Detecting Variability and Analyzing Vineyards Vegetation Characteristics Using Satellite Remote Sensing Data in Aswan, Egypt

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ABSTRACT

Agriculture, being a labor-intensive sector, plays a crucial role in ensuring food security. Scientific advancements have rapidly influenced various fields, including agriculture, with significant impacts on genetics, plant science, environmental studies, climate research, land management, machinery, technology, and remote sensing. These advancements have resulted in improved resource management, leading to a reduction in food crises and famines. The focus of the study was on utilizing satellites images to monitor changes in vegetative growth grapevines, specifically using Sentinel-1 and Satellites-2. The study confirmed the effectiveness of these satellites data in accurately monitoring leaf changes by analyzing the VH and VV bands of Sentinel-1, as well as the NDVI bands 8-4, 5-6, 5-7, and 5-8a of Sentinel-2. The relationships between these bands and leaf changes showed R^2 significant values of 0.72, 0.42, 0.51, 0.51, and 0.52, respectively. However, lower accuracy was observed for chlorophyll. These findings highlight the high precision of satellites in monitoring changes in vegetative growth of grapevines and underscore the importance of developing improved techniques for monitoring and analyzing chlorophyll. That leads in future, to apply pressing Agriculture.

Keywords: Aswan; Satellite remote sensing; Sentinel-1; Sentinel-2; NDVI; Vineyards vegetation; Red edge; Regression analysis.

INTRODUCTION

Grapes, *Vitis vinifera* belongs to Vitaceae family, (Revilla *et al.*, 2018) is the second most important fruit crop in Egypt. The total cultivated area according to the statistics of the ministry of agriculture and land reclamation in 2021 is 210632.73 feddan, productivity is 1,435,000 tons (F.A.O, 2021). Remote sensing has different applications in many fields as oceans, environment, climate and agriculture (Clay & Shanahan, 2011 and Levy *et al.*, 2018). Remote sensing technology is one of the technologies that have been developed rapidly in recent years, especially in agricultural applications (Badr *et al.*, 2015). It is a low cost tool with high temporal and spatial accuracy (Ledderhof *et al.*, 2017). The nations are racing to provide this technology for optimal management of resources (Zude-Sasse *et al.*, 2016). Remote sensing is one of the most important free systems available (Drusch *et al.*, 2012 and Roy *et al.*, 2014). With the advent of applications in agricultural science, the emergence of this science depends on the availability of information in the management of the farm (Bonilla *et al.*, 2014 and Ozdemir *et al.*, 2017). The greater the amount of information available, the better management of agriculture can be achieved in terms of providing moisture, fertilization and appropriate care for each plant and area according to the information, to minimize costs and optimize the management of the resources (Abdel-Rahman *et al.*, 2008 and Addabbo *et al.*, 2016). Remote sensing used widely in precision agriculture (Das *et al.*, 2018). It reduces cost facilitates management and can predict potential problems and provides information and can analyses these information easily. There are many studies had been conducted on using of remote sensing for farm management in grapes, apples, olives, coffee, almonds, citrus, wheat and maize (Revilla *et al.*, 2018; Velazquez-Marti & Cazco-Logroño, 2018; Xiao *et al.*, 2018 and Rabia *et al.*, 2021). These studies include evaluated fertilization, nutritional status, spread of diseases and agricultural climate (Johnson *et al.*, 2001; Zude-Sasse *et al.*, 2016; Alvino & Marino, 2017; Bukata *et al.*, 2018; Das *et al.*, 2018 and Hall, 2018). This gives a comparative advantage to farmers by marketing their products at affordable prices. One of the main problems facing farmers is variability in the growth of grape vines which affects production. The technique of remote sensing is used for the rapid, precise and early detection of these differences within the field (Clay & Shanahan, 2011; Tarara *et al.*, 2013 and Vanino *et al.*, 2015). These studying enable farmers to intervene rapidly to solve the minute problem. By wise control of fertilizer and pesticides and reduction of environmental pollution (Bonilla *et al.*, 2014; Immitzer *et al.*, 2016 and Ozdemir *et al.*, 2017). The aim of this study is to explore the use of satellite remote sensing for estimating and mapping vineyards variability.

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MATERIALS AND METHODS

Study Area

The Flame seedless grapevines grafted of Freedom rootstocks were planted in a private vineyard in the Bllana Village of Aswan. Location (24.36607 degrees north, 32.987283 degrees west) (Right down 24.36375 latitude and 32.97561 longitude) during the 2019 and 2020 growing seasons (Figure 1). At the beginning of this trial, the vines were three years old and were spaced 1.0 meters (between vine) and 1.5 meters (between rows). Drip irrigation was employed along with fertigation, which involved injecting compound fertilizer NPK into the system in accordance with the irrigation guidelines provided by the Ministry of Agriculture.

Vegetation measurements

Number of leaves

Counting number of leaves per vine selected by a random selection of vines in the location

Total chlorophyll

Total chlorophyll content was measured by using a Minolta SPAD chlorophyll meter (model spadso2 plus) the total chlorophyll content (SPAD) of fresh leaves was measured in accordance with the procedure stated by Süß *et al.* (2015).

