Turkish Journal of Engineering
https://dergipark.org.tr/en/pub/tuje
e-ISSN 2587-1366

Cotton yield estimation using several vegetation indices

Bakhtiyar Babashli *1, **Aytaj Badalova** 1, **Ramis Shukurov** 2, **Agil Ahmadov** 3

1 National Aviation Academy, Aerospace Faculty, Azerbaijan, bakhtiyar.babashli@gmail.com, badalova-aytac60@rambler.ru
2 Mil Experiment Station, Azerbaijan, ramis.shukur@gmail.com
3 Azercosmos, Azerbaijan, aqil1964@gmail.com

Cite this study: Babashli, B., Badalova, A., Shukurov, R., & Ahmadov, A. (2024). Cotton yield estimation using several vegetation indices. Turkish Journal of Engineering, 8 (1), 139-151

Keywords
Cotton
Yield
Vegetation indices
Biomass
Satellite images

Research Article
DOI: 10.31127/tuje.1346353

Received:19.08.2023
Revised: 21.11.2023
Accepted:26.11.2023
Published:07.01.2024

Abstract

Accurate yield estimation before harvest is important for farmers and researchers to optimize field management and increase productivity. The purpose of this study is to develop efficient cotton plant productivity using field studies and satellite imagery. Nitrogen (N) fertilizer is an important nutrient in plant development, and when suboptimal amounts are applied, it can cause yield reductions. Different vegetation indices were employed to analyze the dynamics and yield of cotton plants, with a primary focus on the Red, Near-Infrared (NIR), and Red Edge bands derived from satellite imagery. The objective was to assess the nitrogen content in the plants. The present study involved a comparative analysis of various vegetation indicators in relation to cotton plant production. The productivity of the cotton plant was assessed by employing the indices that exhibited the most influence. The analysis revealed that the MCARI index exhibited the worst weaknesses, while the CLRE index demonstrated the main performance. The productivity of each index was computed, and it was observed that the CLRE index exhibited the closest proximity to the average productivity of 34.48 cents per hectare (cent/ha). Similar results have been observed in other indices. The MCARI index exhibits a distinct value of 32.08 in comparison to the others indices. The results of this study illustrate the potential of satellite imaging in monitoring cotton yield, hence offering valuable theoretical and technological assistance for estimating cotton production in agricultural areas.

1. Introduction

Agriculture plays a crucial role in the global economy, and as the world's population grows, the need for agricultural products increases [1]. Cotton belongs to the genus Gossypium L. of Malvaceae family [2]. The cotton industry is of great national economic importance in terms of employment of the population and the development of the textile industry. Cotton is among the most cultivated plants in the world [3]. Today, the most developed countries in the world are engaged in cotton production. Countries such as the USA, Israel, Turkey, China, and India receive quite a lot of income from this field. China, India and the United States are the top three producers of cotton in the world [4-5]. Cotton growing in Pakistan, Uzbekistan and Turkey is developing at a high pace. Along with the development of cotton cultivation in these countries, the textile industry is also expanding.

Crop growth and productivity are the combined effects of the environment, water, soil, nitrogen and other components. This makes product evaluation difficult and often inaccurate. Currently, evaluation of cotton plant productivity plays an important role for agriculture [6]. Conventionally, cotton yield is estimated based on the number of bolls per unit area. However, cotton yield varies according to field irrigation and fertilization. Many researchers have tried to develop different methods to increase the accuracy of productivity estimation [7–9].

The traditional yield survey method relies on the experience of farmers or professionals, which is time-consuming, laborious and uncertain. Recent studies have shown that technological progress can play a crucial role in achieving sustainable intensification in agriculture [10]. In recent years, remote sensing technology has been widely applied in agriculture [11]. At present, relevant scientists also offer various methods for predicting cotton yield.

Quan Xu significantly contributed to the enhancement of precision agriculture by conducting an evaluation of cotton productivity in China [12]. The study introduced a novel approach named SENP (Seedling Emergence and Number of Peaches) that leverages the capabilities of Amazon Web Services (AWS). The assessment of cotton productivity was conducted utilizing high-resolution data collected by an Unmanned Aerial Vehicle (UAV), the U-Net model of deep learning and Sentinel-2 data. It is demonstrated that estimating cotton condition from Normalized difference vegetation index (NDVI) data collected over a specific time is imprecise. The utilization of predominantly time series data has demonstrated that NDVI is a more effective method for monitoring cotton development. The experiment's results indicate that utilizing cotton emergence and growth data is a suitable approach for estimating yield. The reliability and excellent accuracy of the SENP-based cotton yield estimation model have been proven through validation using the real crop. Therefore, a digital platform has been developed utilizing Amazon Web Services (AWS) and ENVI Services Engine (ESE) measure cotton production online. This platform aims to offer valuable data for regional agricultural management and macro-level decision-making, leveraging the benefits of cloud computing. Accuracy of precision achieved in the experiment was 93.88%, recall rate was found to be 97.87% and F value calculated 95.83%.

Guanwei Shi employed a new method to estimate cotton yield by utilizing the density of open Cotton boll Pixels (DCP) derived from unmanned aerial vehicles (UAVs) [13]. Correlation analysis was employed to compare the performance of several indexes. A performance indicator that demonstrates excellence and an index that measures profitability, both obtained from empirical field research, are conceptualized. The study area is partitioned into three distinct regions, each characterized by varying datasets obtained from drone-based observations and traditional field surveys. The findings of the study indicate a significant relationship between the DCP and crop yield, as evidenced by a Pearson correlation coefficient of 0.84. The Random Forest (RF) technique had superior performance in estimating revenue, as evidenced by its average R-squared (R2) value of 0.77 and relative root mean squared error (RMSE) value of 7.5%.

Ping Lang investigated the most significant VIs and CVs for Xinjiang Province district-level cotton productivity estimation [14]. The researcher discovered that the vegetation indices (VIs) pertaining to canopy structure, chlorophyll content, and moisture coefficient of variation (CV) were the primary determinants influencing the growth of cotton. The individual employed various regression methodologies to estimate cotton yield. The study acquired annual (April-September) and monthly averages of MODIS and Sentinel-2 photos pertaining to cotton fields from 2012 to 2019. A total of 14 satellite VIs were computed to forecast fertility. Monthly data was utilized for the purpose of predicting cotton production prior to harvest and examining the temporal progression of cotton growth. Climatic variables are extensively employed in the estimation of crop productivity. The findings of the study indicate that the Long Short-Term Memory (LSTM) model exhibited the highest performance, as evidenced by an R2 value of 0.76, a Root Mean Square Error (RMSE) of 150 kg/ha, and a relative Root Mean Square Error (RMSE) of 8.67%. The study showcased the viability of county-level yield estimation and early forecasting in extensive cotton fields through the integration of satellite imagery and environmental data.

Compared to traditional methods, remote sensing methods are more economical and effective when it comes to cotton yield monitoring [15-16]. Nitrogen (N) is a major nutrient that directly affects plant behavior [17-18]. Both N deficiency and N excess have negative effects on plant development, yield, and fiber quality [19-20]. Insufficient N supply often leads to reduced leaf area and reduced leaf photosynthesis and biomass production, resulting in reduced yield and unsatisfactory fiber quality [21-23]. VIs used in yield calculations are designed to increase sensitivity to vegetation characteristics while minimizing confounding factors such as soil background reflectance, directional, and atmospheric effects [24-25].

The implementation of satellite remote sensing has been widely used in agricultural research. The utilization of satellite data to calculate VIs has emerged as a prevalent approach in predicting crop yields [26]. VIs has the capability to characterize biotic attributes, including vegetation structure, chlorophyll concentration, and nitrogen content. Various VIs, such as the (NDVI), Enhanced Vegetation Index (EVI), and Near Infrared Reflectance of Vegetation (NIR), have been employed in studies to elucidate the fluctuations in yields of wheat, cotton, corn, rice, and soybeans [27-28]. Even though VIs is useful in predicting cotton production, environmental conditions should also be taken into account as a component that affects yield.

The objective of this research is to assess productivity of the cotton plant by determining the growth level (biomass) with the VI based on ground and satellite data. VIs is considered the main factor in agriculture to calculate the biomass of vegetation in cultivated areas.

2. Method

The focus of this study related to the cotton fields located within Beylagan district (Figure 1). Beylagan district has boundaries with the Agjabadi, Zardab, Fuzuli, and Imishli districts of the Republic of Azerbaijan, as well as the Islamic Republic of Iran [29]. Azerbaijan, the nation and former Soviet republic is geographically bounded by the Caspian Sea and the Caucasus Mountains, encompassing territories spanning the continents of Asia and Europe. The geographical location of this entity is situated in the central region of the country, and it is encompassed within the Mil-Mugan Economic Region. The district spans between longitudes 47.46°E and 47.94°E, and latitudes 39.57°N and 40.14°N. The district covers an area of 1.13 thousand square kilometers. Beylagan is the city in the center.

