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Enhancing Agricultural Productivity: Integrating Remote Sensing Techniques for Cotton Yield Monitoring and Assessment

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Abstract: This study assesses soil productivity in a 15-hectare cotton field using an integrated approach combining field data, laboratory analysis, and remote sensing techniques. Soil samples were collected and analyzed for key parameters including nitrogen (N), humus, phosphorus (P_2O_5), potassium (K_2O), carbonates, pH, and electrical conductivity (EC). In addition to low salinity, these analyses showed low results for humus and nutrient parameters. A Pearson correlation analysis showed that low organic matter and high salinity had a strong negative correlation with crop productivity, explaining 37% of the variation in NDVI values. Remote sensing indices (NDVI, SAVI, NDMI, and NDSI) confirmed these findings by highlighting the relationship between soil properties and spectral reflectance. This research demonstrates the effectiveness of remote sensing in soil assessment, emphasizing its critical role in sustainable agricultural planning. By integrating traditional methods with advanced remote sensing technologies, this study provides actionable insights for policymakers and practitioners to improve soil productivity and ensure food security.

Keywords: remote sensing; geographic ınformation systems; soil; cotton; vegetation indices; correlation

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1. Introduction

Increasing productivity requires improving precision agriculture. The development of precision agriculture is possible only with the use of cutting-edge technologies and techniques. Conventional irrigation, applying indefinite amounts of fertilizers, failure to conduct soil analyses in the fields, neglecting the crop rotation system, and other possible problems lead to reduced productivity and soil degradation, as stated, e.g., by [1–3]. These practices frequently result in inefficient utilization of resources, environmental degradation, and reduced productivity, thereby underscoring a substantial gap in contemporary agricultural practices.

One significant shortcoming of conventional approaches is the absence of precise, timely, and comprehensive data on soil and crop conditions. The limited spatial coverage and labor-intensive nature of ground measurements frequently impede comprehensive monitoring and management. It is in this context that the application of cutting-edge techniques, such as remote sensing, can be considered to have a transformative role to play. The integration of remote sensing with conventional soil analysis presents a promising solution to overcome these limitations and enhance agricultural productivity.

In addition to compliance with agrotechnical requirements, monitoring and control of plant development are also significant issues. Along with ground-based research, satellite data monitoring has a special place among the measures taken to increase agricultural productivity.

Mapping arable land, assessing land use, and predicting crop yield are often based on satellite data [4–7]. The indicators obtained as a result of reflection from plant leaves constitute the basis for monitoring. Due to the reflection from leaves, larger leaf plants allow obtaining more detailed information. For instance, cotton can be accounted for among relatively broadleaf plants. Since cotton is grown in arid and semi-arid regions, satellite observation could be more suitable due to favorable natural conditions (a lot of sunny, cloudless days and weather conditions without precipitation).

In general, several studies have been conducted for assessment of agriculture plants based on productivity indicators and in various approaches, analyzing satellite data use has been widely discussed. Meng et al. (2021) evaluated those effects using a flexible spatiotemporal data fusion (FSDAF) model to generate high spatial resolution and frequently covered fusion images in three cotton fields. By comparing different yield estimation models, the study indirectly links vegetation productivity to soil characteristics, as soil health is a critical factor influencing crop yield. Accurate yield estimations and the spatial variation in these estimates can reflect underlying soil issues, such as nutrient deficiencies or salinity, that may be affecting plant growth [8]. Hao Fei et al. proposed a district-scale cotton mapping method using a random forest (RF) feature selection algorithm and a classifier based on the selection of multi-functional features including spectral vegetation indices and texture features. The texture and spectral features detected through remote sensing can reflect differences in soil conditions, such as moisture levels, salinity, and organic matter content. The use of spectral features like NDVI and SAVI, combined with the analysis of texture features, can help to infer soil health and fertility, as vegetation indices are closely linked to soil nutrient availability and moisture [9].

Despite these advances, there is still a need for further integration of remote sensing with conventional soil analysis to enhance yield estimation and management. Our research aims to fill this gap by combining soil sample analysis with satellite data to provide a comprehensive assessment of soil productivity. Thus, in this paper, we will analyze soil samples taken from cotton fields in 2021, investigate land use change, process satellite data on the indices, correlate the results, and assess crop productivity by implementing remote observation of fields.

The State of Cotton Cultivation in Azerbaijan

Cotton is of strategic importance and a widely used plant in Azerbaijan. Since this valuable plant is used in the preparation of various goods and products, special attention is paid to increasing its production in the country. The soil–climate conditions in Azerbaijan are absolutely favorable for the cultivation of this plant [10].

Due to the region's favorable geographical location, climate, and soil characteristics, cotton cultivation in Azerbaijan is concentrated in the Kura-Araz plain, situated between the Greater Caucasus, Lesser Caucasus, and Talish Mountains. The soils of these areas, which are mainly irrigated, are very suitable for the cotton plant. This is because the existing irrigation and collector-drainage systems and the natural climatic conditions of these areas provide a basis for cotton cultivation and obtaining high productivity from this plant.

Soil types such as grey, as well as Kastanozem (also known as "chestnut soil"), Solonchak (saline soils), calcareous soil, alluvial, swamp, etc. are spread in the lowland. The proportion of humus in the upper horizons of these soils reaches 1.5–2% [11]. In these areas where this soil type predominates, salinization, hardening, and other degradation factors can significantly affect the productivity of these areas. Groundwater is one of the main factors affecting salinity. In these areas, the presence of groundwater close to the surface increases this nearness when irrigated. By flowing near the soil surface, mineral groundwater penetrates the topsoil and increases the percentage of soil salinity through evaporation [12].

The period of greatest development of cotton cultivation in Azerbaijan coincided with the 1970s and 1990s, and, according to rough estimates, the highest figure in the country

reached 1 million tons in 1981 [13,14]. Between 2006 and 2010, there was a decline in production in this sector, with the lowest production level being around 32,000 tonnes in 2009. In 2020, it increased again, exceeding 336 thousand tonnes [13]. One of the reasons for this was the fall in the world price of cotton since 1990 [15,16]. Many explain the decline in cotton production in our country by the change in ownership that occurred in the post-Soviet period. The abolition of the large collective farms (kolkhoz) and state farms (sovkhoz), which controlled all the land, made it less profitable for small landowners to grow cotton. There was also the freedom to grow cotton after the land was given to the peasants and the collective and state farms were dismantled. Thus, the production of "white gold", which once brought a lot of money to our republic and became a source of livelihood and income for the population, gradually decreased to a minimum level. However, following the approval of the "State Program for the Development of Cotton Growing in the Republic of Azerbaijan for 2017–2022" [17] and state support for farmers, an increase has been observed in this sector [18]. With the implementation of the State Program, attention has been focused on both the productivity and the improvement of the land management practices. This highlights the need for a comprehensive understanding of soil chemical properties, such as pH, electrical conductivity, and nutrient availability, which are key to sustaining cotton yields. Mapping these soil characteristics using both field data and remote sensing technologies is crucial for optimizing the cotton-growing potential of the region and ensuring long-term soil fertility.

2. Study Area Description

A plot of 22 hectares was selected for study, which has been using as a cotton field in the northwestern part of the Neftchala region (Figure 1). Both an irrigation canal and a collector has been built along the edges of the field. The sown area is 18 ha. The area is located on the Kura-Araz plain and −23 m below the level of the Baltic Sea.

Hydrometeorological data from two nearby stations (Neftchala and Salyan) were used to determine temperature and precipitation for the years 2010–2021 (Figures 2 and 3).

