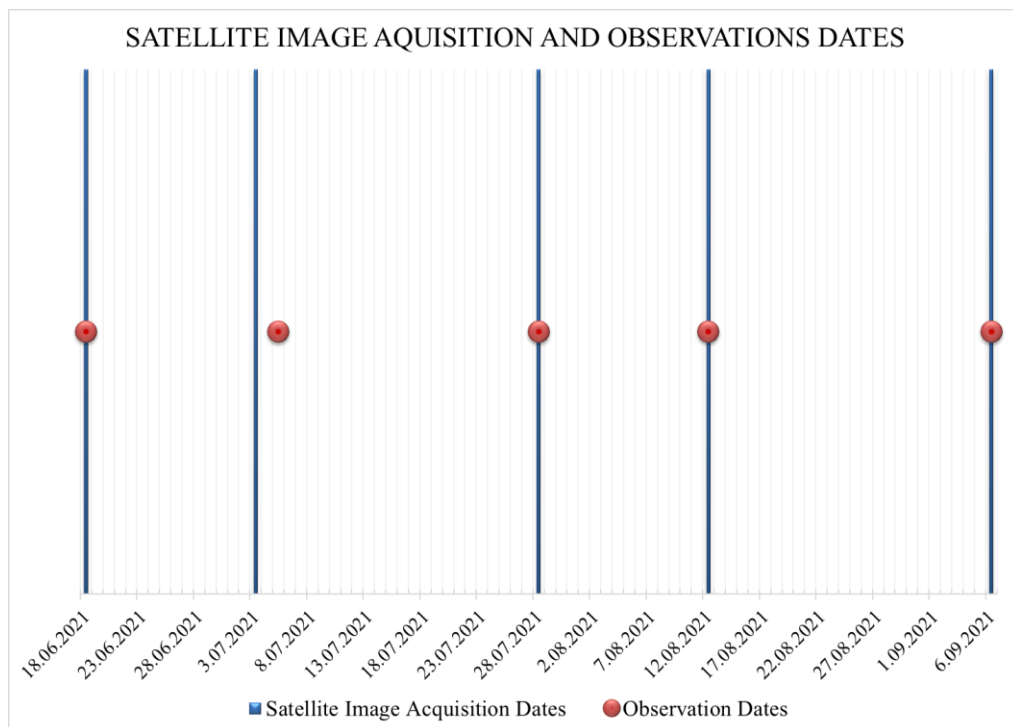


Figure 3. Satellite image acquisition and observations dates

Sentinel-2

Sentinel-2 satellite imagery is provided by the European Space Agency (ESA) and images with 2A surface reflectance processing level were used in this study. At level 2A, images are presented with geometric, radiometric and atmospheric correction processes as pre-processing. The band pixel values of these images were obtained in the Google Earth Engine (GEE) environment. The band pixel values obtained according to the dates of observation were processed into MS Office Excel program, indices were calculated and LAI values were subjected to analysis of variance in JMP 5.0.1 (Copyright © 1989-2002 SAS Institute Inc.) statistical program.

Satellite Indices

Various indices derived from the Sentinel-2 satellite were used in the study. These indices values were compared with LAI values and subjected to regression analysis. Information on the indices used in the study is given in Table 2.