The scope of this study encompasses cultivated cotton fields spanning across 14 villages, occupying a total arable land area of 59,893 hectares. Based on statistical data, it can be observed that the financial backing for planted cotton fields primarily stems from three firms, namely "MTK IK" LLC, "Azer Pambig" LLC, and "P-Agro" LLC [30].

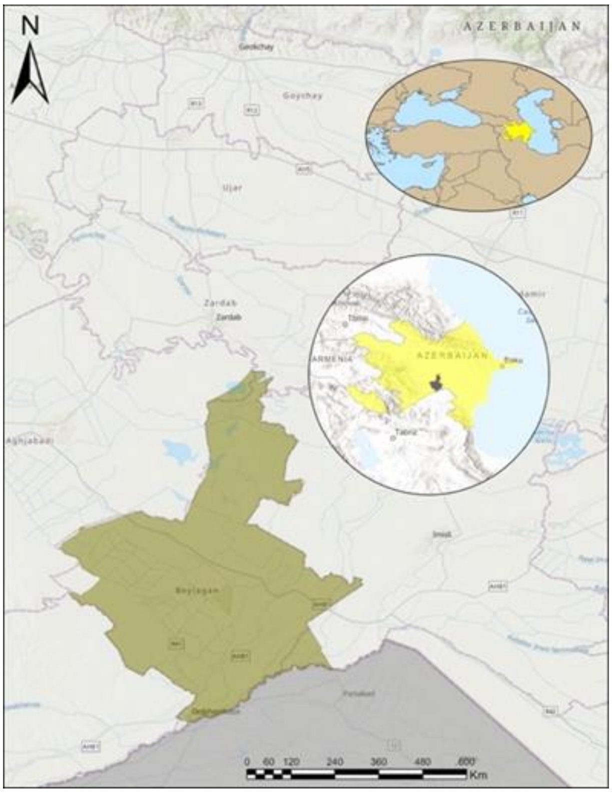

Figure 1. Study area.

2.1. Data

At the initial stage, Azersky/SPOT-7 (Satellite Pour l'Observation de la Terre-7) satellite images taken in periods covering different vegetation stages of cotton were used in the research area [31-32]. SPOT 7 is an Azerbaijan's first commercial high-resolution earth observation satellite. It was launched on 30 June 2014 and ceased operations on 17 March 2023. On December 2, 2014, the name was changed to 'Azersky'. It was providing a consistent stream of high-resolution, wide-swath data. The Panchromatic imagery exhibited a resolution of 1.5 meters, whereas the Multispectral imagery showed a resolution of 6 meters. The imaging system consisted of 1 panchromatic band and 4 multispectral bands, specifically capturing data in the green, blue, red, and near-infrared wavelengths. The shown landscape exhibited a range of dimensions, with a minimum extent of 60 kilometers by 60 kilometers and a maximum extent of 60 kilometers by 600 kilometers. The satellite was deployed in a Sun-synchronous circular orbit at an altitude of 694 km.

Based on the controlled classification algorithm of satellite images, cotton fields were identified in the area [33-34]. Hancong [35] calculated the percentage of cotton area using satellite imagery. By dividing the number of cotton pixels by the total area of the field, they obtained the percentage of cotton area that was strongly correlated with yield. The methodology consists of two main data sources (Figure 2). Satellite images and field research data were used. The image used is the main phase of the plant in the growing season [36]. NDVI was produced based on a satellite image of the study area acquired on August 17, 2022 (Figure 3) to separate the cotton fields [37-38].

Five stationary observation sites were chosen using NDVI images to assess the development state of the cotton fields in the study area (Figure 4). Thus, the stationary areas to be researched cover approximately 2350 ha of cotton cultivation area, which is up to 27% of the total cotton cultivation area. Cotton plantations are categorized into three distinct classes based on their level of development. Weak, medium and high levels of productivity. Field study was conducted in each of the five pee-determined permanent observation areas, following the approved sequence of activities inside the specific cotton fields of the respective areas. The agricultural enterprises in the local area supplied farmers with a range of cultivars, including BA-440, Flash, Lodos, May 344, ADN-123, Ganja-114 and Ganja-160.

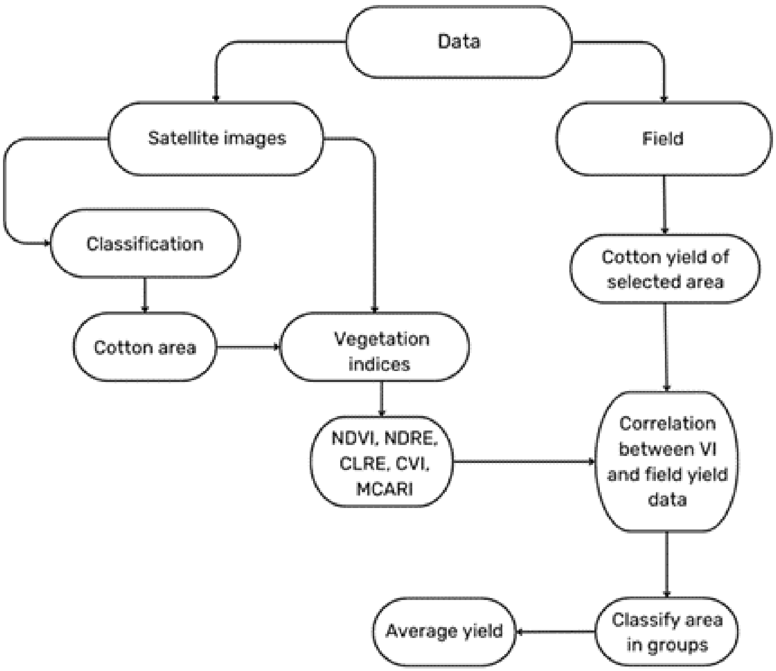

Figure 2. Productivity modeling based on remote sensing and field survey data.

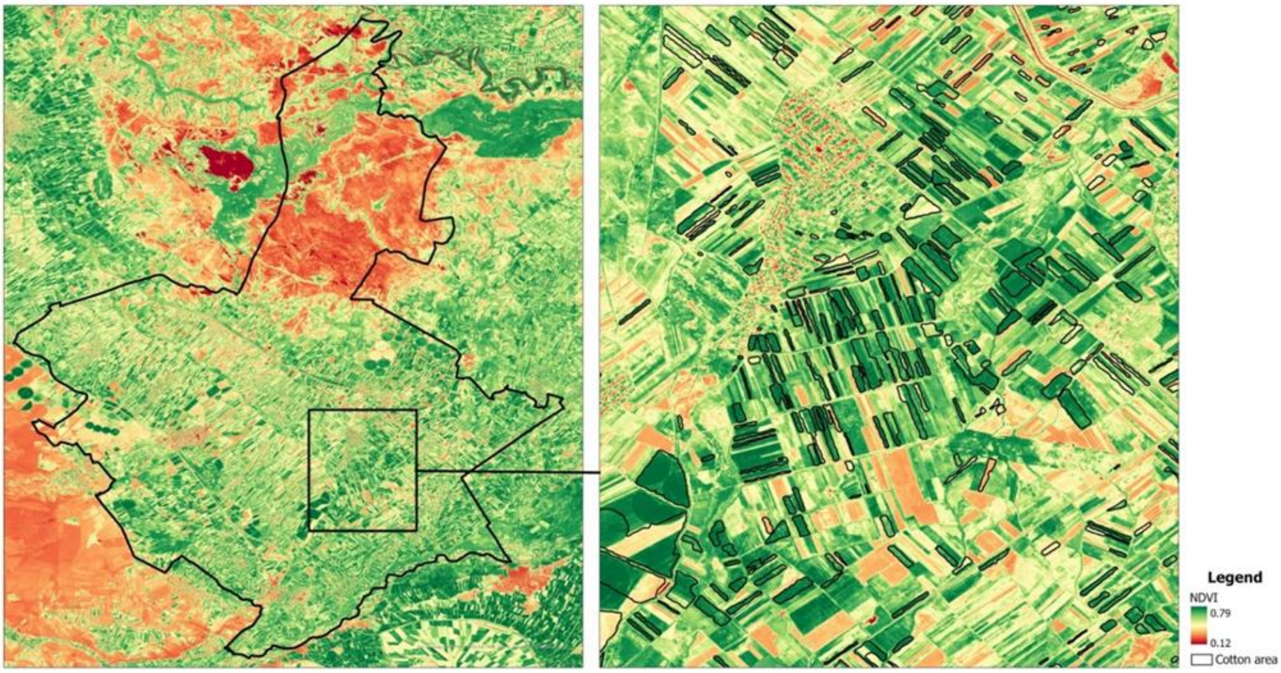

Figure 3. NDVI image of the study area.