The average annual temperature was 15.61 °C in the Neftchala region between the years 1991–2020 and 15.74 °C in the Salyan region. Compared to 1961–1990, the average annual temperature increased by 0.8 °C from 1991–2020. The average perennial precipitation in these regions is in the range of 240–270 mm. From the coastline of the Caspian Sea to the centre of the Kura-Araz plain, the annual amount of precipitation decreases in some places. In comparison with 1961–1990, the amount of perennial precipitation decreased by 15% in the Salyan region and 10% in the Neftchala region from 1991–2020 [19,20].

The Neftchala region's economy is based on cotton cultivation, grain, fodder, and animal husbandry. Although the region has a mild, hot, semi-desert, and dry steppe climate with arid summers, cotton harvesting, like in other regions, was subject to a decline at a certain period, but now this field is also experiencing growth. The lowest figure for cotton harvesting in the Neftchala region was recorded in 2015, standing at 255 tons. In 2020, this indicator increased by 90 times and was approximately 23 thousand tons (Figure 4) [13].

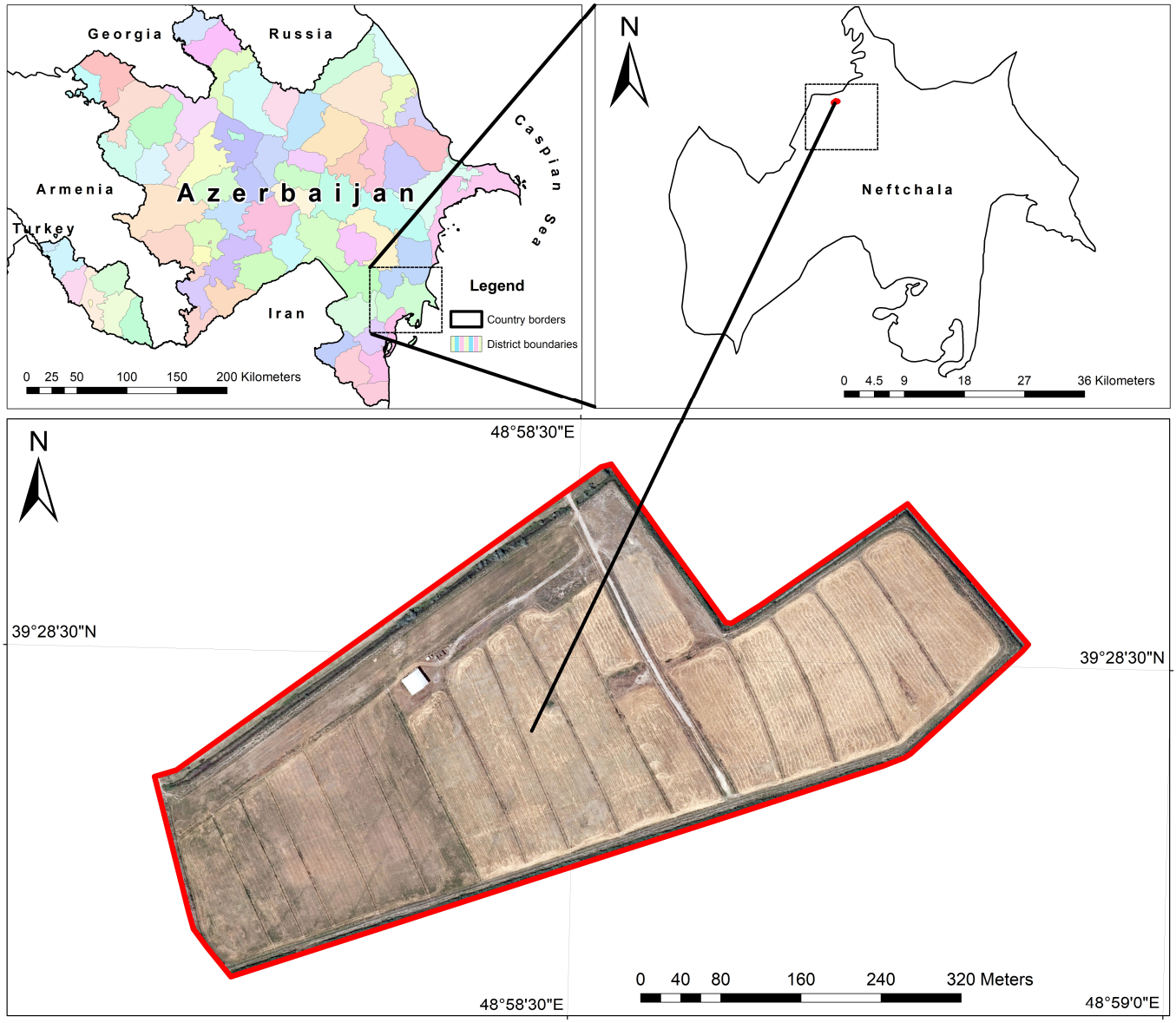


Figure 1. Study area.

According to the topographic map from 1986 in the scale of 1:10,000 [21], the selected area served as an airbase for aerial application in agriculture (Figure 5). This airport also meant a drastic land use change, from arable land to areas with buildings and a runway of the airport made of concrete. Later on, the airfield was abolished in 1996 and the area was taken for cultivation by a farmer for the first time in 1999.

Some buildings were demolished and cotton was planted in between spaces. For the first time, 500 kg of cotton was harvested from just 6 hectares of land. Every year, the cultivated area was expanded (Figure 6), and cotton was planted from 1999–2005, barley and alfalfa from 2006–2016, and since 2017 cotton has been continuously planted.

