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Satellite Data Integration for Citrus Mapping Diyala City, Iraq

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Abstract

Diyala is one of Iraq's largest citrus producer areas, characterized by many orange trees and sour and sweet lemon trees embraced by palm orchards. The absence of outstanding quality and spectral remotely sensed information makes distinguishing between distinct fruit tree species with similar spectral and spatial characteristics difficult, particularly for broadleaf evergreen trees. This work provides a unique decision technique for mapping the geographical distribution of citrus trees using spectral reflectance characteristics taken from Landsat 9 band spectral indices data. The spectrum reflectance of citrus trees was calculated using a seasonal series of data (2018-2023) of spectral indicators such as the Normal Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Natural Chlorophyll Pigment Index (NPCRI), and Normalized Difference Moisture Index (NDMI). The citrus plants exhibited values of reflectance that varied between 0.4 and 0.6, following the results obtained. The research region was identified using a random forest method that combined the spatial resolution of citrus trees with Google Earth images. The findings indicated that the classification model could differentiate citrus plants and generate information about distribution at a total accuracy (OA) of 97% of the respondents and a kappa statistic of 0.91.

Keywords: Citrus, Google Earth's Geographic Information Engine (GEE), Spectral Indices, Landsat 9, the random forest.

دمج بيانات الأقمار الصناعية لرسم خرائط الحمضيات في مدينة ديالى، العراق

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الخلاصة

تعد محافظة ديالى من أكبر مناطق إنتاج الحمضيات في العراق، وتتميز بوجود العديد من أشجار البرتقال والليمون الحامض والحلو في بساتين النخيل. إن غياب الجودة المتميزة والمعلومات الطيفية المستشعرة عن بعد يجعل التمييز بين أنواع أشجار الفاكهة المتميزة ذات الخصائص الطيفية والمكانية المتشابهة أمرًا صعبًا، وخاصة بالنسبة للأشجار دائمة الخضرة عريضة الأوراق. يوفر هذا العمل تقنية قرار فريدة لرسم خريطة التوزيع الجغرافي لأشجار الحمضيات باستخدام خصائص الانعكاس الطيفي المأخوذة من بيانات مؤشرات الطيف الخاصة بنطاق Landsat 9. تم حساب الانعكاس الطيفي لأشجار الحمضيات باستخدام سلسلة موسمية من البيانات (2018-2023) من المؤشرات الطيفية مثل مؤشر الفرق الطبيعي للغطاء النباتي(NDVI) ، ومؤشر الغطاء النباتي المعدل للتربة(SAVI) ، ومؤشر صبغة الكلوروفيل الطبيعية (NPCRI)، ومؤشر الرطوبة الفرق الطبيعي .(NDMI) أظهرت نباتات الحمضيات قيم انعكاس تتراوح بين

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0.4 و 0.6، وفقًا للنتائج التي تم الحصول عليها. تم تحديد منطقة البحث باستخدام طريقة الغابات العشوائية التي جمعت بين الدقة المكانية لأشجار الحمضيات وصور Google Earth. أشارت النتائج إلى أن نموذج التصنيف يمكنه التمييز بين نباتات الحمضيات وتوليد معلومات حول التوزيع بدقة إجمالية (OA) تبلغ 97٪ من المستجيبين وإحصائية كابا 0.91.

1. Introduction

Remote sensing monitoring technology has become valuable for achieving ecological balance and sustainability. It is widely utilized in a variety of applications, including crop categorization, agricultural drought monitoring, and mapping, which is one of the most significant disciplines of remote sensing today, employing remote sensing data from satellites, ground-based spectrometers, and unmanned aerial vehicles (UAVs) [1]. Many studies have used UAVs and satellite imagery to map or categorize crop changes. Over the last two decades, numerous optical remote sensing datasets have been used to identify and map fruit tree species at varying spatial resolutions [2]. With its excellent temporal and spectral resolution, MODIS data is frequently utilized for agricultural and forest monitoring. However, the spatial resolution of MODIS data is inadequate for identifying plant species in highly degraded regions [3]. Satellites like Landsat and Sentinel may give data with high spatial resolution, allowing for reliable categorization and mapping of plant species across huge regions [4]. UAVs and satellites can now capture high-quality multidimensional picture data. However, observational approaches affect the bulk of fruit tree mapping methodologies used to choose features for classification algorithms. When characterizing vegetation-related concerns (i.e., particular occurrences or time series information during the growing season), optical remote sensing data, especially medium-spatial resolution satellite data (e.g., Landsat and SPOT), are constrained by the environment (cloudy and rainy days) [5,6]. While UAV data is less affected by weather than satellite data, it is not practicable to apply it over vast regions [7].