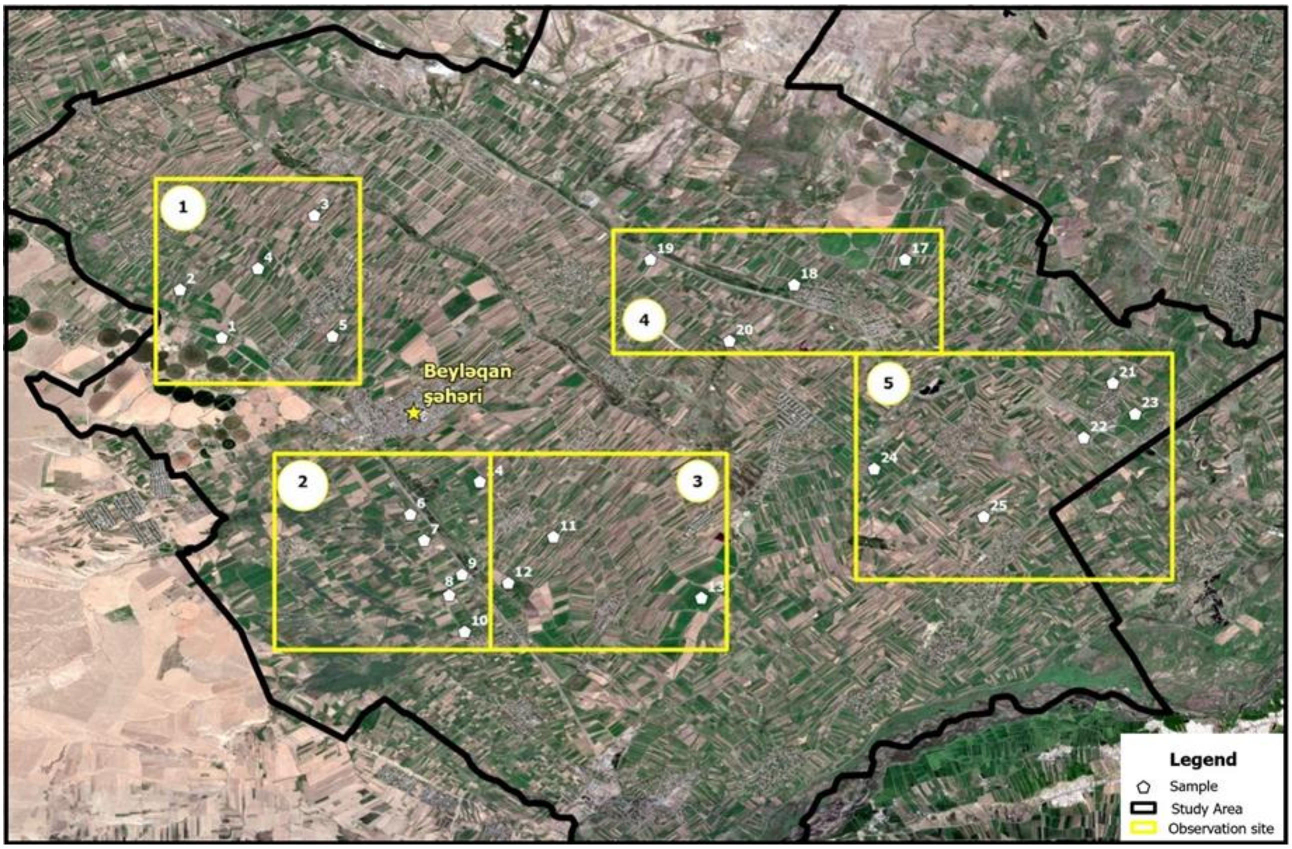

Figure 4. Selected stationary observation sites.

The study involved the random selection of a 1-meter row of plant bushes within a designated region spreading 20-25 meters. The objective was to determine the quantity of plant bushes in this row, as well as the number of productive cotton bolls that were older than 30-35 days, within these bushes. However, it should be noted that the repetition of the same activities was carried out in a diagonal manner with 30-50 meters, depending on the size of the field. The determination and record of both the plant count and boll count were conducted at a minimum of three distinct locations along a single diagonal within each field. Additionally, this process was repeated on the other diagonal in two separate samples. For an example, the product of 219.6 grams of cotton per meter and the row length of 11111.1 meters yields a value of 2440 kg or 24.4 centners per hectare. In each group, a diagonal assessment was conducted across three samples to determine the number of plants within a one-meter radius and the corresponding count of bolls capable of producing crop.

Subsequently, cotton samples were obtained from the opened bolls and quantified by weight using an electronic scale. Multiple independent experiments were done on predetermined regions, referred to as stationary zones (Table 1).

Nowadays, the evaluation of plant production primarily relies on the utilization of satellite remote sensing data. The Sentinel-2 satellite was employed due to the absence of a red edge capability in the Azersky satellite. Multispectral sensors (MSI) with 13 spectral bands and varying spatial resolutions (10, 20, 60 m) are installed on board the twin satellites Sentinel-2, A and B. This provides novel prospects for the monitoring of agricultural activities at both regional and global scales. The utilization of the Sentinel-2 satellite has facilitated the conduction of time-series analysis for monitoring agricultural development and studying productivity.

Table 1. Statistical analysis of field research results.

Study area	Number of samples	Biological productivity cent/ha
1	5	35.1
2	5	43.2
3	5	35.9
4	6	36.6
5	5	34.5
6	6	41.1
7	6	45.4
8	6	36.4
9	6	45.3
10	6	44.4
11	6	31.0
12	6	33.7
13	6	31.8
14	5	33.1
15	6	32.1
16	5	36.8
17	5	29.8
18	6	30.8
19	5	32.7
20	5	32.9
21	6	30.3
22	6	34.7
23	5	30.5
24	6	42.4
25	5	31.2
Sum	139	33.5 cent/ha

2.2. Vegetation indices

The most used indices for vegetation use red and near-infrared (NIR) reflectance or brightness data [39]. For this purpose, some VIs such as NDVI, Chlorophyll vegetation index (CVI), Modified Chlorophyll Absorption in Reflectance Index (MCARI), Normalized Difference Red-Edge (NDRE), Chlorophyll Red Edge Index (CIre) and The Green Normalized Difference Vegetation Index (GNDVI) have been used.

Various VIs is employed in the computation of cotton yield (Table2). NDVI indicates that in healthy vegetation where there is a lot of green foliage, most of the visible light that hits it is absorbed, while NIR light is mainly reflected by the plant [40-41]. Unhealthy vegetation with little or no green foliage reflects most of the visible light, absorbing more NIR light [42-43]. Strong correlations are observed between NDVI measurements and plant biomass, total green area, spikeless green area, and above-ground nitrogen content [44-46]. The calculation procedure of NDVI is as follows [47-48]. CVI has an increased sensitivity to the chlorophyll content of leaf cover [49]. It is used early to mid-crop growth cycle for a wide range of soil and crop conditions by analyzing a large set of synthetic data obtained using a leaf surface contrast model. The increased sensitivity of the index to leaf chlorophyll concentration is due to the effective normalization of different LAI values obtained by applying red and green colors. MCARI measures the depth of chlorophyll absorption and is very sensitive to changes in leaf area index and chlorophyll concentration [50-51]. MCARI values are not affected by lighting conditions, background reflection from soil and other observed non-photosynthetic materials.

Using the Normalized Difference Red-Edge (NDRE) Red edge parameter, a measurement that is not strongly absorbed by the uppermost layers of leaves allows for better information about plants at a later stage [52-53]. These include poor watering, disease, improper fertilizer use, or identifying pests.

CIrededge was developed to estimate the chlorophyll content of leaves using the ratio of reflectance in the near-infrared (NIR) and red-edge bands [54]. Chlorophyll is a good indicator of a plant's production potential. Additionally, it can be utilized to get insight on the nutrient status of plants, the presence of water stress, the prevalence of diseases, and other related factors.

Table 2. Vegetation indices formula.

Index	Formula	Reference
NDVI	(NIR-RED) / (NIR + RED)	[40]
CVI	(NIR * (RED / (GREEN*GREEN)	[49]
MCARI	((RE-RED) -0.2 * / (RE-GREEN)) * (RE + RED)	[50]
NDRE	(RE-RED) / (RE + RED)	[52]
CLRE	(NIR – RE) / 1	[54]
GNDVI	(NIR – Green) / (NIR + Green)	[55]

GNDVI provides an indicator for quantifying the level of "greenness" or photosynthetic activity shown by crops [55]. The vegetation index (VI) under consideration is extensively employed for assessing water and nitrogen absorption inside the crop canopy. The results provided by this index exhibit variation within the range of -1 to 1. Values within the range of -1 to 0 are indicative of the existence of water or exposed soil. The utilization of this measure is primarily observed throughout the intermediate and final phases of the crop cycle. GNDVI is a quantitative measure that utilizes the near infrared and green band wavelengths within the electromagnetic spectrum.