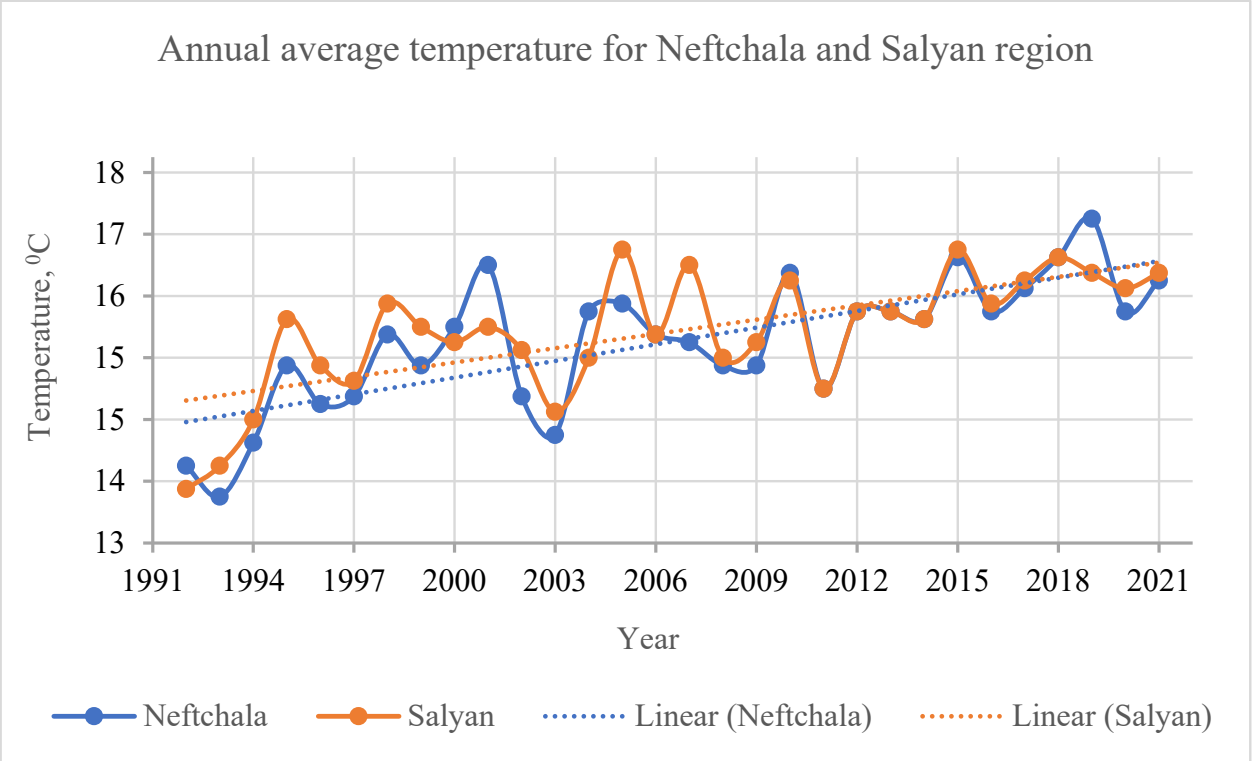


Figure 2. Temperature trends for Neftchala and Salyan regions [19,20].

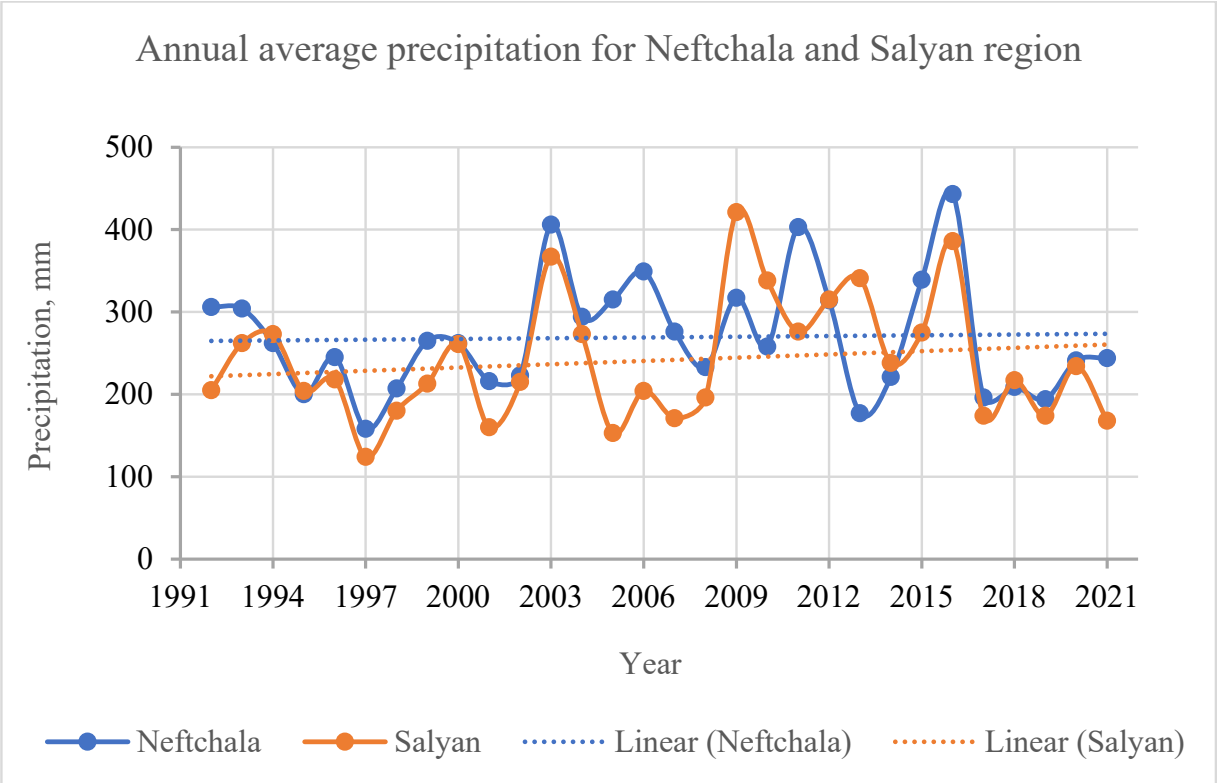


Figure 3. Annual average precipitation for Neftchala and Salyan regions [19,20].

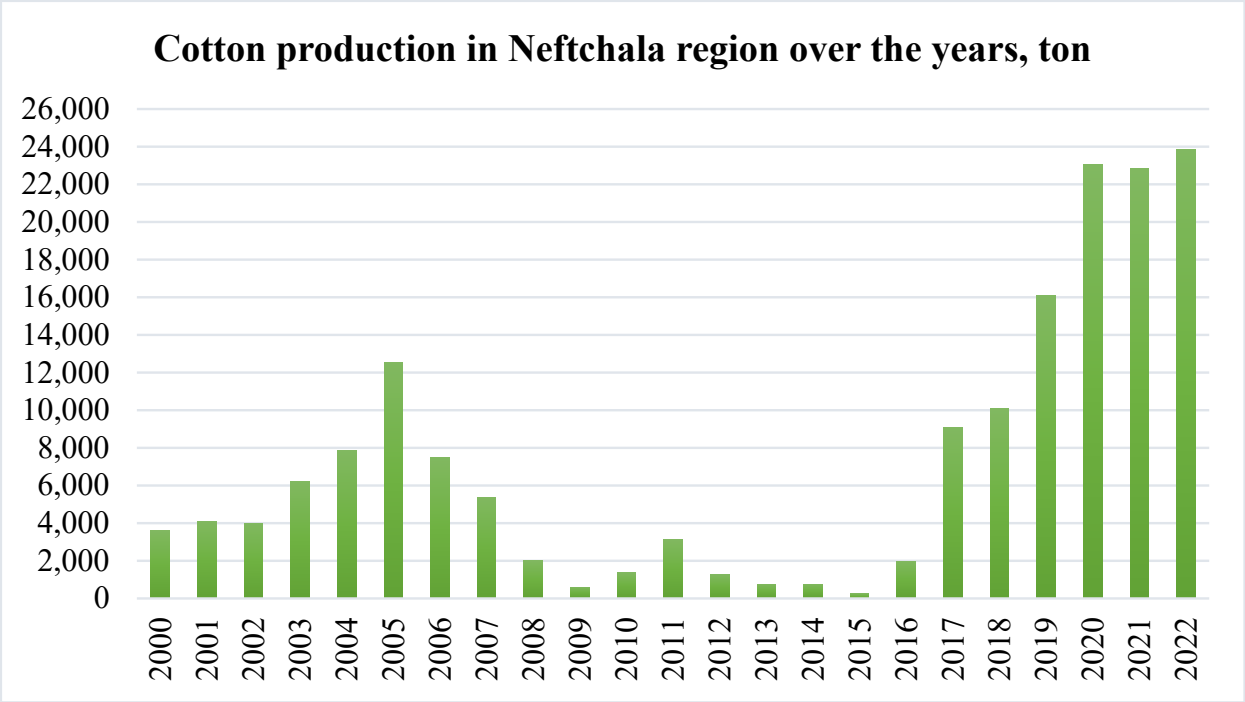


Figure 4. Cotton production over the years [13].