Furthermore, present approaches for mapping fruit-bearing trees focus heavily on the plants' spectral and spatial aspects, which may not be the greatest attributes for distinguishing between distinct fruit tree species due to identical spectral and temporal traits. However, plants with comparable backscattering properties may be difficult to distinguish [8]. The current work presents a method for visualizing citrus trees in Diyala province by combining RS spectral index data with Google Earth and the Random Forest (RF) machine learning algorithm. Many studies have demonstrated that Random Forest, Convolutional Neural Networks, and Artificial Neural Networks outperform other classification methods [9]. This section presents some studies:

- In 2024, Alvaro. Camara-Guerra et al. demonstrated a deep neural network classifier for identifying citrus crops from multispectral satellite images. Pixels and areas in quad-band multispectral pictures obtained by the GeoSat-2 remote sensing satellite platform were identified as bare soil, trees, orange, mandarin, or grapefruit crops, respectively. Combined with spectral indices data, their findings revealed a categorization accuracy of up to 98% [10].
- In 2024, Zongjun Wu et al. exploited multi-modal remote sensing data from unmanned aerial vehicles (UAVs) on citrus orchards, including RGB, TIR, and Mul. They examined the relationships between various sensor data and soil moisture. To estimate soil moisture at various depths, they employed convolutional neural networks (CNN), long-short-term memory (LSTM) models, and a hybrid model (CNN-LSTM). Their findings showed that utilizing a hybrid CNN-LSTM model with RGB+Mul+TIR to forecast soil moisture in a citrus orchard gives support and data for regional precision irrigation choices [11].
- In 2023, Sergio Morell-Monzo et al. used two machine learning techniques, random forest, and support vector machines, to detect citrus parcel status using WorldView-3 data, very

high-resolution aerial images, and The framework from Motion point clouds. They conducted numerous studies using combinations of the three data sources to assess the influence on classification accuracy. The study found aerial images (OA = 0.967) and WorldView-3 (OA ≈ 0.936) had outstanding potential for recognizing parcel status from only one image. They also proved the usefulness of GLCM texture characteristics taken from sub-metric pictures for modeling typical spatial planting patterns of fruit crops [12].

1.1. Study area

Diyala is one of Iraq's eastern governorates, bordering Kirkuk governorate to the north, Iran to the east, Baghdad to the south, and Salah Al-Din governorate to the west. The GPS coordinates for Diyala Governorate in Iraq are 33° 46' 24.055" N and 45° 8' 58.022 E, applying the WGS 1984 system. Diyala is distinguished by its geographical variety, which has extensive agricultural grounds and different topography that help to maintain agriculture. It is distinguished by many rivers and streams, including the Diyala River, that pass across the governorate and help water the land. The soil fertility and environmental diversity make it an ideal agricultural setting for various crops, including wheat, barley, tomatoes, dates, and citrus fruits, the most well-known crops in Diyala. A case study used the research approach in Muqdadiyah district, north of Diyala governorate.