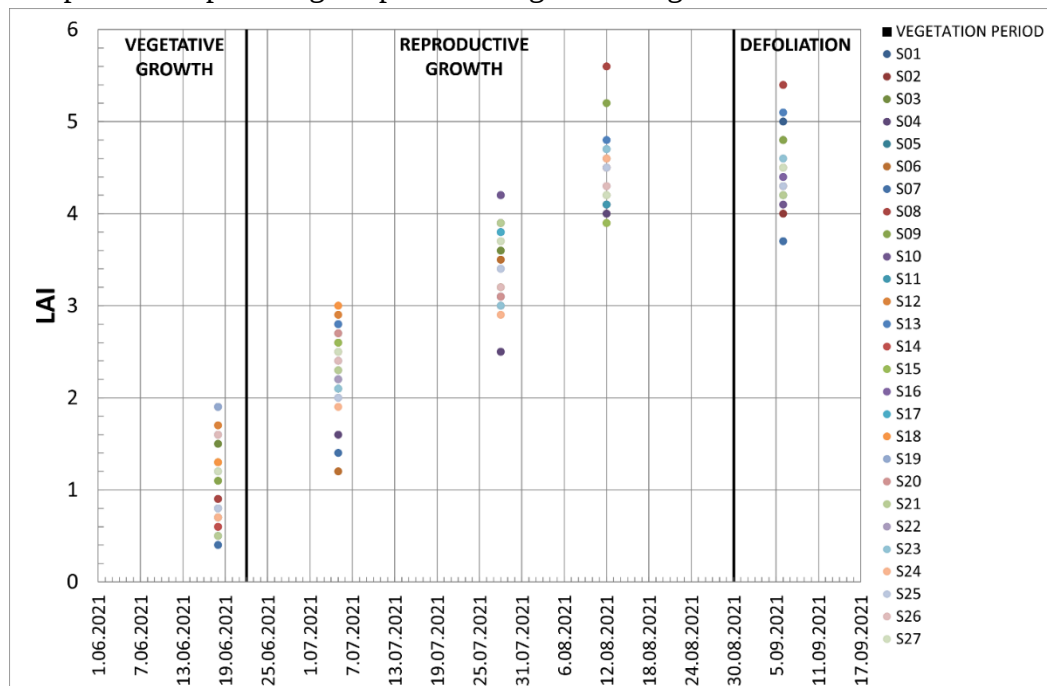
Table 2. Information on the indices used in the study

Indice	Feature	Formula	Reference
ARVI (Atmospherically Resistant Vegetation Index)	Atmospheric	$(\text{NIR} - \text{Red} - 1 * (\text{Red} - \text{Blue})) / (\text{NIR} + \text{Red} - 1 * (\text{Red} - \text{Blue}))$	(Kaufman & Tanre, 1992)
GARI (Green atmospherically resistant vegetation index)	Atmospheric	$(\text{NIR} - (\text{Green} - (\text{Blue} - \text{Red}))) / (\text{NIR} - (\text{Green} + (\text{Blue} - \text{Red})))$	(Gitelson et al., 1996)
EVI 2 (Enhanced Vegetation Index 2)	Basic	$2.4 * ((\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red} + 1))$	(Miura vd., 2008)
NDVI (Normalized Difference Vegetation Index)	Basic	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	(Rouse Jr et al., 1973)
WDRVI (Wide Dynamic Range Vegetation Index)	Basic	$(0.1 * (\text{NIR} - \text{Red})) / (0.1 * (\text{NIR} + \text{Red}))$	(Gitelson, 2004)
MSI (Moisture Stress Index)	Moisture	SWIR/NIR	(Hunt Jr & Rock, 1989)
NBR (Normalized Burn Ratio)	Moisture	$(\text{NIR} - \text{SWIR2}) / (\text{NIR} + \text{SWIR2})$	(Key et al., 2002)
NDMI (Normalized Difference Moisture Index)	Moisture	$(\text{NIR} - \text{SWIR1}) / (\text{NIR} + \text{SWIR1})$	(Cibula et al., 1992)
MTVI2 (Modified Triangular Vegetation Index 2)	Pigment/Color	$(1.5 * ((1.2 * (\text{NIR} - \text{Green}) - 2.5 * (\text{Red} - \text{Green})) / (\text{Sqrt}(((2 * \text{NIR} + 1) ** 2) - (6 * \text{NIR} - 5 * \text{Sqrt}(\text{Red})) - 0.5))))$	(Haboudane, 2004)
SIPI (Structure Intensive Pigment Index)	Pigment/Color	$(\text{NIR} - \text{Blue}) / (\text{NIR} - \text{Red})$	(Penuelas et al., 1995)
OSAVI (Optimized Soil Adjusted Vegetation Index)	Soil	$(1 + 0.16) * ((\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red} + 0.16))$	(Rondeaux et al., 1996)
SAVI (Soil Adjusted Vegetation Index)	Soil	$((\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red} + \text{L})) * (1 + \text{L})$	(Huete, 1988)

References can be consulted for detailed information about the indices.