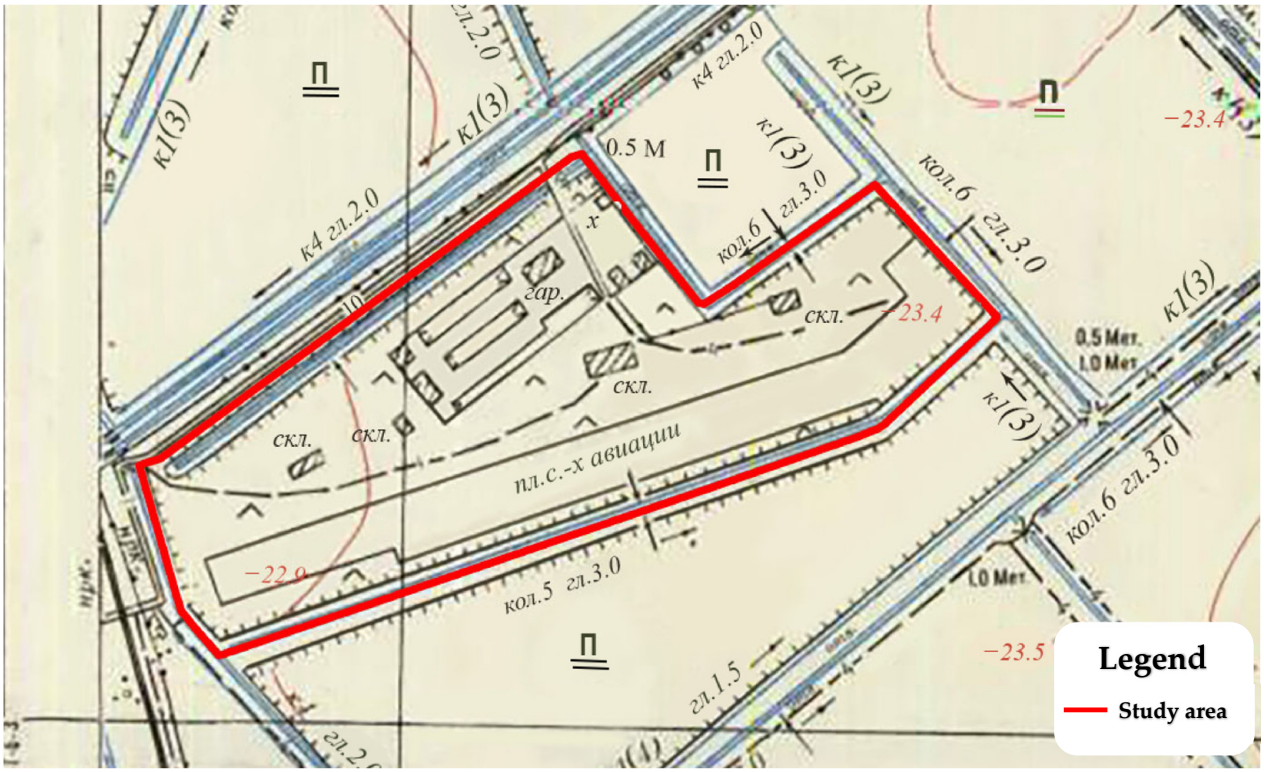


Figure 5. Topographic map (1:10,000) of the study area (before cultivation) [21].

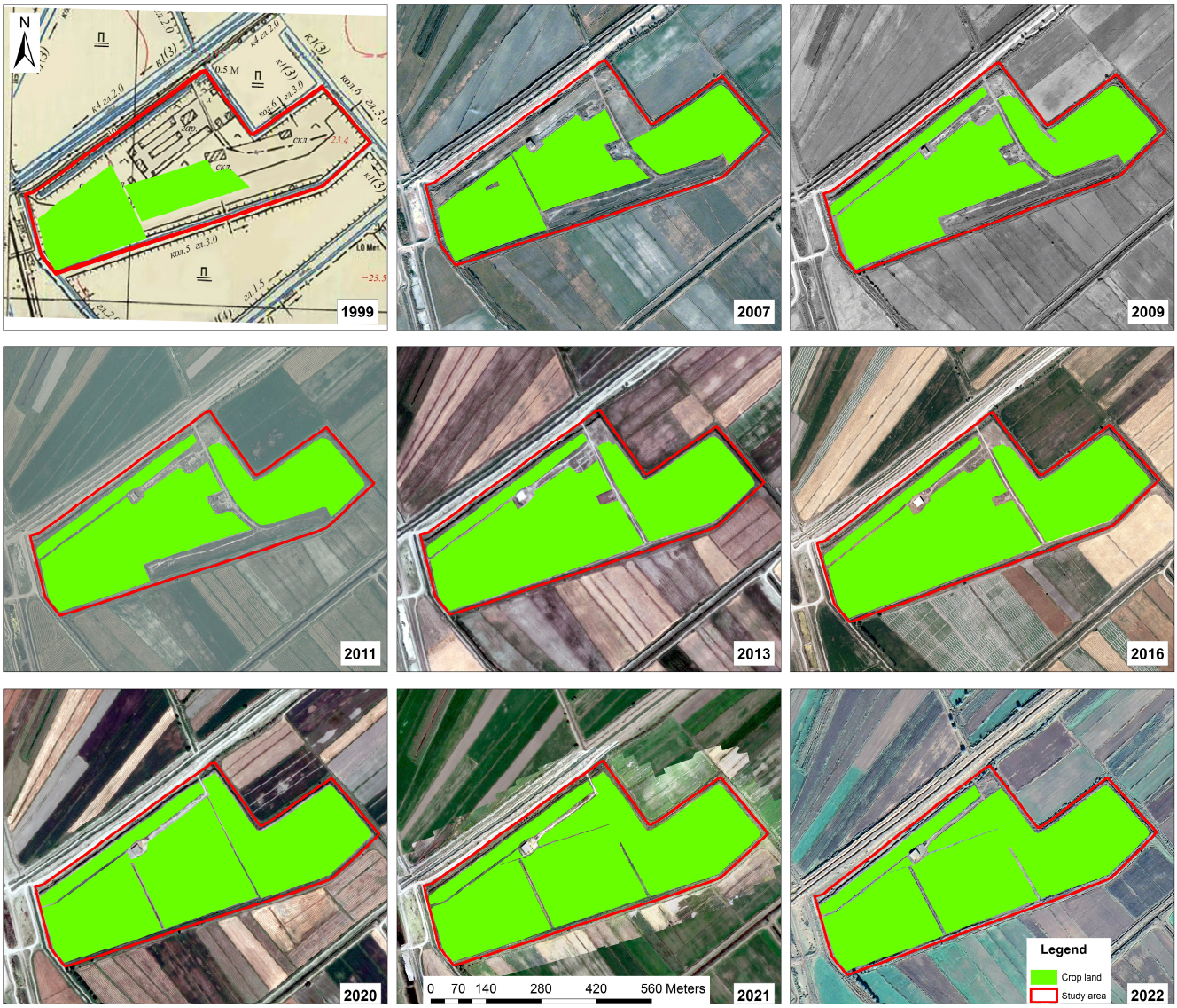


Figure 6. The map of the change of the cultivated area over the years (1999–2022).

During this period, the farmer carried out recultivation works on the land every year. So, a certain amount of soil layer was removed from the places where plants poorly developed in the field and soil was brought from other locations. The brought soil layer was not analyzed in a laboratory but was directly transported and applied to the field. Despite this, the farmer managed to increase the productivity level every year. However, as a result of the drought in 2022, improper distribution of irrigation caused the least indicator in cotton yield. Figure 7 presents the harvested crop from 2017–2023.