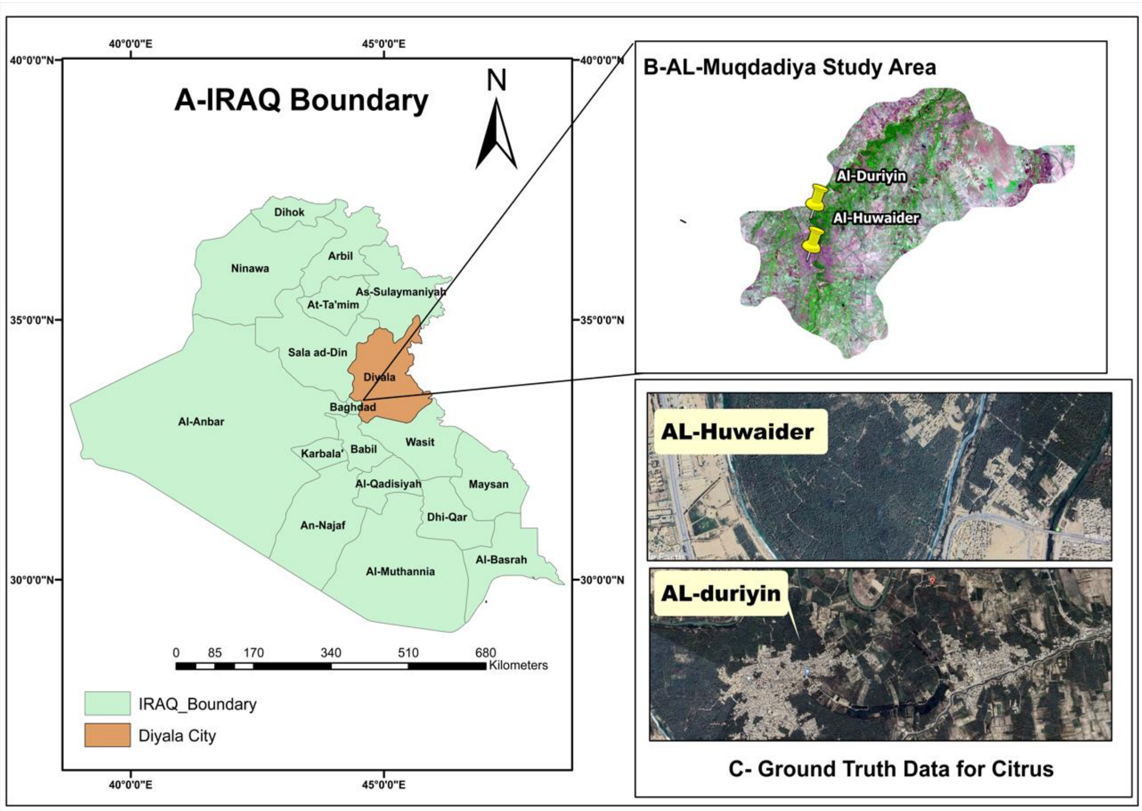

Figure 1: A map of the study's area: A represents Iraq's administrative borders, Figure B represents the Landsat 9 satellite image of the Muqdadiyah study area, and Shape C represents the test area (ground truth data) from Google Earth.

1.2. Satellite images dataset

The present research utilized two kinds of satellite images that offered various types of information. The set encompasses Landsat 8, 9, and Google Earth. The information being provided will be explained below:

- The Landsat 8 OlI and Landsat 9 images: data was collected for four seasons on an annual basis (2018-2023) across eleven wavelength bands, including the ultraviolet (UV) band (the RGB colors), near-infrared (NIR), and shortwave infrared (SWIR) bands applied during this momentous or experimenting enabling preliminary image processing [13].
- Google Earth provides internet utilization of satellite communication images, aerial images, topography, coastal bathymetry, and other geographical information for building a virtual three-dimensional map of the Earth. The latest version of Google Earth Pro's workstation model has multiple features that are particularly useful in educational institutions, including higher-resolution printing presses and storage spaces. Plus, having the capacity to access ESRI-shaped files [14].

The Landsat data satellites provide many excellent-quality images used for Earth observation. Landsat 8 and Landsat 9 capture images in various colors and sizes. They have a 15-meter panchromatic band and a spatial precision of 30 m. These records are vital in several fields, including environmental monitoring, agriculture, and city planning, because they are consistent throughout time and cover the whole world. Scientists use this data to do comprehensive planning and research, which allows us to learn more about the world and make better decisions.

2. Methodology

Citrus trees are evergreen, with a green canopy and a harmonic circular form. This is one of their most prominent traits. Several sets of multispectral pictures from various dates were used to generate maps of citrus trees in Diyala using ArcMap 10.8.1, as illustrated in the phases below:

1- The parts contain pertinent spectral, textural, and contextual features. To measure particular land cover features, the normalized difference vegetation index (NDVI) was derived utilizing the red and near-infrared bands, as in formula 1 [15]:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

The soil-adjusted vegetation index (SAVI) was derived to mitigate the impacts of soil, formula 2, where the soil amendment factor (L) is used to compute the normalized vegetation index to lessen soil's influence on the vegetation spectrum L = 0.5 [16].

$$SAVI = \frac{NIR - Red}{NIR + Red + L} * (1 + L) \tag{2}$$

Plants that have a reduced amount of nitrogen have a higher carotenoids-to-chlorophyll relative. Those features can change vegetation's spectral reaction, permitting them to be acknowledged. Formula 3 shows the natural chlorophyll pigment index (NPCRI). The NPCRI measures leaf chlorophyll content and ground reflectance [17].

$$NPCRI = \frac{Red - Blue}{Red + Blue} \tag{3}$$

Moisture fluctuations in cultivated areas were detected using NIR bands and a short wavelength infrared band to track dehydration and tiny NDMI variations, as described in Formula 4 [18].

$$NMDI = \frac{NIR - WSIR}{NIR + WSIR} \tag{4}$$

2- Spectral data was collected from the indicators, and statistical and variance analyses were used to determine the spectral reflectance of citrus plants.

3- Random Forest (RF) is a machine learning technique utilizing multiple trees of decisions. The training collection is used for producing plenty of independent decision trees (popularly referred to as the "at random forests") via the so-called random forest method, which eliminates Multiple samples for training from the training set and reassembles them each time to establish a new training set. The ultimate classifying outcome of every single tree will be decided by a vote[19,20]. The random forest method, ideal for dealing with high-dimensional classification data, has several advantages, particularly high accuracy, constant performance, and the capacity to judge feature relevance. As a result, it has become increasingly common in land use categorizing modeling. Using GEE data, a Random forest was used to organize the citrus trees throughout the geographical area.

4- Efficiency assessment: The test population evaluates each scheme's performance utilizing multiple metrics, including the overall reliability (OA), κ factor, user correctness (UC), and product efficiency (PA), for both the independent and combination sets of features.

5- The total reflectance of citrus plants was determined and mapped according to the study region's specific requirements and research objective. The method may be transformed and adjusted.

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3. Results and discussions

Citrus plant identification depends on Google Earth ground truth sampling from the study region (Al-Huwaider and Al-Daryan). The NDVI score for real-world truth sampling was determined using Landsat satellite-9. The two samples have comparable values for the NDVI (-0.023 to 0.51). Observations were analyzed for spectrum and spatial data, assigned to "citrus" or "non-citrus" according to the highest NDVI values. Figure 2 demonstrates that citrus reflectance ranges from 0.38 to 0.5, whereas the remainder of the plant categories have values between 0.17 and 0.37.