CLRE enhances vegetation detection in areas with little vegetation cover by utilizing the difference between the NIR and red edge bands. It can be used to monitor vegetation change in dry and semi-arid locations. The NDRE is calculated using the nir and red edge bands. The NDRE system is intended for observing the depth of dense vegetation. This makes it an excellent instrument for monitoring densely planted crops such as coffee, corn, cotton, grapes, sunflowers, and others. CVI estimates chlorophyll concentration in plants using the ratio of NIR and red bands. It can be used to monitor plant health and detect nutritional deficits in crops. MCARI reacts to chlorophyll content in the leaf and ground reflectance. In general, high MCARI readings suggest a poor chlorophyll concentration in the leaf. MCARI has a deficit in forecasting low chlorophyll concentrations, which is exacerbated by the influence of the soil signal. The Nir and red bands are used to calculate NDVI. The density and greenness of vegetation in a field can be measured using NDVI. Dense green vegetation is a good general sign of crop health under the proper conditions and at the right time of year. However, cotton is a unique plant, it produces varied results when calculating productivity. The NDVI is primarily used to calculate the degree of photosynthesis in plants. As a result, the healthier and denser the plant tissues are, the more energy they absorb while also reflecting the NIR spectrum. Vegetation covers have indicators ranging from 0.3 to 0.8 (tall and dense plants) as biomass increases. MCARI is the proportion of the green, Nir and red bands.

According to the field samples collected to determine the biological productivity and the calculations made, the productivity of the cotton fields was divided into 3 classes according to the following up criteria:

Poorly developed, up to 60-62 cones per meter:
61 x 4.5** = 180 g x 11111* = up to 31 cent/ha

Medium developed, up to 65-70 cones per meter:
67 x 4.5 = 225 x 11111 = up to 34 cent/ha

Strongly developed, up to 75-80 cones per meter:
80 x 4.5 = 363 x 11111 = up to 40 cent/ha

* 11111 - row length in 1 hectare.
** 4.5 – average cotton weight from field data

Based on statistical indicators, 2350 hectares of the 9122 ha of cotton area planted in the region formed the scope of our research, and the biological productivity of cotton was studied in 139 samples in those areas. This includes one sample for every 16.9 hectares of cotton.

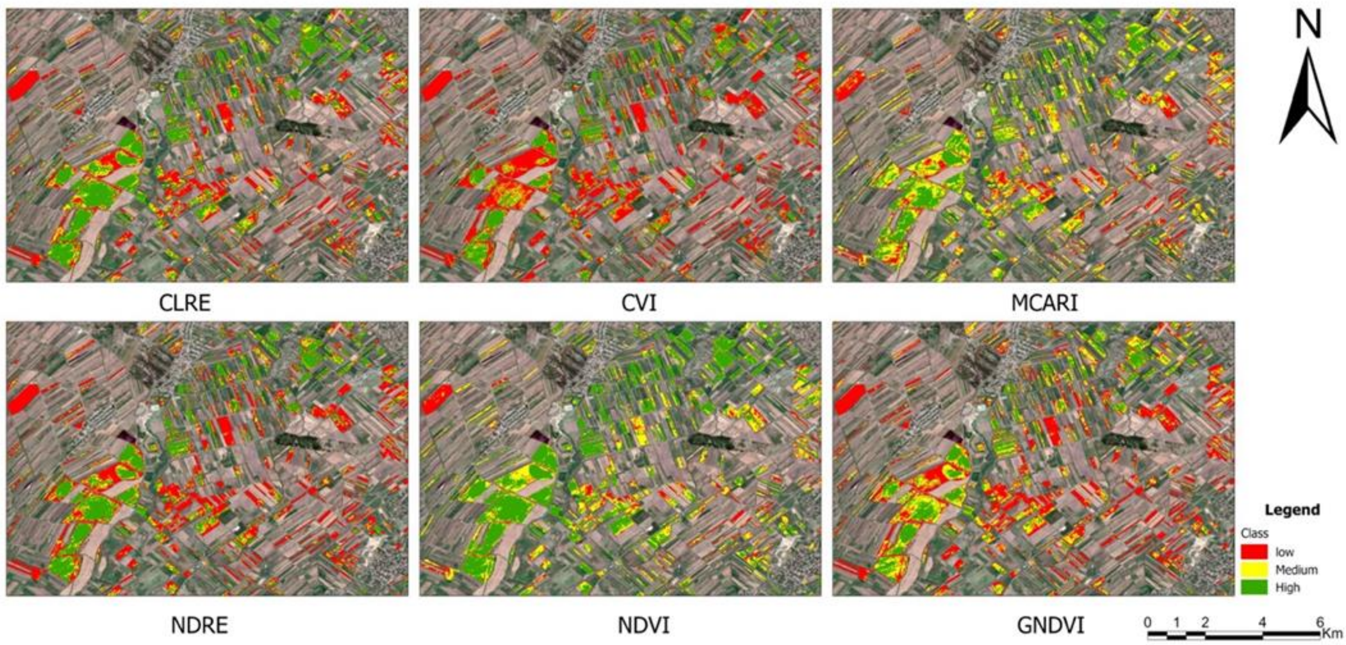

Figure 5. Development levels of vegetation indices.

The most critical phase in cotton irrigation is the second vegetation irrigation. If the second vegetation irrigation of cotton is not carried out on time, we can face a 25-40 percent decrease in yield. The maximum consumption of water by the plant falls during the period of flowering and ripening. In this period, the lack of water leads to a sharp decrease in the yield and its quality. During the period of mass ripening, cotton shows relatively little demand for water shortage. The total water used for crop production in a cotton field consists of the part absorbed by the plant and the part that evaporates from the soil. If we consider the total amount of water used by the field as 100%, then the water used by the plant (for transpiration) will be 60-80% and the water evaporated from the soil will be 20-40%. The more fertile the soil and the higher the applied agrotechnical measures, the less the amount of water that will be used for evaporation, and the more efficient its use by the plant will be. Irrigation mode and volume of cotton should be organized based on the biological characteristics of cotton varieties and the conditions of agrotechnics. Experiments show that increasing the density of the cotton plant increases the total amount of water consumed by the cotton field. This is related to the increase of dry mass and leaf area in the same unit area, which should be considered when determining the irrigation rate. The variety of irrigation also depends on the distance between rows. NDVI is mainly used in the calculation of biomass density. It is observed that the correlation relationship between biomass and productivity is not high. For this reason, measuring the amount of nitrogen in plants is a more reliable way to determine the condition of crops. Based on the results of the field samples and the values of the VIs, the cotton fields were divided into 3 classes, and the development group was determined by using the classified satellite images of the areas belonging to each class (Figure 5).

3. Results

NDVI measurements produce different results while calculating cotton plant yield during the vegetation season by the biomass technique, hence other indices were examined in the project while accounting for the data mentioned above. It is clear from the graph that CVI, MCARI, NDRE, CIrededge and NDVI indices have more influence factors during the growing season (Figure 6). Therefore, in addition to the NDVI index, the CVI, MCARI, NDRE, and CIrededge indexes were utilized.

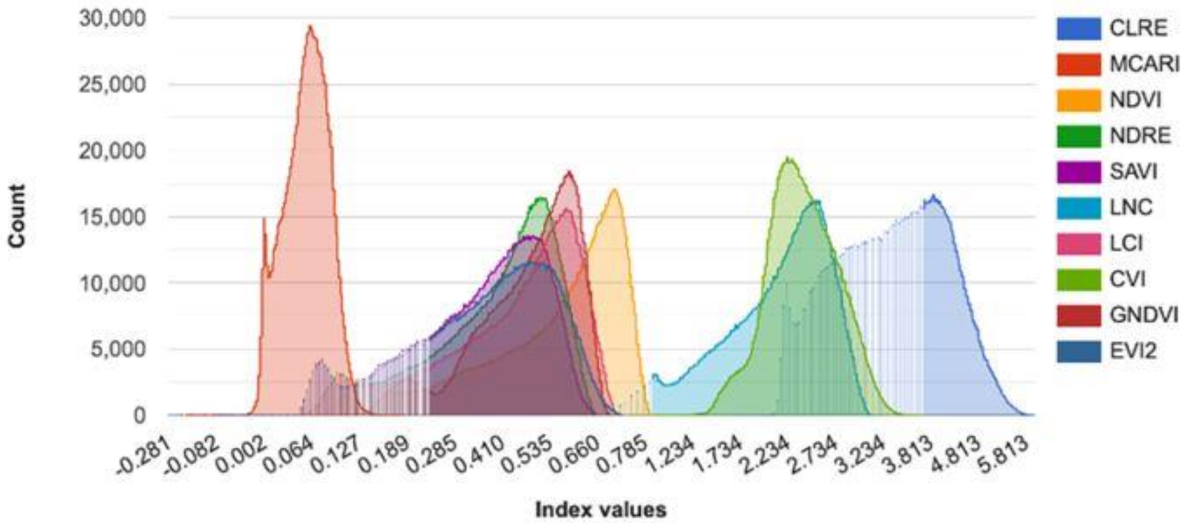

Figure 6. Comparison of different vegetation indices on cotton fields.