In 2021, the planting was carried out from 1 May to 5 May. The type of planted cotton was Bayaz Altin R-1. At planting, the entire field was evenly spread with 100 kg of amphoras fertilizer and once the cotton reached a certain level, 200 kg of carbamide was applied in the same manner. The field was cleared of weeds in June and July. Prior to the harvesting period, irrigation was carried out three times using the old irrigation method, by laying ditches between crops. The harvesting process was carried out at different times from the beginning of September to the end of November.

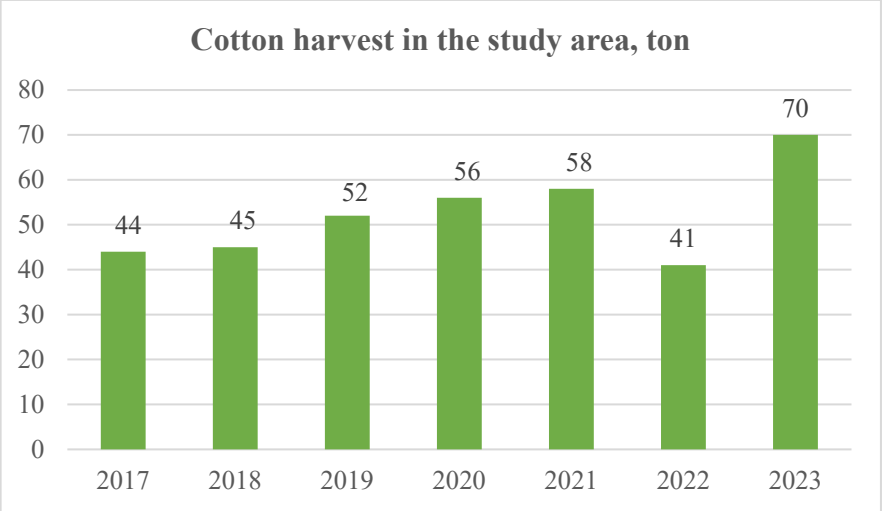


Figure 7. Cotton harvesting of the study area over years.

3. Materials and Methods

Archival materials and aerial images were used to map the study area between 1986 and 2022. As a second method, UAV (unmanned aerial vehicle) and satellite images together with field surveys were used to capture the soil and cotton conditions between 2021 and 2023.

While the archive material consists of a topographic map at a scale of 1:10,000, obtained from aerial photography in 1986 (Figure 5), the 2011 National Cadastral Survey (Figure 6) and the 2016 Agricultural Survey (Figure 6) are other possible aerial photographs. Additional drone (UAV) surveys were also conducted to evaluate the current situation. Drone photography was carried out from a height of 100 m using a DJI Phantom 4 drone.

Land use was vectorized with the ArcGIS 10.3 program on orthophotos that were obtained from DJI Phantom 4 drone imagery; attributive data (water channel, collector-drainage systems, dirt roads, etc.) were collected by specifying the area and entered into the database.

Sentinel-2B satellite images of the EU Copernicus program were used for the observation of the study area [22]. The value of Sentinel-2B satellite images to estimate cotton yield was proved by He et al., Kaplan et al., and Li et al. [23–25]. From this point of view, the images covering 18 August 2021 were derived from the mentioned satellite. Images were selected mainly for cloud-free weather conditions.

In order to increase soil productivity, the chemical properties of the soil must be determined first. Each of these chemical properties provides an important insight into different aspects of soil quality and basic concepts to support healthy crop growth. While the study of nitrogen (N) determines soil fertility, humus serves soil health and supports its ability for sustainable agriculture; phosphorus (P_2O_5) serves to identify deficiencies that can limit crop yields; potassium (K_2O) ensures proper plant development; carbonates can determine soil pH dynamics; pH can determine soil compatibility for different crops; and electrical conductivity (EC) can control soil salinity. By analyzing these specific parameters, our research provides a comprehensive understanding of soil health and how it influences cotton productivity. This holistic approach ensures that all critical aspects of soil fertility are considered, enabling informed decision-making for efficient soil management and sustainable agricultural practices. Taking into account the above-mentioned, soil samples are taken from different parts of the cultivated area and analyzed in laboratory conditions. Soil samples were taken on 15 August 2021 from 12 different places of the study area and the mentioned places were numbered and their geographical coordinates were determined (Figure 8). The coordinates of the test points were performed using GNSS Geomax zenith 25 equipment. Soil samples were analyzed according to several properties and the following methods were applied in the analysis process (Table 1).

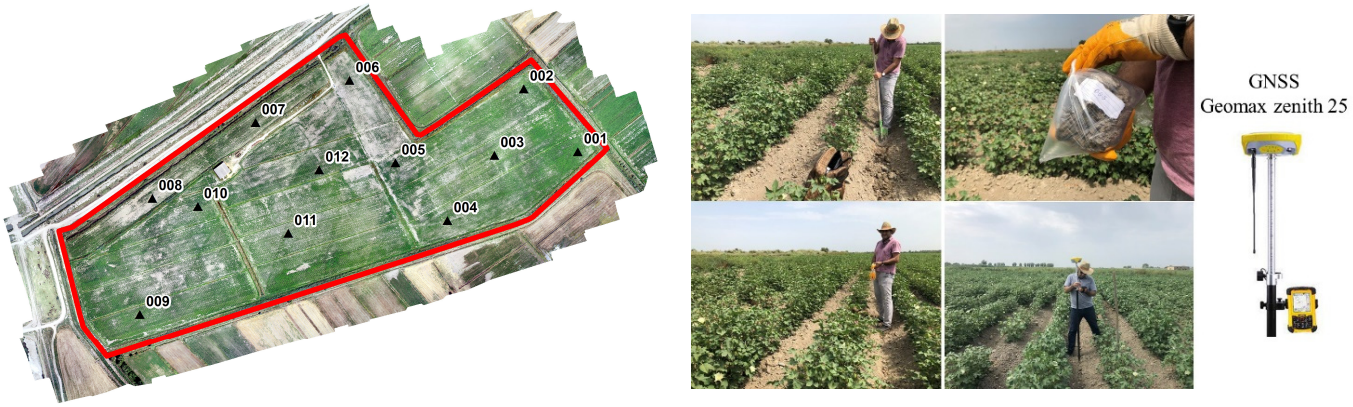


Figure 8. Orthophoto from DJI Phantom 4 drone, points where soil samples were taken, and the GNSS equipment used.

Table 1. Used methods of soil sampling analysis on different parameters.

Analysis	Extraction Methods
N	Keldal [26]
Humus	Walkley–Black [27]
P_2O_5	OLSEN [28]
K_2O	Maslovıy [29]
Carbonates	Scheibler [30]
pH	GOST26423-85 [31]
EC	GOST26423-85 [32]

According to the WRB (World Reference Base) classification, this soil cover is included in the Calcisol soil group. These soils are classified as irrigated grass-grey soils in the Azerbaijan soil classification. The profiles are carbonated and the carbonates in the soil profile are mainly a form of reaccumulation. These lands are mainly used for grain and cotton cultivation with conventional irrigation.

Although the soil samples were analyzed for 7 parameters, the main focus was on electrical conductivity. As we know, EC (electrical conductivity) analysis is used to evaluate soil salinity, which can significantly impact agricultural productivity. Electrical conductivity (EC) is a measure of a soil's ability to conduct electricity and is commonly used as an indicator of soil salinity. High soil salinity can have a negative impact on plant growth and productivity. Comparing soil conductivity with satellite data is a suitable method for estimating productivity. Therefore, the EC indicator was used as the basis for subsequent research procedures.

A layer named Soil_Samples was created with ArcGIS 10.3 to map the soil analysis results. The results were added to the attribute table of the mentioned layer and were only interpolated for the EC indicator. The interpolation was performed using the IDW tool from the Interpolation Section of the Geostatistical Analyst Tools Menu of that program.