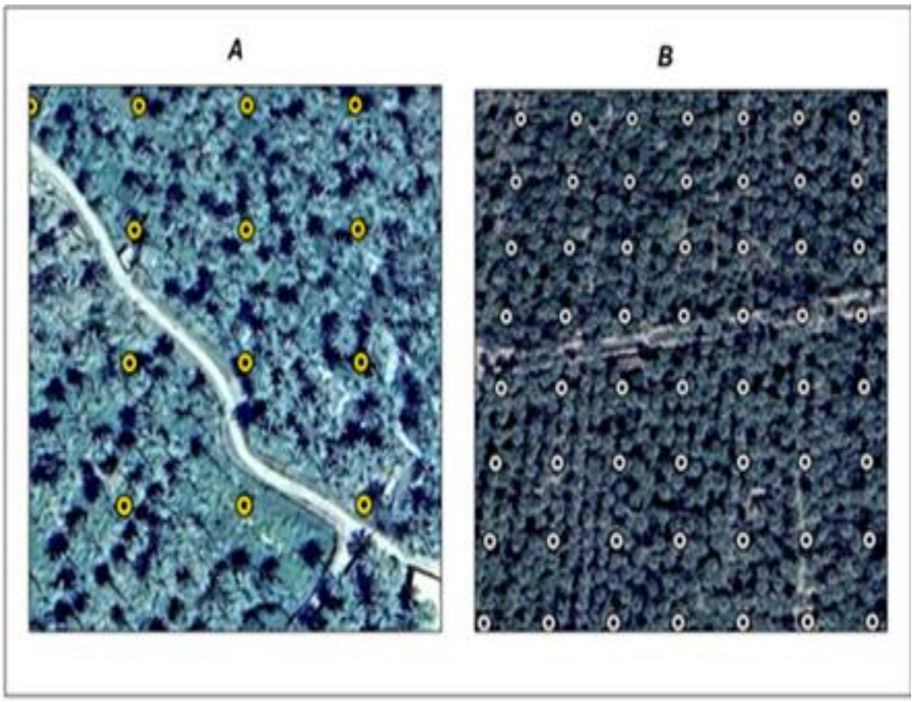

Figure 2: Collecting sites (2-A) where the greatest reflection is located in the covering under the palm trees, and (2-B, on the other) where the smallest reflective reflects the foliage of palm trees.

Citrus plants in the research area are challenging to observe with medium-resolution satellite images because the vegetation in the area has palm trees that hinder daylight from accessing individual citrus. This section starts by discussing the data produced from the spectrum indexes. The NDVI, SAVI index, (NPCRI), and (NDMI) index were determined as the consequence of pixels overlapping and the resulting environmental effects. Table 1 shows the mean scoring information for each time frame (2018-2023).

Table 1. The indices information

Data source/ year	Index	Min	Max	Mean	Std
Landsat 8/2018	NDVI	-0.39	0.5	0.03	0.07
	SAVI	-0.37	0.80	0.23	0.11
	NPCRI	-0.19	0.30	0.06	0.04
	NMDI	-0.23	0.37	0.08	0.05
Landsat 9/2023	NDVI	-0.29	0.5	0.1	0.07
	SAVI	-0.3	0.7	0.21	0.09
	NPCRI	-0.25	0.46	0.11	0.06
	NMDI	-0.27	0.5	0.12	0.07

The results showed a somewhat regular pattern of spectral indices. The winter month (January) had the lowest vegetation indices, which was explained by decreased vegetation due to peak water stress and soil and climatic influences. Figure 3 displays the seasonal vegetation index series.