The graph provides evidence indicating that CVI exhibits a higher level of sensitivity in relation to cotton fields. Simultaneously, MCARI has a higher level of sensitivity in comparison to other alternatives. The values of NDVI, NDRE, and CLRE exhibit a high degree of similarity. Distribution percentages and "Impact index" (Ti) coefficient were calculated based on the values of VIs selected according to the obtained indicators and the state of development (Table 3). As we defined earlier, weak areas were considered as 31 cent/ha, medium areas as 34 cent/ha and strong areas as 40 cents/ha. As a result of the observations, the weakest areas are observed in the MCARI, and the strongest areas are observed in the CLRE index (Figure 7).

Table 3. Vegetation indices results.

	Level of development	Values	Area*	Impact index**, Ti
NDVI	Low	< 0.66	4901.4 ha	53.68 %
	Mid	0.66 - 0.72	2887.18 ha	31.6 %
	High	> 0.72	1342.77 ha	14.7 %
NDRE	Low	< 0.52	5175.64 ha	56.06 %
	Mid	0.52 - 0.55	1529.56 ha	16.7 %
	High	> 0.55	2438.73 ha	26.7 %
MCARI	Low	< 0.07	6522.41 ha	71.33 %
	Mid	0.07 - 0.09	2292.76 ha	25.07 %
	High	> 0.09	328.72 ha	3.59 %
CVI	Low	< 2.5	5768.76 ha	63.09 %
	Mid	2.5 – 2.6	1161.93 ha	12.71 %
	High	> 2.6	2213.28 ha	24.2 %
CLRE	Low	< 4	4214.11 ha	46.09 %
	Mid	4 – 4.34	2096.26 ha	22.93 %
	High	> 4.34	2833.6 ha	30.99 %
GNDVI	Low	< 0.55	2639.27 ha	28.59 %
	Mid	0.55 – 0.6	2339.95 ha	25.34 %
	High	> 0.6	4253.53 ha	46.07 %

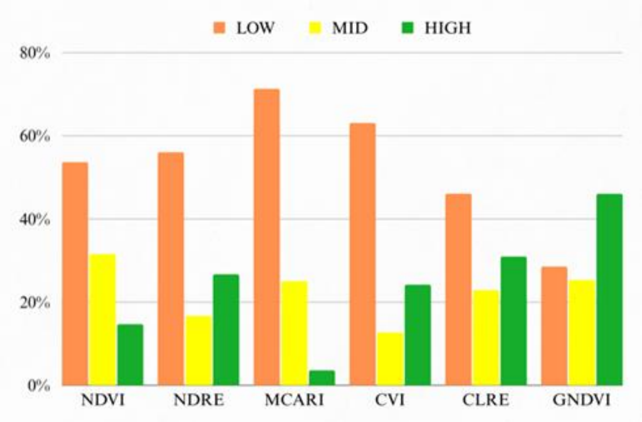

Figure 7. Grouping of various vegetation indices on cotton fields.

Based on the impact indices, the generalized Sylvester-transfer matrix equation [56] can be used to calculate the average biological productivity for the region as shown in Equation 1.

$$MBio = Mlow*Tilow + Mmid*Timid + Mhigh*Tihigh \quad (1)$$

Cotton harvested from cultivated fields yielded an average of 34.4 cents per hectare in 2022 [57]. The various VIs yielded diverse outcomes. Among the indices considered, the CLRE index had a level of production that closely approximated the average value of 34.48 (Figure 8). Similar values have been obtained for other indices. The MCARI index exhibits a distinct value in comparison to the remaining indices.

Figure 8. Average cotton yield of vegetation indices.

4. Discussion

The objective of this work is to forecast the yield of cotton by utilizing VIs that are derived from satellite imagery. One notable advantage associated with the utilization of satellites for plant monitoring is the capacity for remote control, which consequently leads to reduced maintenance expenses.

A total of six VIs were chosen for the purpose of conducting a comprehensive assessment of vegetation within the designated experimental region, as indicated in Table 3. The calculation of VIs was performed by utilizing multispectral reflectance measurements taken at certain wavelengths, including the visible, near-infrared, and red-edge regions. The range of lengths has been employed in several applications within the field of precision agriculture, ranging from to plant counting, growth tracking, and chlorophyll measurement.

Currently, the assessment of plant productivity is carried out mainly based remote sensing data. The red edge band is used to measure chlorophyll levels. The Sentinel-2 satellite was utilized because the Azersky satellite does not have a red edge band. The fundamental issue with these techniques is that Sentinel images' resolution is low for some uses. Nevertheless, Sentinel images are sufficient for vegetation monitoring.

The primary objective of our initial experiment was to examine the significance of various satellite data and VIs in the assessment of cotton yield. After conducting a screening process on a sample of 10 variables of interest (VIs), a total of six VIs were chosen for further analysis. They exhibit a heightened sensitivity for cotton fields compared to other individuals. Similar to the majority of crops, reflectance exhibits its maximum values throughout the infrared range, while displaying relatively minimal absorption within the green range and total absorption within the red range. According to Meng et al. (2017), VIs has proven to be a successful approach in the monitoring of crop development and yield.

NDVI is extensively employed for assessing crop health. However, it is important to note that the calculated productivity of different crop types using the NDVI index may yield varying results. According to a study conducted by [58], it has been observed that high NDVI values throughout the developmental phase of cotton do not necessarily correlate with high productivity. The timely implementation of irrigation practices has a significant impact on plant development in regions where it is not promptly executed. If the crops receive further irrigation from underground water sources, this simply impacts the growth and maturation of the leaves. During this phase, the growth of the cotton plant is inhibited, resulting in stunted development. Consequently, the assessment of production through the evaluation of NDVI values becomes complex. Hence, the growth of additional leaves does not invariably serve as the main reason for the formation of cones. In the context of cotton fields, there is a notable proximity in values seen between areas characterized by both low and high production. Consequently, this difference leads to different outcomes while calculating productivity. This rationale was employed in further indices apart from NDVI.

Measuring the amount of nitrogen in plants is a more reliable technique to estimate crop condition when calculating biomass density. The classification of cotton fields into three classes was based on the findings from field samples and the analysis of VI values. Subsequently, satellite images were utilized to classify the areas of each class, and the development group was identified (Figure 5).

The analysis involved conducting an overall assessment of the VI values obtained from the sample locations utilized in the field investigation. Each VI possesses distinct values. The graph (Figure 9) illustrates the range of values for the CLRE index, with the minimal value being 3.22 and the highest value being 4.99 du. The

NDVI index ranges from a minimum value of 0.51 to a maximum value of 0.71. Similarly, the NDRE index ranges from a minimum value of 0.38 to a maximum value of 0.6. The MCARI index ranges from a minimum value of 0.03 to a maximum value of 0.09. The CVI index ranges from a minimum value of 2.03 to a maximum value of 2.87. Lastly, the GNDVI index ranges from a minimum value of 0.44 to a maximum value of 0.62.

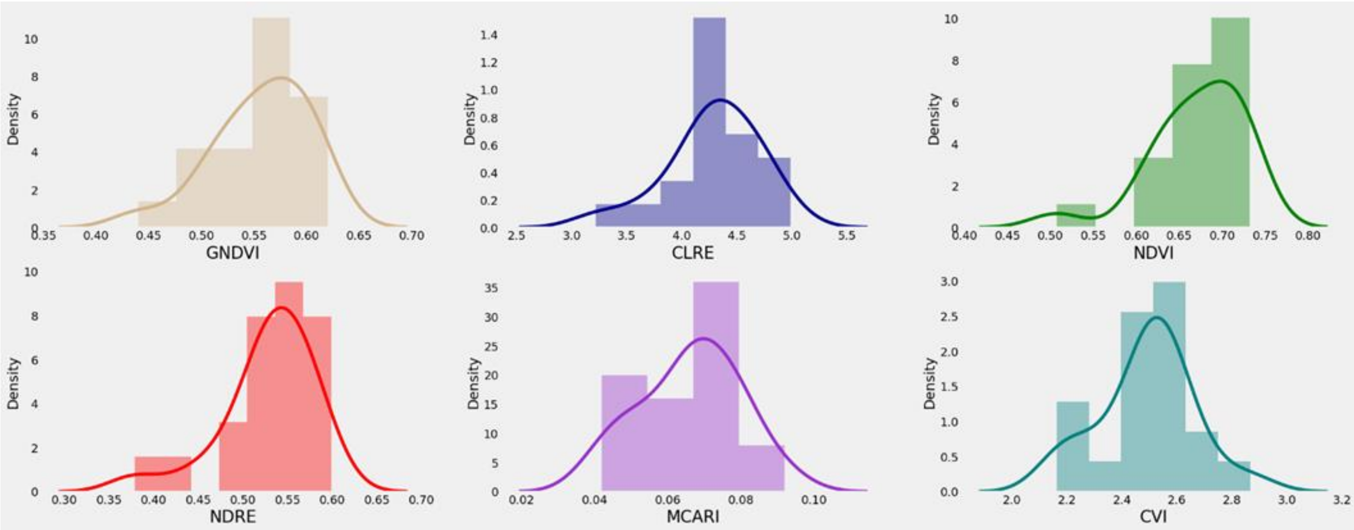

Figure 9. Distribution values of vegetation indices.