In addition to ground-based surveys, remote sensing allows to determine changes in the land surface [33,34]. On this account, processing of the satellite data according to various parameters is necessary (required). The processing is arranged by analyzing different bands with indices. These indices allow to identify vegetation cover, humidity (humidity), soil surface salinity (salinity), temperature, and other properties by comparing them over time [35–38]. Hence, 4 remote sensing indices were used in the study: the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Moisture Index (NDMI), and Normalized Difference Salinity Index (NDSI).These indices were used to correlate spectral reflectance with key soil chemical properties such as nitrogen (N), phosphorus (P_2O_5), potassium (K_2O), and electrical conductivity (EC). The integration of remote sensing data with soil analysis allows for a comprehen-

sive understanding of soil health and crop productivity, providing critical insights for precision agriculture.

1. NDVI was selected for its ability to accurately monitor crop health by analyzing vegetation greenness. This index is significant for the identification of areas of stressed and healthy vegetation, which is directly related to our crop productivity assessment objective. It is particularly effective at detecting chlorophyll levels in plants, providing information on crop health and productivity [39–41]:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}$$

2. As our study area has sparse vegetation and high soil exposure, the SAVI index was chosen to measure brightness. This index minimizes the soil influence on vegetation monitoring, which is particularly relevant in arid and semi-arid environments. SAVI allows us to more accurately assess plant growth in such conditions, thus providing a better understanding of plant health where NDVI may be less reliable due to the exposed soil [42–44]:

$$\mathrm{SAVI} = \frac{(1 + \mathrm{L})(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED} + \mathrm{L})}$$

3. One of the critical factors in productivity is soil moisture, which was measured by the use of the NDMI index. This index has been crucial in understanding availability water availability and its direct impact on the health of the plants in our cotton fields, helping us to guide our water management strategies and optimize irrigation. As a result, water stress in plants is important for the irrigation and the maintenance of the soil moisture balance [45–47]:

$$\mathrm{NDMI} = \frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})}$$

4. Soil salinity is a significant limiting factor for crop productivity, particularly in regions prone to salinization. NDSI was selected to detect and evaluate soil salinity levels across the study area. By identifying saline-affected zones, we can better understand the spatial distribution of soil salinity and its influence on plant health and yield. This information is vital for implementing soil management practices aimed at reducing salinity and enhancing overall productivity [48–50]:

$$\mathrm{NDSI} = \frac{(\mathrm{GREEN} - \mathrm{NIR})}{(\mathrm{GREEN} + \mathrm{NIR})}$$

NDVI and SAVI were calculated using 10-m-resolution Sentinel-2B satellite imagery, while NDMI and NDSI were calculated using 20-m-resolution imagery with the corresponding bands.

First, the satellite images were cropped within the boundaries of the study area, as they cover a large area. They were then processed on the 4 indices mentioned above. The soil samples were taken to the prepared indices and the indicators of each index were determined in the geolocation of the samples. The mentioned processes were performed using the following ArcGIS 10.3 tools:

- Image clipping—Image Analysis, Clip;
- Index processing—Spatial Analyst Tools, Map Algebra, Raster Calculator;
- Raster values—Spatial Analyst Tools, Extract Values to Points.

Finally, Pearson correlation was used to measure the linear relationship between soil chemical properties and satellite-derived indices (NDVI, SAVI, NDMI, and NDSI). Htun et al. [51] conducted a regression analysis to establish the relationship between a

number of vegetation index-based variables and their effects on rice plant productivity. In the mentioned study, rice yield was predicted for 6 years from analysis based on the vegetation index by applying linear and multiple regression models. The analysis showed that the highest predicted rice yield was obtained from the NDWI and the lowest from the RGVI. We aimed to use correlation to understand how changes in soil nutrients, humus, and salinity were reflected in spectral data obtained from satellite imagery. This allowed us to determine the strength and direction of the linear relationship between the variables, confirm the reliability of the satellite indices, and identify which soil characteristics had the greatest influence on spectral reflectance. To further assess the accuracy and consistency of the data, Root Mean Square Error (RMSE) and R-squared values were calculated. The RMSE supports the measurement of prediction error by quantifying the differences between the predicted values by the model and the observed values. R-squared indicates the proportion of variance in the dependent variable that is predictable by the independent variable(s), i.e., the strength of the relationship.

4. Results and Discussion

Land use was vectorized manually (Figure 9) on the orthophoto and the result revealed that the crop area was surrounded by collectors. This helps to maintain control of groundwater and prevent salinization.



Figure 9. Land use map of study area.

Acquired soil samples were analyzed in the laboratory using appropriate methods, as described in Table 1, for seven properties (Table 2), and the following results were obtained.

Table 2. Main diagnostic indicators of soil samples.

Sample Number	Depth, sm	N, %	Humus, %	P_2O_5, mg/kg	K_2O, mg/kg	Carbonates, %	pH, mS/sm	EC, mS/sm
		Norm 0.09–0.17	Norm 2–3	Norm 24–48	Norm 100–220	Norm 0–1	Norm 6.6–7.5	Norm < 2
001	30	0.143	5.37	129.39	676	9.41	7.68	0.49
002	30	0.1	2.93	14.43	710	13.6	8.2	0.52
003	30	0.112	2.47	58.62	709	13.9	7.55	0.644
004	30	0.079	2.7	74.2	492	18	7.73	2.1
005	30	0.131	2.96	90	908	11.4	7.66	2.32
006	30	0.098	2.64	66.41	602	15.2	7.65	1.814
007	30	0.091	2.41	35.72	492	12.8	8.08	0.777
008	30	0.077	1.13	34.04	370	12.2	7.6	3.48
009	30	0.112	2.59	54.5	573	12.1	8.1	0.609
010	30	0.097	2.29	52.21	930	13.6	7.48	2.67
011	30	0.108	2.53	88.39	610	12.2	8.05	1.223
012	30	0.1	2.59	43.97	624	13.8	7.97	1.088

The table presented in this study characterized various soil properties across the twelve collected samples. Each sample was assigned a unique identifier (sample number) and its depth of collection within the soil profile was recorded (depth, cm). Nitrogen (N, %), a crucial element for plant growth, was measured to assess the soil's potential for supporting plant nutrition. Humus content (humus, %), representing soil organic matter, was determined to evaluate the soil's fertility and water retention capacity. Phosphorus (P_2O_5, mg/kg) and potassium (K_2O, mg/kg), essential plant nutrients alongside nitrogen, were quantified to assess their availability for plant uptake. Carbonate content (carbonates, %), known to influence soil pH and fertility, was also measured. Soil pH, a measure of acidity or alkalinity, was determined to provide insights into the overall soil chemical environment. Finally, electrical conductivity (EC, mS/cm), reflecting the level of dissolved salts in the soil, was measured to assess potential salinity concerns. This comprehensive analysis of various soil properties provides valuable information for understanding the overall soil quality and its potential to support plant growth.

By using analysis results, the following maps were developed as a result of evaluation of salt-affected areas (electrical conductivity, EC) through the interpolation method and the calculation of indices in four directions (Figure 10).

As depicted in the maps in Figure 10, there is some visual consistency in the results of both the interpolation of the laboratory results and the analysis of the satellite images with different indices. To clarify this correspondence, we correlated 12 field measurement results with satellite image indices. The results are presented in Table 3.

The obtained figures have been graphically compared on the EC indicator (Figure 11).