RESULTS AND DISCUSSION

LAI values obtained as a result of observations made in the field on dates determined according to plant development and phenological periods are given in Figure 4.

**Figure 4.** LAI observation values

LAI values remained low from planting and throughout the vegetative development period, increased during the flowering and boll formation periods with the growth and branching of the plant's

height, and although there was a slight decrease until the middle of the maturation period, they were still observed at high values. Regression analyses were performed between these data and Sentinel-2 indices (Table 3).

Table 3. LAI values and Sentinel-2 indices regression analysis results

INDICES	R ²	RMSE	REGRESSION FORMULA
ARVI	0.74**	0.70	$LAI = 3.19 \cdot ARVI^2 + 1.84 \cdot ARVI + 0.31$
GARI	0.76**	0.75	$LAI = 6.74 \cdot GARI^2 - 3.51 \cdot GARI + 1.09$
EVI2	0.74**	0.71	$LAI = 0.25 \cdot EVI2^2 + 2.06 \cdot EVI2 - 1.10$
NDVI	0.74**	0.71	$LAI = 1.46 \cdot NDVI^2 + 4.93 \cdot NDVI - 1.10$
WDRVI	0.75**	0.70	$LAI = -3.18 \cdot WDRVI^2 + 4.14 \cdot WDRVI + 2.94$
MSI	0.77**	0.65	$LAI = 4.27 \cdot MSI^2 - 11.91 \cdot MSI + 8.11$
NBR	0.79**	0.63	$LAI = 1.97 \cdot NBR^2 + 4.55 \cdot NBR - 0.01$
NDMI	0.77**	0.66	$LAI = -1.56 \cdot NDMI^2 + 9.31 \cdot NDMI + 0.31$
MTVI2	0.73**	0.72	$LAI = 6.76 \cdot MTVI2^2 - 2.05 \cdot MTVI2 + 0.70$
SIPI	0.74**	0.70	$LAI = 10.93 \cdot SIPI^2 - 34.92 \cdot SIPI + 28.15$
OSAVI	0.74**	0.71	$LAI = 1.08 \cdot OSAVI^2 + 4.25 \cdot OSAVI - 1.10$
SAVI	0.74**	0.71	$LAI = 0.65 \cdot SAVI^2 + 3.29 \cdot SAVI - 1.10$

R²: Regression Coefficient, RMSE: Root Mean Square Error, **Significant at 0.01 level