In the context of CLRE, low area values classified up to 4, medium areas to 4-4.34, and high area with values over 4.34. The selection criteria for categorizing areas based on NDVI values up to 0.66 were classified as low, areas with NDVI values ranging from 0.66 to 0.72 were classified as medium, and areas with NDVI values greater than 0.72 were classified as high. The selection criteria for NDRE values below 0.52 were classified as low, areas with NDRE values ranging from 0.52 to 0.55 were classified as medium, and areas with NDRE values greater than 0.55 were classified as high. The selection criteria for MCARI involved categorizing areas as low if their values were up to 0.07, if their values were from 0.07 to 0.09 as medium, and high if their values exceeded 0.09. In the context of CVI, regions with a CVI value of up to 2.5 were classified as low areas, while places with CVI values ranging from 2.5 to 2.6 were categorized as medium areas. CVI values over 2.6 were designated as good areas. Lastly, GNDVI areas with values below 0.5 were categorized as low, areas with values ranging from 0.5 to 0.55 were classified as medium, and areas with values above 0.55 were designated as high.

The categorization of cotton fields based on VIs were conducted, taking into consideration the productivity of each field. Based on the data derived from field research, places exhibiting lower levels of performance were categorized as weak, with an average cost of 31 cents per hectare. places demonstrating moderate levels of performance were classified as medium, with an average cost of 34 cents per hectare. Lastly, areas displaying higher levels of performance were designated as strong, with an average cost of 40 cents per hectare. The VIs of the respective locations were compared using the provided data. Therefore, the development groups and intermediate values derived from each index have been identified. Once the identification of each development area was completed, the respective area was quantified and subsequently assigned a percentage value, referred to as the impact index. The average productivity of the development groups and the region was determined based on data collected from impact and field studies.

According to statistics data, the mean productivity in the region was calculated to be 34.4 cents per hectare. Based on the calculations derived from the ClRE values in our investigation, the productivity observed was found to be near the average value with 34.48 (Figure 8). The analysis reveals that there is no significant difference in the mean productivity achieved across other indices. The MCARI index exhibits a distinct value in comparison to the remaining indices. The primary factor contributing to this phenomenon is the prevalence of underdeveloped regions in MCARI, as depicted in Figure 7. Furthermore, it is evident that there are comparatively few high areas (3.59%), which is the lowest percentage when compared to other indices. The medium areas exhibit a range of 12-31% across all indices.

The occurrence of moderate weather during the months of May and June in 2022 resulted in delays in the vegetation season of plants and restricted their growth. The growing season was extended beyond expectations due to the negative impact of prolonged overcast and foggy days on the cotton plant. The process of maturation and boll opening is experiencing a delay. Additionally, Insufficient exposure to sunlight can also lead to the deterioration of internal organs [59]. All varieties of cotton plants necessitate exposure to shorter daylight periods. While the plant development levels in past years exhibited distinct visibility, the development levels in the current year displayed a notable proximity to one another. Crop yields can fluctuate from year to year due to a combination of various genotypes, management approaches, and extreme weather conditions, including high temperatures, precipitation, floods, and droughts [60]. The precise and punctual assessment of cotton output is crucial to implement efficient agronomic management strategies intended for mitigating potential losses [61]. Due to this factor, there existed distinct variations in the values of the acquired VIs. Furthermore, the cotton plant's development is adversely impacted by drought conditions and water scarcity.

Nitrogen plays a crucial role in promoting plant development and enhancing productivity. The proper growth and physiological development of cotton are crucial factors to consider [62]. Analyzing the anomalies that have occurred within the cotton fields over the previous five years has revealed various consequences depending on the amount of nitrogen. The categorization led to the identification of areas with excellent, good, efficient, and poor performance (Figure 10). Poor areas are more visible in 2019 than other years. In 2020, high areas are more dominant. In the year 2022, there is a greater prevalence of fields that are considered medium or good. Upon analyzing the five-year statistical data pertaining to the Beylagan region, it is evident that the agricultural production in the year 2020 surpassed that of previous years, reaching a notable value of 35.5 cents per hectare [30].

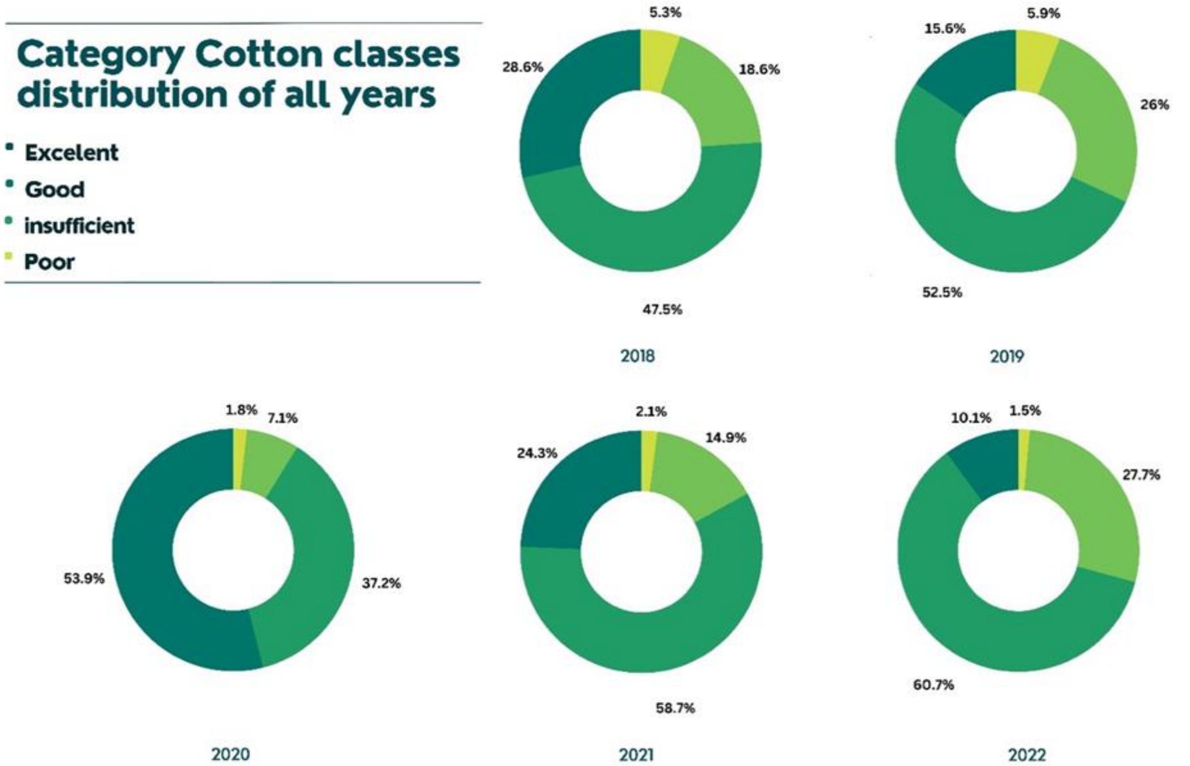

Figure 10. Classification of 5-year cotton fields.

5. Conclusion

In this study, satellite imagery was used to monitor cotton yield before harvest. VIs and field samples were used to estimate pre-harvest cotton yield from the images. Since nitrogen plays an important role in aphid development, several VIs have been used to estimate plant height in cotton with high accuracy based on remote sensing data in the visible, NIR and Red Edge regions of the spectrum. VIs extracted from the obtained images and sample yield were significantly correlated and therefore could be used in cotton yield monitoring. This shows us that it is possible to obtain practical and economic solutions with satellite observations.