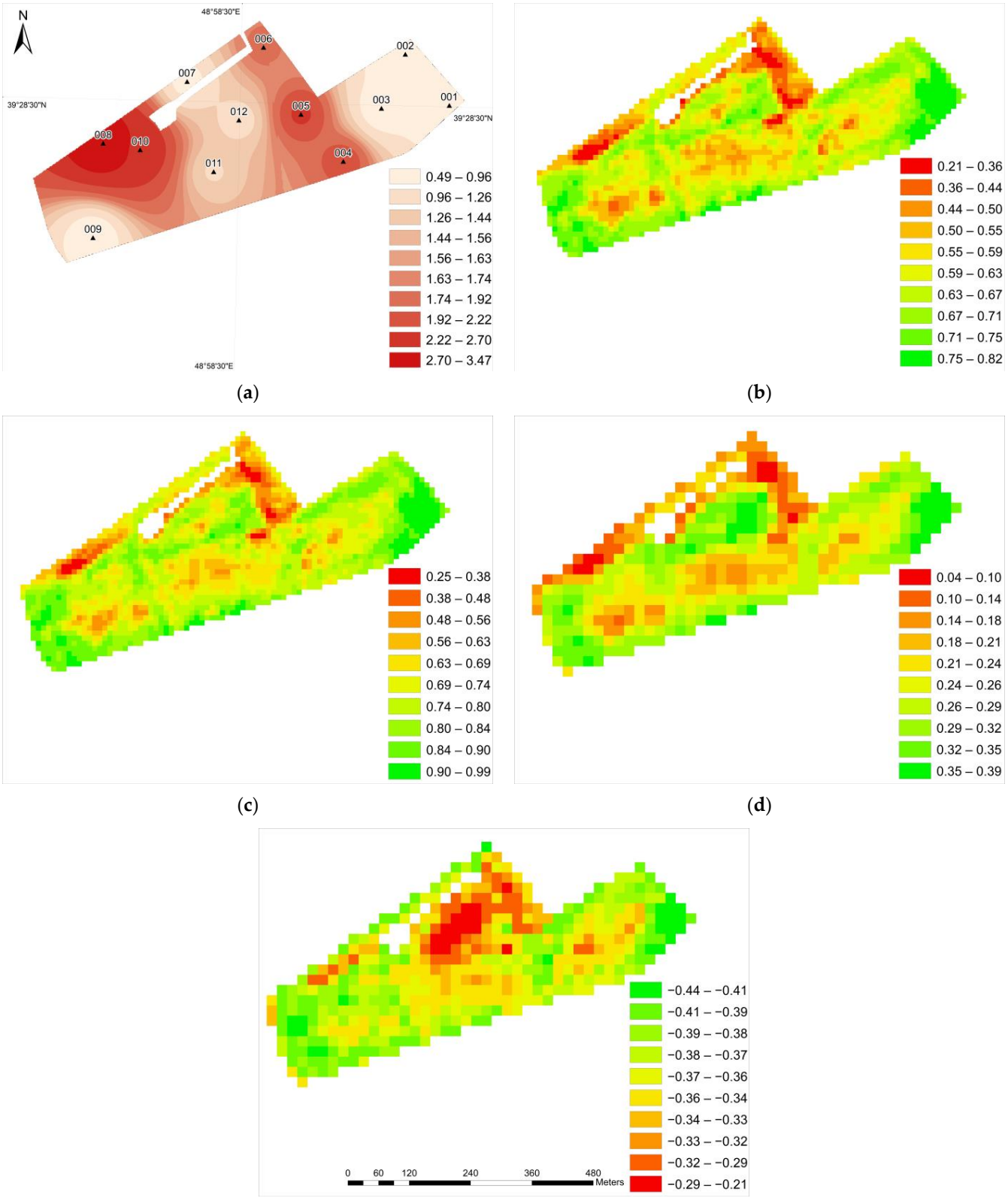


Figure 10. (**a**) EC (Geostatistical Analyst Tools, IDW); (**b**) Sentinel-2B, NDVI; (**c**) SAVI; (**d**) NDMI; (**e**) NDSI.

Table 3. The results of the electrical conductivity (EC) measurements and the corresponding index values at the geolocation of the samples.

Sample Number	EC	NDVI	SAVI	NDMI	NDSI
001	0.49	0.797	0.956	0.397	−0.437
002	0.52	0.681	0.817	0.277	−0.377
003	0.644	0.62	0.744	0.259	−0.366
004	2.1	0.64	0.768	0.262	−0.369
005	2.32	0.573	0.687	0.248	−0.385
006	1.814	0.505	0.606	0.131	−0.369
007	0.777	0.585	0.701	0.149	−0.39
008	3.48	0.412	0.494	0.125	−0.371
009	0.609	0.701	0.841	0.338	−0.403
010	2.67	0.697	0.836	0.31	−0.384
011	1.223	0.569	0.683	0.171	−0.332
012	1.088	0.729	0.875	0.376	−0.306