Remote sensing measurements

Data Processing Software Idrisi Tools from Google Earth Engine are needed to track, measure, examine, assess, and simulate Earth observation data. In 2005, Google formally debuted Google Earth (GE) as a "geobrowser," and in 2010, Google Earth Engine (GEE), a cloud computing platform (Gorelick *et al.*, 2017). Sentinel-2 multi-spectral bands (MSI) with 13 spectral bands (Gomarasca *et al.*, 2019) and Sentinel radar imaging (Bousbih *et al.*, 2017) a European Space Agency (ESA) satellites.

Vegetation Indices: Red edge normalized difference vegetation index (NDVI)

NDVI, or normalized difference vegetation index, is a measure of vegetation. Vegetation indices (VI) are useful for boosting vegetation-related signals and attenuating unwanted sounds. The NDVI, which is well-known and frequently used, is a straightforward (Gomarasca *et al.*, 2019) but the efficient indicator for measuring is a green vegetation.

It correlates chlorophyll absorption in red wavelengths with near-infrared leaf scattering in green leaves (黄林生 *et al.*, 2019 and Liu *et al.*, 2022) this identical as following.

(1)NDVI (8-4) = (B8-B4)/ (B8+B4)

B8 and B4 are the satellite spectral bands for VNIR and Red wavelengths, respectively (Table 1)

Satellite Sentinel-2 can be used to calculate the normalized difference vegetation index (NDVI), which is a commonly used indicator of plant health Table (1). The red edge band in Sentinel-2 data can be particularly useful for NDVI calculations as it captures the subtle differences in plant reflectance in the red edge spectral region. This makes it possible to more accurately estimate vegetation density and chlorophyll content, which are important factors in assessing plant health.

The farm has been divided on NDVI maps into 4 blocks. Each block consists of three replicates with a total of 12 Location. Data were collected over a period of 2 years. Table (2) (Figure 2 and 3).

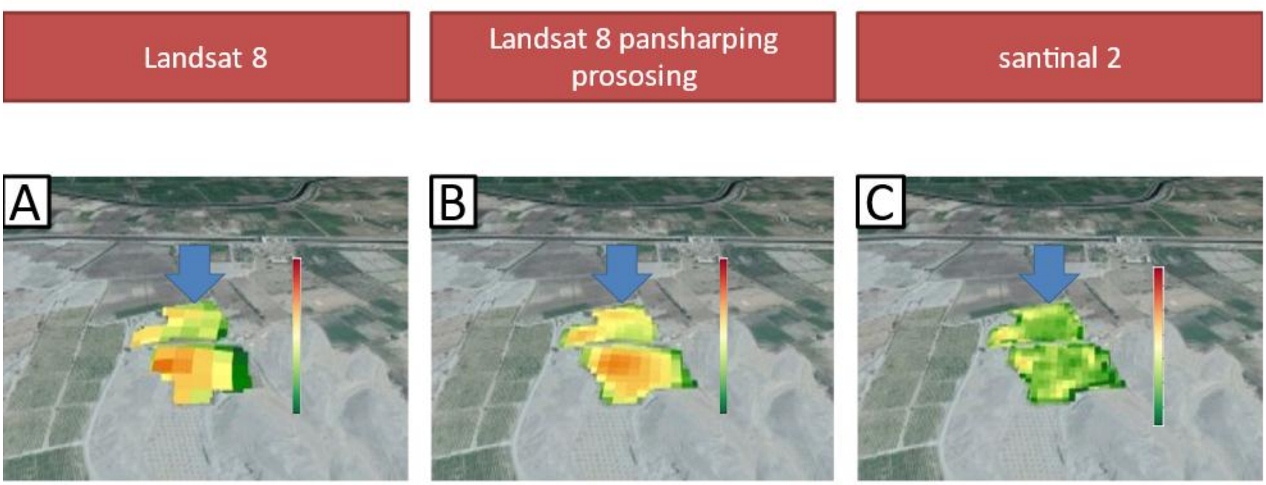
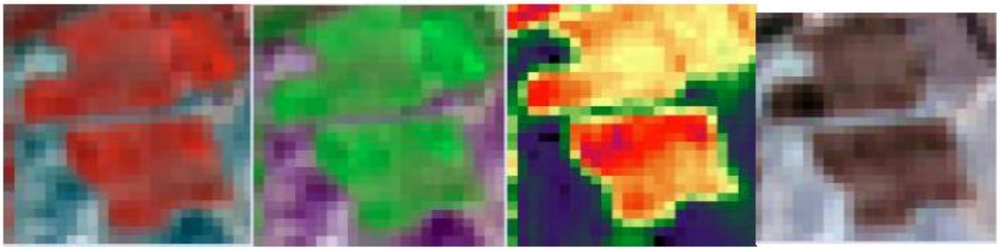


Figure 1. Maps of the study area (A-B-C) from Landsat 8, Landsat 8 pansharpening and Santinal -2, respectively