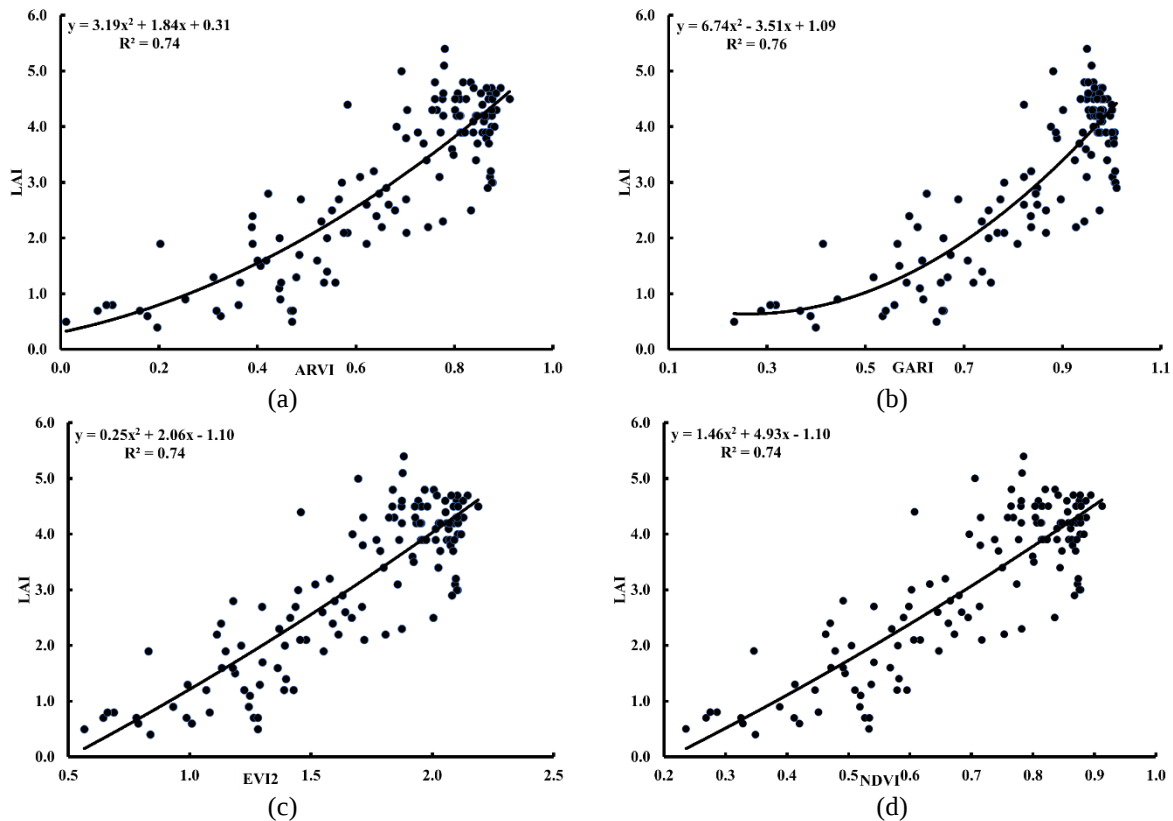


Figure 5. (a) LAI-ARVI regression analysis results, (b) LAI-GARI regression analysis results, (c) LAI-EVI2 regression analysis results, (d) LAI-NDVI regression analysis results