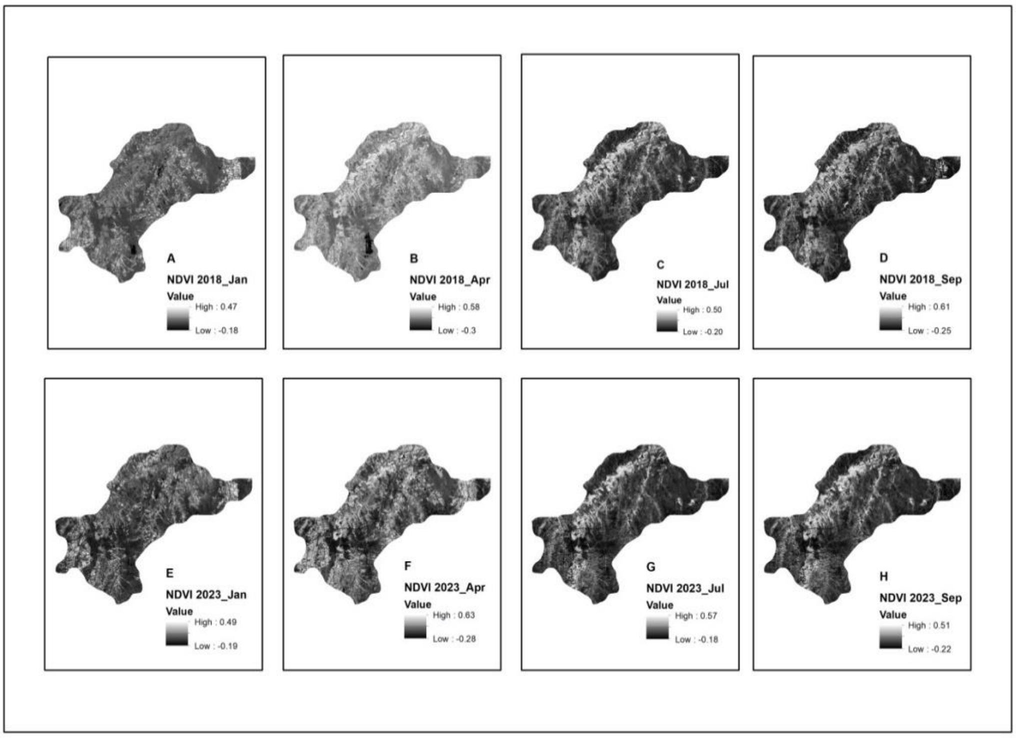

Figure 3: The NDVI seasonal

NDVI < 0.1 indicates desolate areas of sand, stone, or snow. Trees and grasses possess average levels of 0.2-0.3, but moderate and tropical rainforests exhibit greater values of 0.6-0.8. NDVI values reflect bare terrain around zero and water bodies with negative NDVI values. Figure 4 depicts the seasonal SAVI series. Removing the soil influence increases vegetation definition, as opposed to the NDVI, which indicated saturation at around 0.5. The short-wave and near-infrared wavelengths include a wealth of information about crops. The moisture index was used to quantify the spectral reflectance of citrus trees and calculate their water content. Citrus crops had a greater water content than those in the research region.

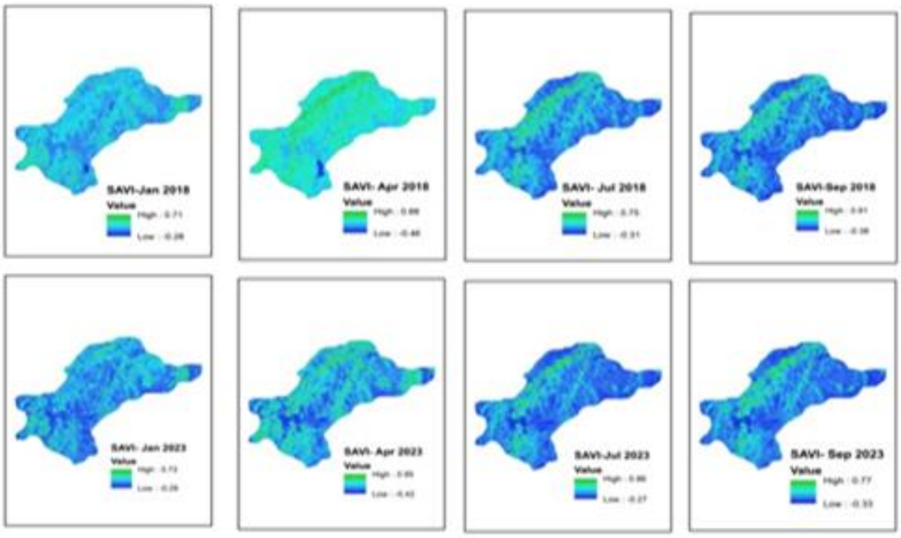

Figure 4: The SAVI seasonal

Figure 5 shows that NMDI values range from -1 to 1; zero values indicate low canopy cover; negative values indicate no canopy cover; medium canopy cover of 0.2-0.4 indicates little water pressure. Values of 0.6 and above indicate high canopy cover with no water content. Plants might have the same structural properties but varying pigment contents (chlorophyll).