Acknowledgement

The author thanks The Mil Experimental Station for the data.

Author contributions

Bakhtiyar Babashli: Conceptualization, Methodology, Software, Collected the data, Performed the analysis, writing original draft preparation; Writing-Reviewing and Editing. **Aytaj Badalova:** Writing original draft preparation and analysis; **Ramis Shukurov:** Field data collection and preparation data. **Agil Ahmadov:** Contributed data and performed the analysis.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Giller, K. E., Delaune, T., Silva, J. V., Descheemaeker, K., van de Ven, G., Schut, A. G., ... & van Ittersum, M. K. (2021). The future of farming: Who will produce our food?. Food Security, 13(5), 1073-1099. https://doi.org/10.1007/s12571-021-01184-6
2. Kim, H. J., & Triplett, B. A. (2001). Cotton fiber growth in planta and in vitro. Models for plant cell elongation and cell wall biogenesis. Plant physiology, 127(4), 1361-1366. https://doi.org/10.1104/pp.010724
3. Ashraf, K. H., & Hanif, M. (2010). Screening of cotton germplasm against cotton leaf curl virus. Pakistan Journal of Botany, 42(5), 3327-3342.

4. Ridley, W., & Devadoss, S. (2023). Competition and trade policy in the world cotton market: Implications for US cotton exports. American Journal of Agricultural Economics, 105, 1365-1387. https://doi.org/10.1111/ajae.12370
5. Aytaç, S., Başbağ, S., Arslanoğlu, F., Ekinci, R., & Ayan, A. K. (2020). Lif bitkileri üretiminde mevcut durum ve gelecek. Türkiye Ziraat Mühendisliği IX. Teknik Kongresi Bildiriler Kitabı-1, 463-491.
6. He, L., & Mostovoy, G. (2019). Cotton yield estimate using Sentinel-2 data and an ecosystem model over the southern US. Remote Sensing, 11(17), 2000. https://doi.org/10.3390/rs11172000
7. Tariq, A., Siddiqui, S., Sharifi, A., & Shah, S. H. I. A. (2022). Impact of spatio-temporal land surface temperature on cropping pattern and land use and land cover changes using satellite imagery, Hafizabad District, Punjab, Province of Pakistan. Arabian Journal of Geosciences, 15(11), 1045. https://doi.org/10.1007/s12517-022-10238-8
8. Corwin, D. L., Lesch, S. M., Shouse, P. J., Soppe, R., & Ayars, J. E. (2003). Identifying soil properties that influence cotton yield using soil sampling directed by apparent soil electrical conductivity. Agronomy Journal, 95(2), 352-364. https://doi.org/10.2134/agronj2003.3520
9. Tran, D. X., Pla, F., Latorre-Carmona, P., Myint, S. W., Caetano, M., & Kieu, H. V. (2017). Characterizing the relationship between land use land cover change and land surface temperature. ISPRS Journal of Photogrammetry and Remote Sensing, 124, 119-132. https://doi.org/10.1016/j.isprsjprs.2017.01.001
10. Zambon, I., Cecchini, M., Egidi, G., Saporito, M. G., & Colantoni, A. (2019). Revolution 4.0: Industry vs. agriculture in a future development for SMEs. Processes, 7(1), 36. https://doi.org/10.3390/pr7010036
11. Zhang, D., & Zhou, G. (2016). Estimation of soil moisture from optical and thermal remote sensing: A review. Sensors, 16(8), 1308. https://doi.org/10.3390/s16081308
12. Ahmad, T., Sud, U. C., Rai, A., & Sahoo, P. M. (2020). An Alternative Sampling Methodology for Estimation of Cotton Yield using Double Sampling Approach. Journal of the Indian Society of Agricultural Statistics, 74(3), 217–226.
13. Shi, G., Du, X., Du, M., Li, Q., Tian, X., Ren, Y., ... & Wang, H. (2022). Cotton Yield Estimation Using the Remotely Sensed Cotton Boll Index from UAV Images. Drones, 6(9), 254. https://doi.org/10.3390/drones6090254
14. Lang, P., Zhang, L., Huang, C., Chen, J., Kang, X., Zhang, Z., & Tong, Q. (2023). Integrating environmental and satellite data to estimate county-level cotton yield in Xinjiang Province. Frontiers in Plant Science, 13, 1048479. https://doi.org/10.3389/fpls.2022.1048479
15. Pantazi, X. E., Moshou, D., Alexandridis, T., Whetton, R. L., & Mouazen, A. M. (2016). Wheat yield prediction using machine learning and advanced sensing techniques. Computers and Electronics in Agriculture, 121, 57-65. https://doi.org/10.1016/j.compag.2015.11.018
16. Zhang, J., Huang, Y., Pu, R., Gonzalez-Moreno, P., Yuan, L., Wu, K., & Huang, W. (2019). Monitoring plant diseases and pests through remote sensing technology: A review. Computers and Electronics in Agriculture, 165, 104943. https://doi.org/10.1016/j.compag.2019.104943
17. Hou, P., Liu, Y., Liu, W., Liu, G., Xie, R., Wang, K., ... & Li, S. (2020). How to increase maize production without extra nitrogen input. Resources, Conservation and Recycling, 160, 104913. https://doi.org/10.1016/j.resconrec.2020.104913
18. Ekinci, M., Atamanalp, M., Turan, M., Alak, G., Kul, R., Kitir, N., & Yildirim, E. (2019). Integrated use of nitrogen fertilizer and fish manure: Effects on the growth and chemical composition of spinach. Communications in Soil Science and Plant Analysis, 50(13), 1580-1590. https://doi.org/10.1080/00103624.2019.1631324
19. Guo, Z., Luo, C., Dong, Y., Dong, K., Zhu, J., & Ma, L. (2021). Effect of nitrogen regulation on the epidemic characteristics of intercropping faba bean rust disease primarily depends on the canopy microclimate and nitrogen nutrition. Field Crops Research, 274, 108339. https://doi.org/10.1016/j.fcr.2021.108339
20. Dhivya, R., Amalabalu, P., Pushpa, R., & Kavithamani, D. (2014). Variability, heritability and genetic advance in upland cotton (Gossypium hirsutum L.). African Journal of Plant Science, 8(1), 1-5. https://doi.org/10.5897/AJPS2013.1099
21. Onoda, Y., Wright, I. J., Evans, J. R., Hikosaka, K., Kitajima, K., Niinemets, Ü., ... & Westoby, M. (2017). Physiological and structural tradeoffs underlying the leaf economics spectrum. New Phytologist, 214(4), 1447-1463. https://doi.org/10.1111/nph.14496
22. Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., & Garnier, J. (2014). 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environmental Research Letters, 9(10), 105011. https://doi.org/10.1088/1748-9326/9/10/105011
23. Singh, R. J., & Ahlawat, I. P. S. (2012). Dry matter, nitrogen, phosphorous, and potassium partitioning, accumulation, and use efficiency in transgenic cotton-based cropping systems. Communications in Soil Science and Plant Analysis, 43(20), 2633-2650. https://doi.org/10.1080/00103624.2012.716125
24. Alganci, U., Ozdogan, M., Sertel, E., & Ormeci, C. (2014). Estimating maize and cotton yield in southeastern Turkey with integrated use of satellite images, meteorological data and digital photographs. Field Crops Research, 157, 8-19. https://doi.org/10.1016/j.fcr.2013.12.006
25. Liu, Q. S., Li, X. Y., Liu, G. H., Huang, C., & Guo, Y. S. (2016). Cotton area and yield estimation at Zhanhua County of China using HJ-1 EVI time series. In ITM Web of Conferences, 7, 09001. https://doi.org/10.1051/itmconf/20160709001
26. Bian, C., Shi, H., Wu, S., Zhang, K., Wei, M., Zhao, Y., ... & Chen, S. (2022). Prediction of field-scale wheat yield using machine learning method and multi-spectral UAV data. Remote Sensing, 14(6), 1474.