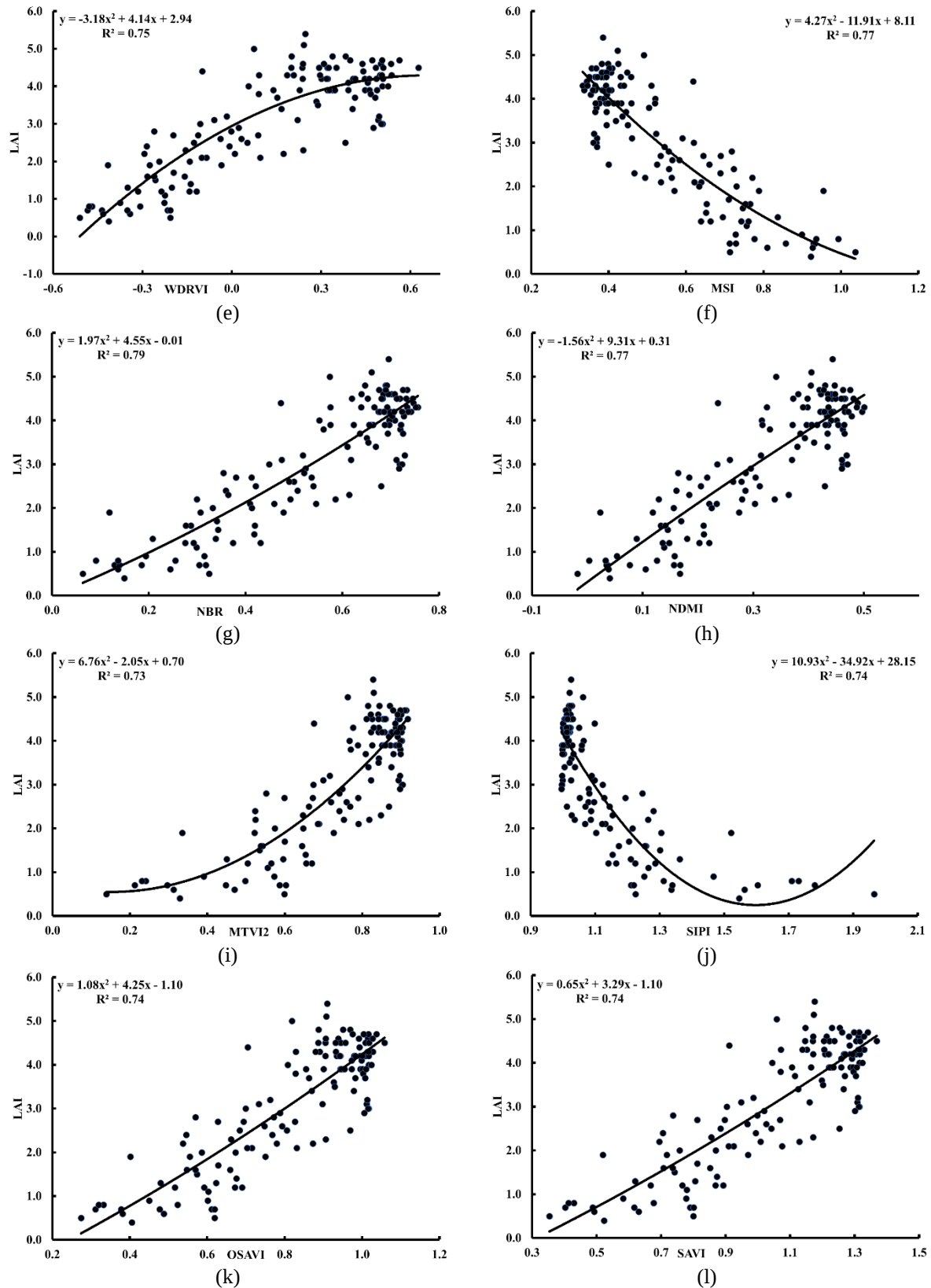


Figure 5. (g) LAI-NBR regression analysis results, (h) LAI-NDMI regression analysis results, (i) LAI-MTVI2 regression analysis results, (j) LAI-SIPI regression analysis results, (k) LAI-OSAVI regression analysis results, (l) LAI-SAVI regression analysis results

A significant (0.01) and high relationship ($R^2=0.73-0.79$) was found between the twelve indices used in the study and LAI values (Table 3) (Figure 5). These results indicate that these indices can be used to estimate LAI.

The ARVI2, derived as a version of NDVI, includes correction factors for atmospheric effects such as absorption and scattering and is 4 times less sensitive to atmospheric effects than NDVI (Kaufman & Tanre, 1992). ARVI2 is an indice related to vegetation greenness and there is a relationship between vegetation greenness and leaf area. Vegetation greenness rises with increasing leaf area, and the ARVI2 displays high values. Thus, a direct relation exists between ARVI2 and LAI. The plant becomes greener as the leaf area grows, and the ARVI2 displays high values. Our findings; who used Landsat imagery for LAI estimation with the Random Forest (RF) algorithm on lands under meadow-pasture cover and reported that ARVI, OSAVI and WDRVI are the 3 most important variables in the algorithm (Zhenwang et al., 2017); it is compatible with, (Hassan et al., 2023) who analyzed the relation between LAI and Photosynthetically Active Radiation Fraction (FAPAR) and seven VIs, in green onion plantations and found a relationship between LAI and ARVI, NDVI and SAVI with $R^2= 0.75, 0.78$ and 0.66 in the first season and $R^2= 0.77, 0.82$ and 0.68 in the second season, respectively.