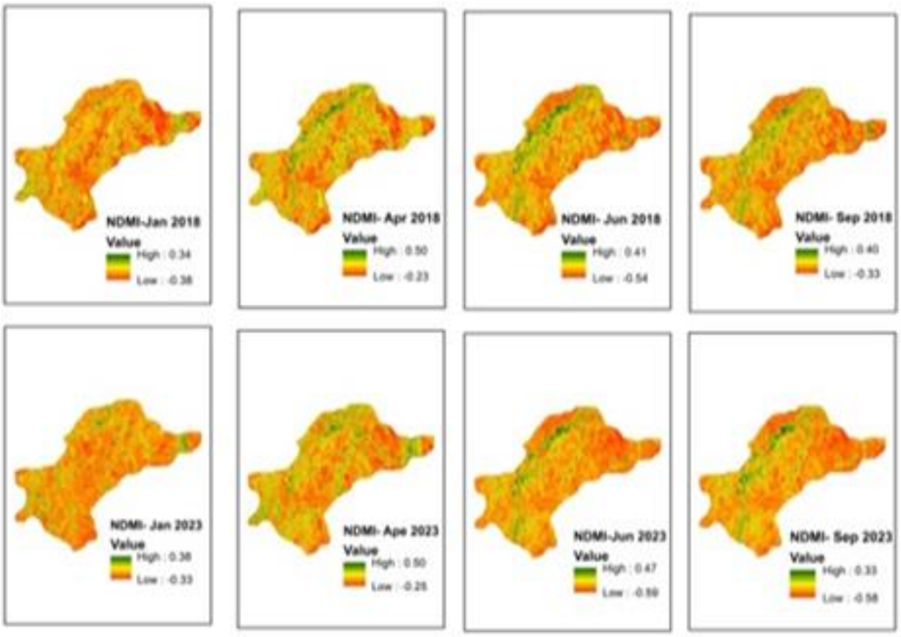

Figure 5: The NDMI seasonal

Plants are essential in numerous biophysical processes, including transpiration and carbon dioxide exchange. These functions are crucial for comprehending the interactions between plants and the atmosphere. The NPCRI index's time series was calculated (Figure 6).

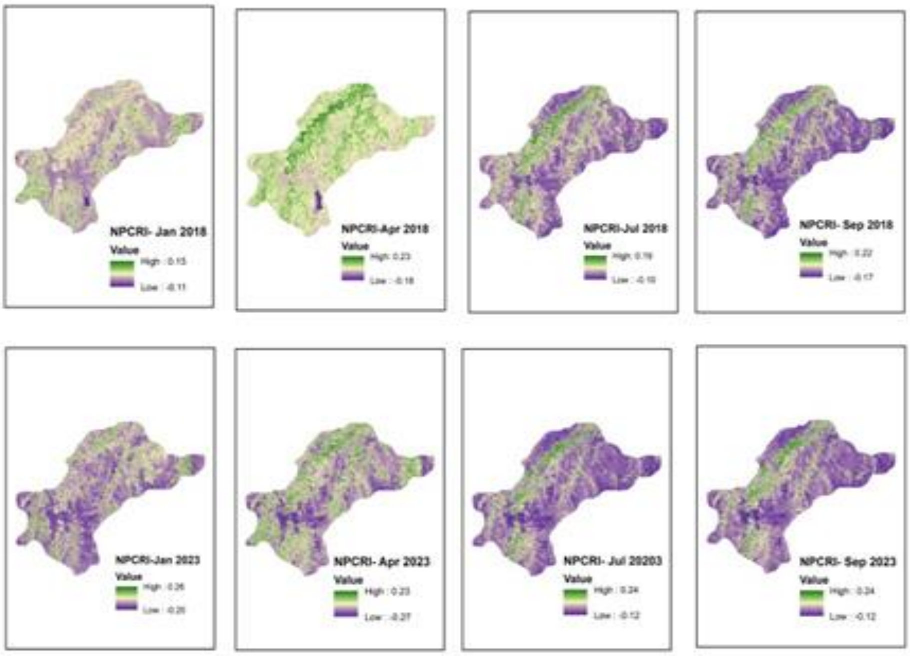

Figure 6: The NPCRI seasonal

Several factors influence the chlorophyll index, including illumination, temperature, irrigation, air pollution, soil conditions, plant stress, and pests. The moisture index (water content) was used to verify the correctness of pixels designated as citrus trees, Figure 7.