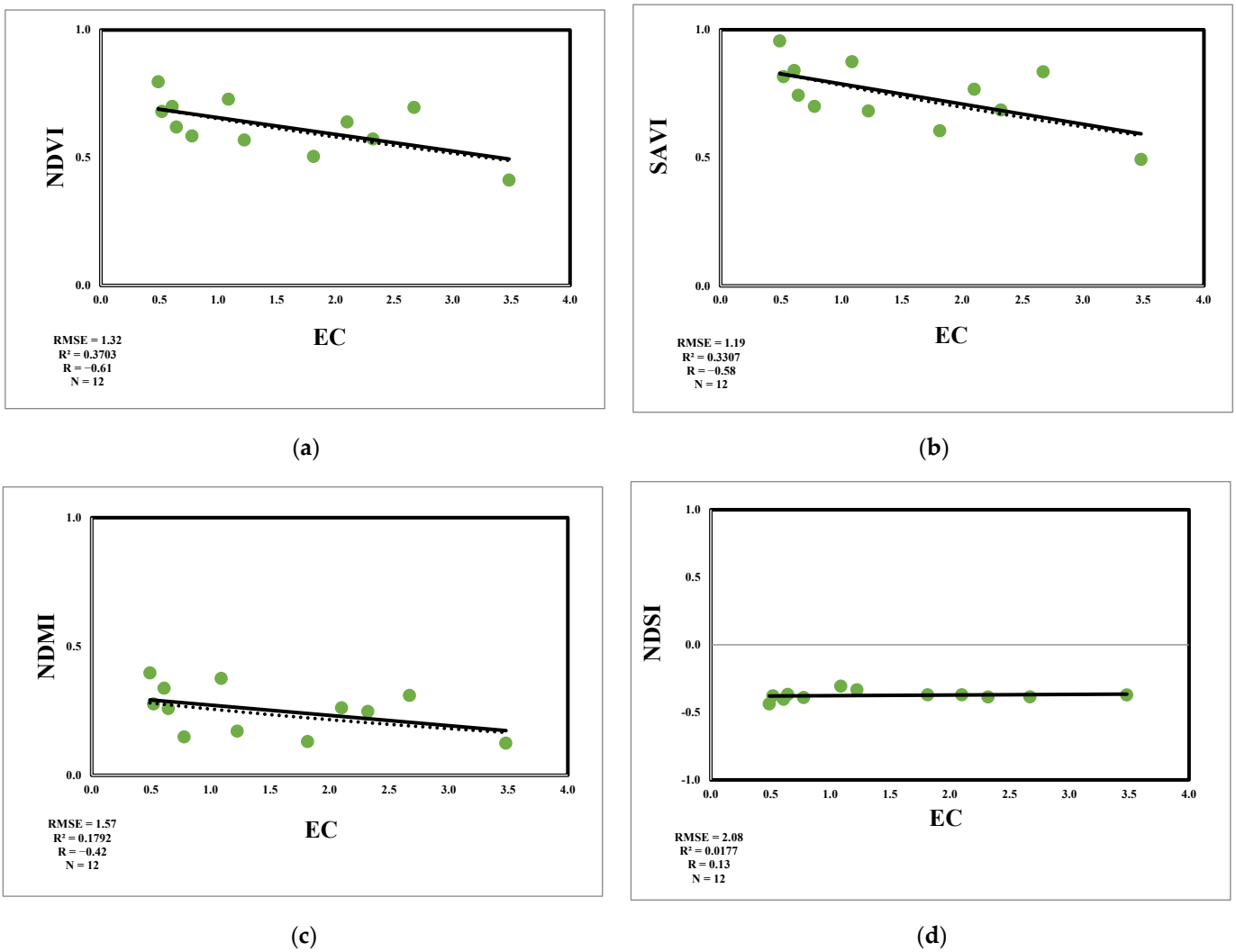


Figure 11. The graph of the relationship between the EC indicator and the mean of the indices: (**a**) EC–NDVI; (**b**) EC–SAVI; (**c**) EC–NDMI; (**d**) EC–NDSI.

Correlation coefficient (R): The correlation coefficient, denoted as R, measures the strength and direction of the linear relationship between two variables—in this case, electrical conductivity (EC) and the vegetation indices (NDVI, SAVI, NDMI, NDSI). A negative R

value indicates an inverse relationship, meaning that as one variable increases, the other tends to decrease. Conversely, a positive R value indicates a direct relationship.

- NDVI and EC: The R value of −0.61 suggests a moderate to strong negative correlation;
- SAVI and EC: The R value of −0.58 also suggests a moderate to strong negative correlation;
- NDMI and EC: The R value of −0.42 indicates a weaker negative correlation;
- NDSI and EC: The R value of 0.13 indicates a very weak positive correlation.

Coefficient of determination (R^2): The R^2 value represents the proportion of the variance in the dependent variable (e.g., NDVI, SAVI, NDMI, NDSI) that can be explained by the independent variable (EC). It is important to note that R^2 is always a positive value, ranging from 0 to 1, and it reflects the strength of the relationship in a different way compared to R.

- NDVI and EC: With an R^2 of 0.3703, approximately 37.03% of the variance in NDVI can be explained by EC, while the remaining variance is due to other factors;
- SAVI and EC: An R^2 of 0.3307 means that 33.07% of the variance in SAVI is explained by EC;
- NDMI and EC: An R^2 of 0.1792 indicates that only 17.92% of the variance in NDMI is explained by EC;
- NDSI and EC: The R^2 of 0.0177 suggests that only 1.77% of the variance in NDSI is explained by EC, indicating a very weak relationship.

Clarification on negative correlation and R^2 values: It is essential to clarify that R^2 is not directly dependent on the sign of R. While R indicates the direction of the relationship, R^2 only measures the strength of the relationship in terms of how much variance is explained by the independent variable. Therefore, negative correlations (R) can still yield positive R^2 values because R^2 is calculated by squaring the R value.

In summary, our findings indicate that while there is a negative correlation between EC and the vegetation indices NDVI, SAVI, and NDMI, the strength of this relationship varies. The R^2 values reflect the proportion of variance explained by EC in each index, and as such, they are positive regardless of the correlation's direction.

Concluding remarks: Our study demonstrates that while there is a relationship between EC and various vegetation indices, the strength and direction of these relationships differ. These findings are crucial for understanding how electrical conductivity impacts vegetation health and can inform more targeted strategies in precision agriculture. We acknowledge that correlation does not imply causation, and further studies are needed to explore the underlying mechanisms driving these relationships.

Since there is correlation between laboratory analysis results of the soil samples and satellite data, this could help to form an idea about different aspects of environment and land management. The existence of correlation on the soil surface could be beneficial for observing time-related changes of plant health and development. Concurrently, it could provide the tracking of larger areas and evaluating crops on soil productivity.

This study is novel in its comprehensive approach to integrating field data with remote sensing techniques to assess soil productivity. Unlike previous studies which focused primarily on either field data or independent remote sensing, our study integrates both soil health and its impact on agricultural productivity for a holistic view.

Furthermore, our study uniquely demonstrates the practical application of different vegetation indices (NDVI, SAVI, NDMI, and NDSI) in the assessment of soil properties such as humus content, nutrient content, and salinity. In doing so, it provides a robust methodology for assessing soil productivity that can be adapted to suit different farming environments.

Carneiro et al. [52], Serrano et al. [53], González-Dugo and Mateos [54], and Xu et al. [55] have assessed productivity using similar indices. In contrast to previously published studies, our study focuses on the interaction between soil chemistry and spectral reflectance in cotton fields. This approach not only emphasizes the effectiveness of remote

sensing in soil assessment but also the importance of integrating traditional soil analysis with advanced remote sensing techniques.

The conducted field research is of 2021 materials, and the following paper will examine the research materials of 2023 and reveal how the productivity tendency will change in the next years.

5. Conclusions

The study demonstrates the effectiveness of remote sensing data in assessing soil productivity. By analyzing soil samples from 12 different locations and using indices such as NDVI, SAVI, NDMI, and NDSI we were able to establish correlations between soil chemical composition and satellite imagery. Our results show that humus, pH, and electrical conductivity are key factors in soil productivity. The interpolation method allowed us to assess the distribution of salinity in the soil, which was then compared to NDVI, SAVI, NDMI, and NDSI results obtained from satellite imagery. The combined use of these techniques provides a comprehensive understanding of soil productivity that can be used for future agricultural planning and management. The results of chemical analysis of soil samples revealed that the soil was slightly saline and the humus and nutrient content were low, indicating low soil fertility. The values of EC, NDVI, SAVI, NDMI, and NDSI obtained from satellite images also confirmed these results.

Based on the results, the following conclusions can be drawn:

1. Soils in the study area have low natural fertility due to a lack of humus and nutrients. Low soil organic matter and nutrient content directly affects plant growth and development, resulting in low productivity;
2. Salinization is an ongoing process in the soil that negatively affects soil structure and productivity. High soil salinity impedes the uptake of water and nutrients by plants;
3. Low soil moisture content reduces the mineralization of nutrients and their accessibility to plants. The lack of soil moisture directly affects plant growth, development, and yield;
4. The values of NDVI, SAVI, NDMI, and NDSI obtained from multispectral satellite images can be used to evaluate the current condition and productivity of the soils. The results were consistent with the laboratory analysis of soil samples;
5. To increase the productivity of soils, measures should be taken to improve soil fertility and soil moisture, reduce salinity, and prevent degradation processes. Organic and mineral fertilizers should be used and scientifically based crop rotations should be developed.

In conclusion, this study highlights the potential of remote sensing data in assessing soil productivity and identifies key factors that impact soil fertility, including humus, pH, electrical conductivity, and salinity. The results indicate that the soils in the study area have low natural fertility and are susceptible to degradation processes, particularly salinization. The use of multispectral satellite imagery, along with laboratory analysis of soil samples, provides a comprehensive understanding of soil productivity that can be used for future agricultural planning and management. In order to increase soil productivity, measures such as the improvement of soil fertility and moisture, the reduction in salinity, and the prevention of degradation processes should be taken. This study emphasizes the importance of an integrated approach that combines traditional methods with advanced technologies for effective soil management practices. In addition, the findings of this study can guide policymakers and agricultural practitioners in making informed decisions regarding soil management practices to improve soil productivity and enhance food security.

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