The GARI is 4 times more resistant to atmospheric effects than NDVI, shows higher sensitivity to chlorophyll concentrations than NDVI and can be used to estimate leaf chlorophyll content with high accuracy (Gitelson et al., 1996). The relationship between GARI and LAI stems from the direct relationship between the photosynthetic capacity of plants and leaf area. As leaf area increases, the photosynthetic capacity of plants also increases, leading to higher GARI values. Therefore, GARI and LAI are closely related and can be used together to determine plant health, growth potential and productivity. Our findings; who conducted a study to evaluate vegetation indices for the estimation of LAI in different leaf structures and plant species (wheat, oats, soybean and maize) and recommended the use of NDVI and GARI in areas $<2\text{m}^2/\text{m}^2$ (Vina et al., 2011); it is compatible with (Prananda et al., 2020) who tried to create a model for LAI prediction with vegetation indices.

The EVI2 was designed to minimize soil and atmospheric effects and to increase sensitivity in areas with high LAI, but it has limitations in creating long-term time series due to its use of red, near infrared and blue bands. The use of 2 bands (red and near infrared) with a correction factor (EVI2) has been found to be successful when atmospheric effects are insignificant and data quality is sufficient (Jiang et al., 2008). EVI2 is an indice that measures the photosynthetic activity of vegetation. The relationship between EVI2 and LAI is based on the direct relationship between the photosynthetic activity of vegetation and the density of leaf cover. So, high LAI values mean that the photosynthetic activity of vegetation will be high, while high EVI2 values indicate that vegetation is greener and healthier. Our findings; (Rocha & Shaver, 2009), who reported that EVI2 gave better results than NDVI under different background soil reflection conditions in burnt areas the arctic tundra for LAI measurement purposes; (Feng et al., 2019), who studied to increase prediction accuracy in high LAI conditions where prediction saturation weakens in wheat plants; evaluated various VIs for LAI prediction at different growth stages in winter wheat (Zhao et al., 2012); who investigated the suitability of using LAI to develop landscape maps using vegetation indices in in forest, woodlands, swamps and agricultural areas East Africa (Pfeifer et al., 2012); who conducted a study to evaluate the saturation effects of vegetation indices on soil background reflection and chlorophyll concentration (Fu et al., 2013); which evaluated the overall accuracy of vegetation indices with LAI (Kang et al., 2016); it is compatible with (Prananda et al., 2020) who tried to create a model for LAI prediction with vegetation indices.

The relation between plant growth and health is the natural source of the link between NDVI and LAI. Higher LAI values and thus higher NDVI values are a result of denser and healthier vegetation. Lower NDVI and LAI readings are related with reduced vegetation density or plant stress. Our findings; Explaining that NDVI, LAI and fractional vegetation cover are dependent on each other using the simple

radiative transfer method (Carlson & Ripley, 1997); who reported a strong correlation between specific leaf area and NDVI and SARVI2 indices in their study conducted in cereal, forest and marsh areas. (Lymburner et al., 2000); which evaluated spectral vegetation indices for LAI estimation in maize, sorghum cotton and soya bean fields (Gowda et al., 2015); who evaluated the relationship between NDVI-LAI in their studies aimed at evaluating the biomass of afforestation areas (Wei et al., 2020); which evaluated the relationship between LAI and NDVI for various optical satellite bands in cultivated fields such as wheat, onion, mustard, potato and cabbage (Gupta et al., 2000); which investigated the relationship between NDVI and LAI in grassland areas (Fan et al., 2009); who reported that the indices showed good relation in studies aimed at estimating plant leaf nitrogen content (Singh et al., 2012); Reporting that VENμS and Sentinel-2 images are suitable for vegetation indices and LAI values and that these two satellite images help to determine LAI values accurately (Herrmann et al., 2011); which uses NDVI, NDWI, SCRI and MSI indices for wheat plant irrigation management (Solgi et al., 2023); it is compatible with (Prada et al., 2020) who conducted a study to determine the most appropriate vegetation indices to measure the response of vegetation in forest areas after thinning.