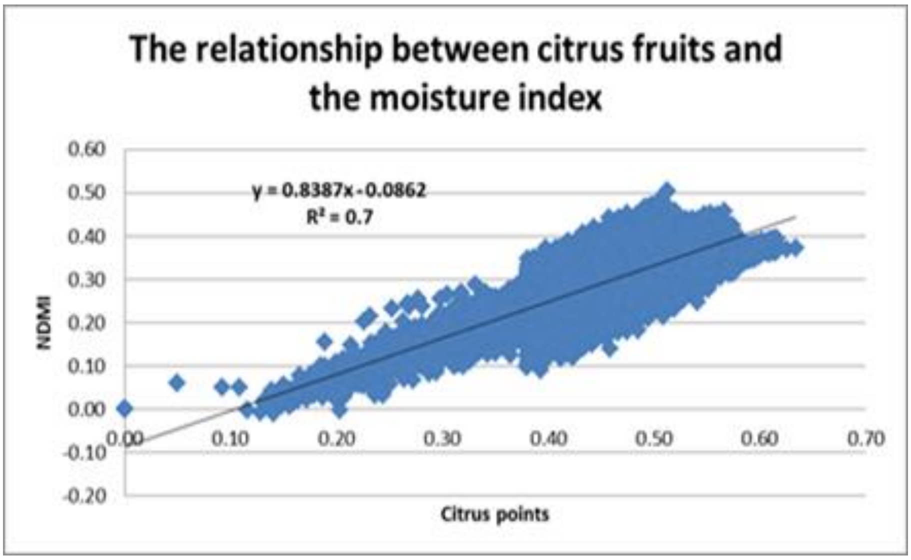

Figure 7: The relationship between Citrus Point and NDMI

Linear correlation analysis between pixels identified as citrus trees and the NDMI revealed a correlation coefficient of 0.7, indicating water content in vegetation pixels. Citrus plants contain more chlorophyll and water than other plants, including palm trees. The analysis variances revealed that the threshold for citrus trees in the research region is larger than or equal to 0.4. Subsequently, for creating high-resolution images of citrusy maps before the research's findings and Google Earth imagery data were incorporated utilizing a random forest methodology, and the land covering with citrusy tree information for Al-Muqdadiyah was analyzed employing random selections from all of the categories, depicted in Figure 8.

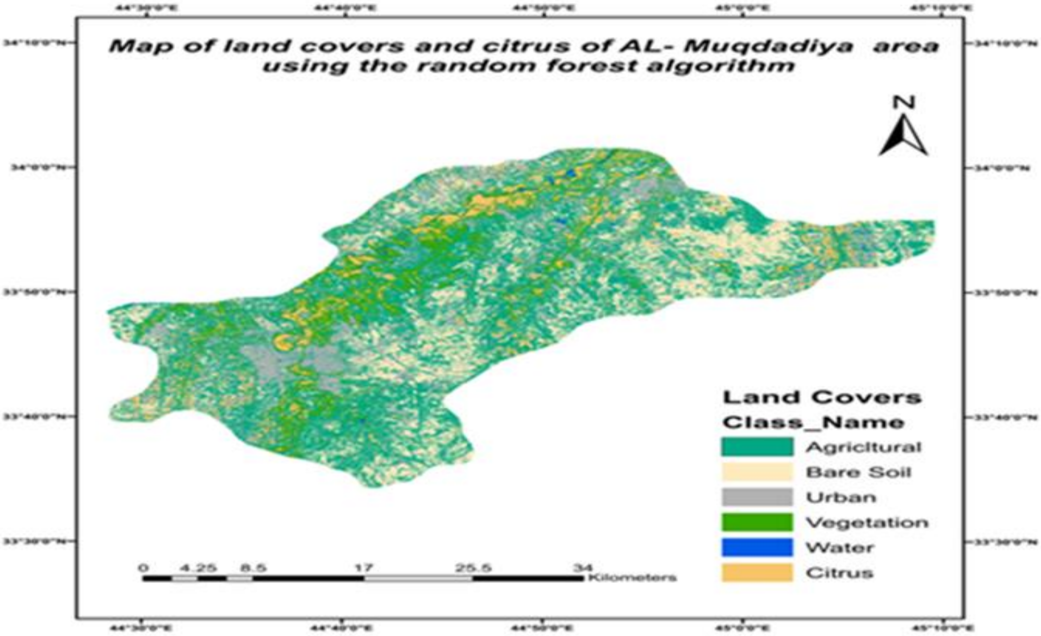

Figure 8: Land covers map of the study area

Figure 9 illustrates the application of learning information from the completion of Diyala. Accuracy, kappa factor, manufacturing efficiency, and user correctness were utilized to assess the findings of citrus fruits and land cover mapping in Diyala. The reliability confirmation results (Figure 10) demonstrate that the suggested technique, which brings together GEE data, index of vegetation over time, and machine learning techniques, has the potential to comprehend crops grown in agriculture with high accuracy.