https://doi.org/10.3390/rs14061474
27. Leroux, L., Castets, M., Baron, C., Escorihuela, M. J., Bégué, A., & Seen, D. L. (2019). Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. European Journal of Agronomy, 108, 11-26. https://doi.org/10.1016/j.eja.2019.04.007
28. Elders, A., Carroll, M. L., Neigh, C. S., D'Agostino, A. L., Ksoll, C., Wooten, M. R., & Brown, M. E. (2022). Estimating crop type and yield of small holder fields in Burkina Faso using multi-day Sentinel-2. Remote Sensing Applications: Society and Environment, 27, 100820. https://doi.org/10.1016/j.rsase.2022.100820
29. Azərbaycan Respublikası Beyləqan Rayon İcra Hakimiyyəti (2023). Coğrafi mövqeyi. http://www.beyleqan-ih.gov.az/az/page/13.html
30. State Statistical Committee of the Republic of Azerbaijan (2022). Main economic indicators of agricultural enterprises and private owner farms.
31. Simarmata, N., Nadzir, Z. A., & Agustina, L. K. (2022). Application of Spot6/7 Satellite Imagery for Rice Field Mapping Based on Transformative Vegetation Indices. Jurnal Geografi, 14(1), 69. https://doi.org/10.24114/jg.v14i1.29036
32. Ismatova, K. H. R., Badalova, A. N., Ismailov, A. I., Aliyev, Z. H., & Talibova, S. S. (2019). Features of the Use of Aerospace Methods in Soil Science. Journal of Medical Care Research and Review, 2(5), 149-154.
33. De Wit, A. J. W., & Clevers, J. G. P. W. (2004). Efficiency and accuracy of per-field classification for operational crop mapping. International Journal of Remote Sensing, 25(20), 4091-4112. https://doi.org/10.1080/01431160310001619580
34. Beriaux, E., Jago, A., Lucau-Danila, C., Planchon, V., & Defourny, P. (2021). Sentinel-1 time series for crop identification in the framework of the future CAP monitoring. Remote Sensing, 13(14), 2785. https://doi.org/10.3390/rs13142785
35. Fu, H., Zhao, H., Song, R., Yang, Y., Li, Z., & Zhang, S. (2022). Cotton aphid infestation monitoring using Sentinel-2 MSI imagery coupled with derivative of ratio spectroscopy and random forest algorithm. Frontiers in Plant Science, 13, 1029529. https://doi.org/10.3389/fpls.2022.1029529
36. Hümbətov, H. S., X. Q. Xəlilov, X. Q. (2012). Pambiq lifinin texnologiyasi.
37. Zheng, B., Myint, S. W., Thenkabail, P. S., & Aggarwal, R. M. (2015). A support vector machine to identify irrigated crop types using time-series Landsat NDVI data. International Journal of Applied Earth Observation and Geoinformation, 34, 103-112. https://doi.org/10.1016/j.jag.2014.07.002
38. Barriere, V., & Claverie, M. (2022). Multimodal crop type classification fusing multi-spectral satellite time series with farmers crop rotations and local crop distribution. Computer Vision and Pattern Recognition. https://doi.org/10.48550/arXiv.2208.10838
39. Fridgen, J. L., & Varco, J. J. (2004). Dependency of cotton leaf nitrogen, chlorophyll, and reflectance on nitrogen and potassium availability. Agronomy Journal, 96(1), 63-69. https://doi.org/10.2134/agronj2004.6300
40. Ravandi, S. H., & Valizadeh, M. (2011). Properties of fibers and fabrics that contribute to human comfort. Improving Comfort in Clothing, 61-78. Woodhead Publishing. https://doi.org/10.1533/9780857090645.1.61
41. Roznik, M., Boyd, M., & Porth, L. (2022). Improving crop yield estimation by applying higher resolution satellite NDVI imagery and high-resolution cropland masks. Remote Sensing Applications: Society and Environment, 25, 100693. https://doi.org/10.1016/j.rsase.2022.100693
42. Ramoelo, A., Cho, M. A., Mathieu, R., Madonsela, S., Van De Kerchove, R., Kaszta, Z., & Wolff, E. (2015). Monitoring grass nutrients and biomass as indicators of rangeland quality and quantity using random forest modelling and WorldView-2 data. International Journal of Applied Earth Observation and Geoinformation, 43, 43-54. https://doi.org/10.1016/j.jag.2014.12.010
43. Pettorelli, N. (2013). The normalized difference vegetation index. Oxford University Press, USA.
44. Leo, S., Migliorati, M. D. A., Nguyen, T. H., & Grace, P. R. (2023). Combining remote sensing-derived management zones and an auto-calibrated crop simulation model to determine optimal nitrogen fertilizer rates. Agricultural Systems, 205, 103559. https://doi.org/10.1016/j.agsy.2022.103559
45. Li, Z., Menefee, D., Yang, X., Cui, S., & Rajan, N. (2022). Simulating productivity of dryland cotton using APSIM, climate scenario analysis, and remote sensing. Agricultural and Forest Meteorology, 325, 109148. https://doi.org/10.1016/j.agrformet.2022.109148
46. Mumtaz, F., Tao, Y., de Leeuw, G., Zhao, L., Fan, C., Elnashar, A., ... & Wang, D. (2020). Modeling spatio-temporal land transformation and its associated impacts on land surface temperature (LST). Remote Sensing, 12(18), 2987. https://doi.org/10.3390/rs12182987
47. NASA (2000). Normalized Difference Vegetation Index (NDVI). https://earthobservatory.nasa.gov/features/MeasuringVegetation/measuring_vegetation_2.php
48. Dalezios, N. R., Domenikiotis, C., Loukas, A., Tzortzios, S. T., & Kalaitzidis, C. (2001). Cotton yield estimation based on NOAA/AVHRR produced NDVI. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, 26(3), 247-251. https://doi.org/10.1016/S1464-1909(00)00247-1
49. Vincini, M., Frazzi, E., D'alessio, P., & Stafford, J. V. (2007). Comparison of narrow-band and broad-band vegetation indexes for canopy chlorophyll density estimation in sugar beet. Precision agriculture, 7, 189-196. https://doi.org/10.3920/978-90-8686-603-8
50. Daughtry, C. S., Walthall, C. L., Kim, M. S., De Colstoun, E. B., & McMurtrey Iii, J. E. (2000). Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote sensing of Environment, 74(2), 229-239. https://doi.org/10.1016/S0034-4257(00)00113-9

51. Elfanah, A. M., Darwish, M. A., Selim, A. I., Shabana, M. M., Elmoselhy, O. M., Khedr, R. A., ... & Abdelhamid, M. T. (2023). Spectral reflectance indices' performance to identify seawater salinity tolerance in bread wheat genotypes using genotype by yield* trait biplot approach. Agronomy, 13(2), 353. https://doi.org/10.3390/agronomy13020353
52. Barnes, E. M., Clarke, T. R., Richards, S. E., Colaizzi, P. D., Haberland, J., Kostrzewski, M., ... & Moran, M. S. (2000, July). Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data. In Proceedings of the fifth international conference on precision agriculture, Bloomington, MN, USA, 1619, 6.
53. Zhang, K., Ge, X., Shen, P., Li, W., Liu, X., Cao, Q., ... & Tian, Y. (2019). Predicting rice grain yield based on dynamic changes in vegetation indexes during early to mid-growth stages. Remote sensing, 11(4), 387. https://doi.org/10.3390/rs11040387
54. Gitelson, A. A., Viña, A., Ciganda, V., Rundquist, D. C., & Arkebauer, T. J. (2005). Remote estimation of canopy chlorophyll content in crops. Geophysical research letters, 32(8), 1-4. https://doi.org/10.1029/2005GL022688
55. Kaya, Y., & Polat, N. (2021). Sulu ve kuru tarım alanlarında buğday verim tahmininde bitki örtüsü indekslerinin kullanımı. Türk Tarım ve Doğa Bilimleri Dergisi, 8(3), 736-746. https://doi.org/10.30910/turkjans.864231
56. Sasaki, N., & Chansangiam, P. (2020). Modified Jacobi-gradient iterative method for generalized Sylvester matrix equation. Symmetry, 12(11), 1831. https://doi.org/10.3390/sym12111831
57. Azərbaycan Respublikasının Dövlət Statistika Komitəsi (2023). Tarla bitkilərinin əkin sahəsi, məhsul yığımı və məhsuldarlığı.
58. Zhao, D., Reddy, K. R., Kakani, V. G., Read, J. J., & Koti, S. (2007). Canopy reflectance in cotton for growth assessment and lint yield prediction. European Journal of Agronomy, 26(3), 335-344. https://doi.org/10.1016/j.eja.2006.12.001
59. Sawan, Z. M. (2018). Climatic variables: Evaporation, sunshine, relative humidity, soil and air temperature and its adverse effects on cotton production. Information processing in agriculture, 5(1), 134-148. https://doi.org/10.1016/j.inpa.2017.09.006
60. Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. Nature, 525(7567), 47-55. https://doi.org/10.1038/nature14956
61. Li, Z., Ding, L., & Xu, D. (2022). Exploring the potential role of environmental and multi-source satellite data in crop yield prediction across Northeast China. Science of The Total Environment, 815, 152880. https://doi.org/10.1016/j.scitotenv.2021.152880
62. Iqbal, A., Qiang, D., Zhun, W., Xiangru, W., Huiping, G., Hengheng, Z., ... & Meizhen, S. (2020). Growth and nitrogen metabolism are associated with nitrogen-use efficiency in cotton genotypes. Plant Physiology and Biochemistry, 149, 61-74. https://doi.org/10.1016/j.plaphy.2020.02.002