The WDRVI formula uses a correction factor for the NIR band to remove the saturation of vegetation reflections. WDRVI is more accurate than NDVI in areas of high-density vegetation. WDRVI provides information on vegetation health and density. The relationship between WDRVI and LAI is that vegetation health depends on leaf density. As vegetation health improves, leaf density and leaf surface area increase, resulting in higher LAI and WDRVI values. Our findings; (Zhao et al., 2007), who conducted a study to investigate the relationships between cotton leaf yield, aboveground biomass and LAI of different N rates with the help of vegetation indices; (Hancock & Dougherty, 2007), who reported that vegetation indices can be used to estimate plant growth, LAI and yield; (Ahamed et al., 2011), who reported that remote sensing data can be used in resource planning in bioenergy production; (Prananda et al., 2020), who tried to create a model for LAI prediction with vegetation indices in mangrove areas; it is compatible with (Vina et al., 2011) who conducted a study to evaluate vegetation indices for estimating LAI in different leaf structures and plant species such as maize and soybean.

MSI is a parameter that measures plant water stress. This indice is determined by measuring the difference between the amount of water required by the plant and the amount of water available. LAI is a parameter that measures the capacity of plants to photosynthesize. Plant growth and yields depend on photosynthetic capacity. There is an inverse relationship between MSI and LAI; as water stress increases, the growth rate and yield of the plant decreases and the photosynthetic capacity decreases. Our findings; (Heiskanen, 2006); who studied biomass and LAI via ASTER satellite data and found a significant relationship in a mountain birch forest; (Quang et al., 2022), who conducted a study to estimate LAI with the help of satellite indices in monitoring deforested lands; (Solgi et al., 2023), which uses NDVI, NDWI, SCRI and MSI indices for wheat plant irrigation management; (Singh et al., 2012), who reported that the indices showed good relation in studies aimed at estimating plant leaf nitrogen content in wheat cultivated areas; it is compatible with (Srinet, et al., 2019) who conducted a study to estimate the spatial distribution of LAI with the help of Landsat-8 images in a tropical areas.

NBR is a measure used to determine the degree of damage to the plant. Low values indicate extensive damage and high values indicate minor damage. Accordingly, NBR and LAI values will increase as the density of healthy vegetation increases. Our findings; using LAI and NBR to identify burnt or fire-prone areas (Boer et al., 2008; Filipponi, 2018); It is consistent with (Peppo et al., 2021) who conducted a study to evaluate the potential of non-parametric approaches in LAI estimation in a wheat, maize and alfalfa cultivates areas.

NDMI is related to the moisture content of the vegetation. The higher the moisture content of the vegetation, the higher the NDMI value, because the vegetation is greener and healthier. The relationship between NDMI and LAI varies depending on changes in the moisture content and density of the vegetation. As vegetation moisture increases, vegetation density and leaf surface area increase, and so do LAI and NDMI. When vegetation moisture decreases, vegetation density and leaf surface area decrease, and therefore LAI and NDMI values decrease. Our findings; (Solgi et al., 2023), which uses NDVI, NDWI, SCRI and MSI indices for wheat plant irrigation management; (Srinet et al., 2019); who conducted a study to estimate the spatial distribution of LAI with the help of Landsat-8 images; (Blinn et al., 2019); who work to eliminate or reduce errors in LAI estimation calculations with the help of Landsat images and multi-temporal measurements (Kinane et al., 2021); it is consistent with (Ochtyra et al., 2020), which compares Chlorophyll content, LAI, absorbed photosynthetic active radiation, and spectral signatures with vegetation indices to study disturbances in mountainous areas.