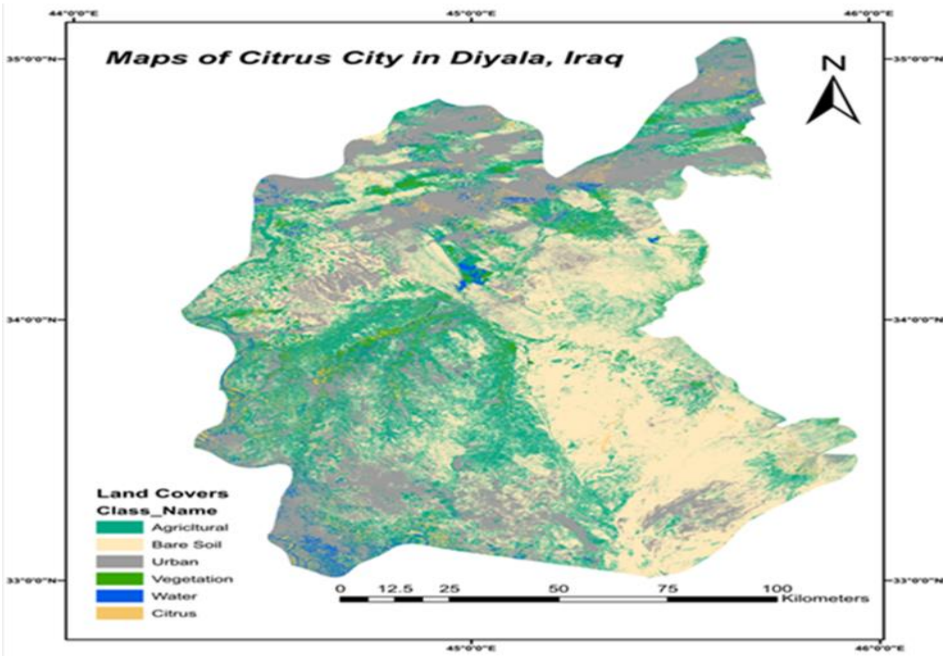

Figure 9: Map of citrus in Diyala

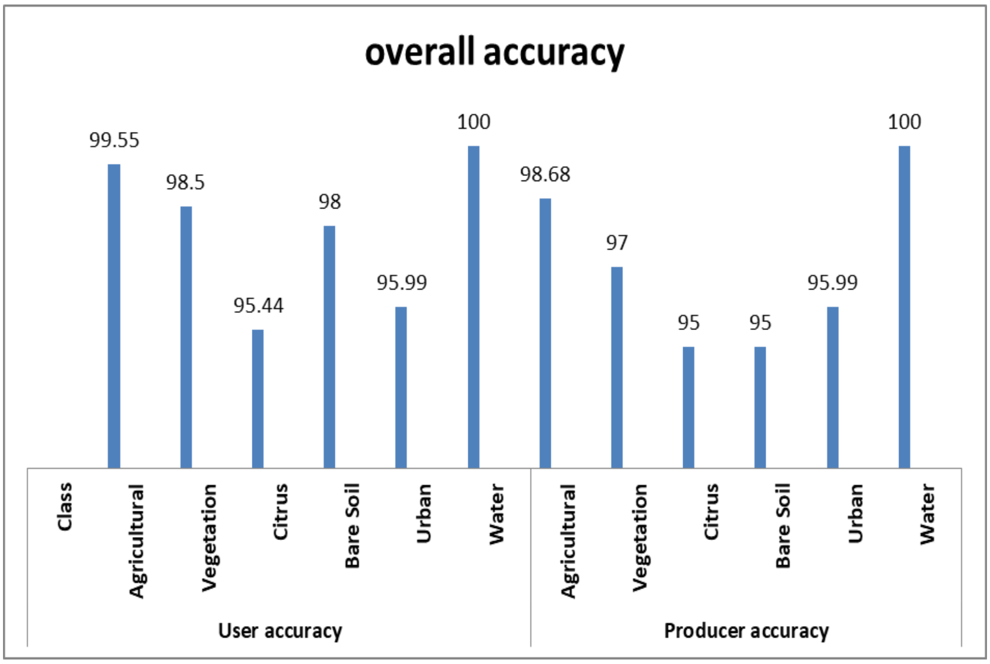

Figure 10: The overall accuracy

Remote sensing implies good land-use map classification. Many factors, including classifiers decision-making, data for training excellence, and even mapping references, may affect efficiency. The GEE platform's huge information financial institution supplied high-resolution image data for subject matter classification. The investigation's approach showed that the RF algorithm could map citrus, classify land cover, find explained relationships, and produce precise projections. The utilization of RF has contributed to land cover research, monitoring of the environment, and land management by combining the strength of collective learning with the capability to analyze enormous quantities of geospatial information. The average variance (OA) and Kappa values with RF reported 0.91 and 97, respectively.

4. Conclusion

The findings of this study show that combining remote sensing techniques with machine learning algorithms like Random Forest (RF) is a strong and effective method for categorizing agricultural land cover, especially citrus trees in the Diyala area. We were able to extract reliable spectral information on agricultural tree features and detect distinct chlorophyll concentrations utilizing satellite images (Landsat 8 and 9) and high-resolution Google Earth data, as well as NPCRI and NDMI moisture index. By examining the spectrum reflectance of agricultural regions, the results demonstrated that spectral indices, such as NPCRI and NDMI, were very helpful in enhancing the precision of tree categorization. Predicting the spectral reflectance of trees at a threshold of 0.4–0.6 was also demonstrated to aid in the creation of precise land cover maps and to create opportunities for additional uses, such as tracking crop health and water usage efficiency. Using machine learning algorithms, such as Random Forest, in classifying spectral data significantly improved modeling accuracy compared to traditional methods, highlighting the potential of these techniques in smart agriculture and natural resource management applications. This approach can effectively enhance agricultural sustainability by improving the ability to monitor and analyze crop distribution and estimate the environmental factors affecting plant growth. Future research will combine crop physical properties with deep-learning approaches to improve classification and spectrum forecasts. High-resolution remote sensing data may broaden the research area and improve spatial and spectral categorization accuracy.

Furthermore, techniques such as deep neural networks may improve the capacity to cope with vast and complicated datasets, allowing for more thorough and accurate land cover mapping. Finally, future studies might combine remote sensing techniques with other field information, such as weather data and ground observations, to improve prediction models. These approaches might be the foundation for building creative and effective agricultural crop monitoring technologies supporting environmental sustainability.

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