SIPI was designed to increase the sensitivity of carotenoids to chlorophyll content and decrease their sensitivity to changes in canopy structure (Penuelas et al., 1995b). Therefore, there is a relationship between LAI and SIPI based on plant development and maturity. Our study findings using multispectral data are similar to those of a study that used hyperspectral indices for the detection of bacterial wilt disease and reported that SIPI and other indices were highly related with LAI ($R^2 > 0.9$) (Srivastava et al., 2019); (Routh et al., 2019) which used hyperspectral remote sensing to estimate biophysical parameters (especially LAI) in sunflower and reported that SIPI was more highly correlated with LAI than other indices, and which investigated the ability of artificial neural network (ANN) and least squares regression (LSR) techniques to predict LAI using Landsat data in cotton, maize, sorghum and soybean crops and reported that SIPI and LAI were highly correlated ($R^2 > 0.91$ and 0.84) (Bajwa vd., 2008).

MTVI2 is more resistant to chlorophyll and background soil effects than MTVI (Haboudane, 2004). Thus, it can better monitor plant growth and predict LAI better. Our findings; (Haboudane, 2004), who examined some vegetation indices using PROSPECT and SAILH models and reported that MTVI2 and MCARI2 were the best LAI estimators in corn, wheat and soybean cultivated areas; it is consistent with (Feng et al., 2019), who conducted a study to increase prediction accuracy in high LAI conditions where prediction saturation in wheat plant weakens.

OSAVI uses a constant value for soil effect and takes values according to vegetation density. In this respect, it can be used to estimate LAI in sparse, normal and densely vegetated areas. Our findings; (Lipovac et al., 2022), who evaluated the use of Unmanned Aerial Vehicle (UAV) multispectral images in bean plants under different planting periods and irrigation practices and reported that there were significant relationships between LAI and OSAVI; Wheat etc. (Gao et al., 2022), who reported that OSAVI and MCARI2 were the best LAI estimators among twelve vegetation indices in their studies aimed at predicting leaf chlorophyll content (Cab) and LAI under various background effects in the global spectrum of plants in wheat planting areas; (Rosso et al., 2022), who reported that all methods using vegetation indices, machine learning (ML) and radiative transfer models (RTM) were highly related ($R^2 = 0.7-0.9$) for LAI prediction in barley plants; (Marino & Alvino, 2019), which relates ground measurements with VIs for early detection of agronomic spatial change; it is consistent with (Das et al., 2020) who reported that OSAVI is the best predictor in studies aimed at estimating LAI with plant indices in wheat plants.

SAVI is an indice designed to reduce the background soil effect (Huete, 1988). In areas where vegetation density varies, reducing saturation effects is important to provide a better LAI estimate (Zhen et al., 2021). Our findings; (Huete, 1988), who developed a new indice by minimizing the background

soil effect in the red and NIR bands in cotton and grass areas; (Rondeaux et al., 1996; Prada et al., 2020), who conducted studies to determine the most suitable vegetation indices to measure the response of vegetation in forest areas after thinning; (Zhao et al., 2012), which evaluated various VIs for LAI prediction at different growth stages in winter wheat; it is consistent with (Zhen et al., 2021) which uses vegetation indices to estimate LAI in areas with high plant density.

CONCLUSION

This study was conducted to evaluate 12 spectral indices (ARVI, GARI, EVI2, NDVI, WDRVI, MSI, NBR, NDMI, MTVI2, SIPI, OSAVI, SAVI) recorded in the literature for LAI estimation in cotton plants. The indices were compared with the LAI values obtained from ground observations, and their LAI prediction status was analyzed. Accordingly, all indices were found significant at 0.01 level. ARVI and GARI with atmospheric correction effect ($R^2=0.74-0.76$), the basic indices EVI2, NDVI and WDRVI ($R^2=0.74-0.74-0.75$), plant moisture content sensitive MSI, NBR and NDMI ($R^2=0.77-0.79-0.77$), pigment sensitive MTVI2 and SIPI ($R^2=0.73-0.74$), OSAVI and SAVI designed against background soil effect ($R^2=0.74-0.74$) showed high relationship. As a result of these results, it is recommended that the indices be used as they are good LAI estimators in cotton plants and can provide information about plant development and health, pigment and moisture content, so that irregularities in plant health and development can be detected quickly and non-destructively and provide quick intervention.

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Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

The authors declare that they have contributed equally to the article.

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