Table 1. The Spectral Bands and Resolutions of Sentinel-2 msi sensor

Band	Resolution	Central Wavelength	Description
B1	60 m	443 nm	Ultra Blue (Coastal and Aerosol)
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Visible and Near Infrared (VNIR)
B6	20 m	740 nm	Visible and Near Infrared (VNIR)
B7	20 m	783 nm	Visible and Near Infrared (VNIR)
B8	10 m	842 nm	Visible and Near Infrared (VNIR)
B8a	20 m	865 nm	Visible and Near Infrared (VNIR)
B9	60 m	940 nm	Short Wave Infrared (SWIR)
B10	60 m	1375 nm	Short Wave Infrared (SWIR)
B11	20 m	1610 nm	Short Wave Infrared (SWIR)
B12	20 m	2190 nm	Short Wave Infrared (SWIR)

Types of used NDVI red edges (Table1):
(2) NDVI red edge (5-6) = (B5-B6)/ (B5+B6)
(3) NDVI red edge (5-7) = (B5-B7)/ (B5+B7)
(4) NDVI red edge (5-8a) = (B5-B8a)/ (B5+B8a)



A B C D

Figure 2. (A and B) displays a false color image (238-284) and (C and D) presents the NDVI (4-8) and True color image derived from Sentinel-2 imagery. Upon analyzing the Figure, noticeable variations can be observed between the regions in the NDVI image when compared to the other images

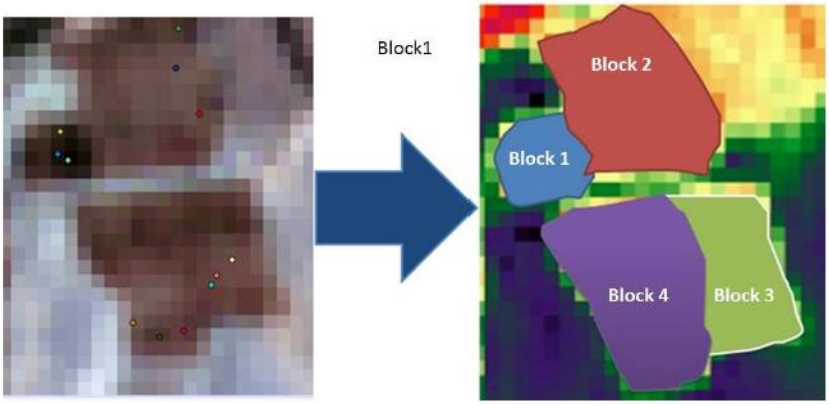


Figure 3. Represents the study's twelve location treatments based on vegetation indices, specifically NDVI (Normalized Difference Vegetation Index)

Table 2. Location treatments based on vegetation indices (NDVI)

		BLOT ID	Location	
			Longitude	**Latitude**
Block1	1	A1	32.97350886	24.36505465
	2	A2	32.97343046	24.36509542
	3	A3	32.973451	24.365239
Block2	4	B1	32.9744795	24.3653563
	5	B2	32.97431	24.365667
	6	B3	32.974326	24.365929
Block3	7	C1	32.97472654	24.3643864
	8	C2	32.974608	24.36429
	9	C3	32.9745735	24.36422568
Block4	10	D1	32.97436405	24.36391952
	11	D2	32.9741869	24.36387705
	12	D3	32.973989	24.363969

The Sentinel-2A Multispectral Instrument

Images from the Sentinel-2A Multispectral Instrument of the European Space Agency (ESA) were used in the analysis. Every five days, the Sentinel-2A satellite gathers data from the earth. The GEE platform specifies a dataset availability window for 03/28/2019 to 09/22/2020, Table (3), The time periods 07/27/2020–08/12/2020 and 07/27/2021- 08/12/2021 were considered in the analysis. The table below provides specifics regarding the satellite image's band and resolution.

Table 3. Displays the dates when Sentinel-2 satellite images were utilized in the experiment

	2019	**2020**
1	11/4/2019	15/4/2020
2	16/5/2019	15/5/2020
3	10/6/2019	14/6/2020
4	15/7/2019	14/7/2020
5	14/8/2019	13/8/2020
6	13/9/2019	17/9/2020

Season average:
determine the different growth stages of a vineyard, per-pixel season average were used Table (4).

Table 4. Satellite images per seasons rang from the spring and the summer

1	the spring	20/3/2019- 21/6/2019
2	the summer	21/6/2019-22/9/2019
3	the spring	20/3/2020-21/6/2020
4	the summer	21/6/2020-22/9/2020

Statistical Analysis.

Python, Google Colab (Canesche *et al.*, 2021), and Wekeo (Zhongming *et al.*, 2021) were utilized to gather proof. Satellite data from Sentinel-1 and Sentinel-2 were obtained and combined with actual data. Excel was employed to process directory data. The relationship between variables was examined through regression analysis. Regression analysis is a statistical tool used to investigate the relationships between variables, aiming to determine the causal effect of one variable on another. To compare means, the Tukey mean comparison analysis was performed using R.

Results and Discussion

Vegetation measurements

Number of leaves

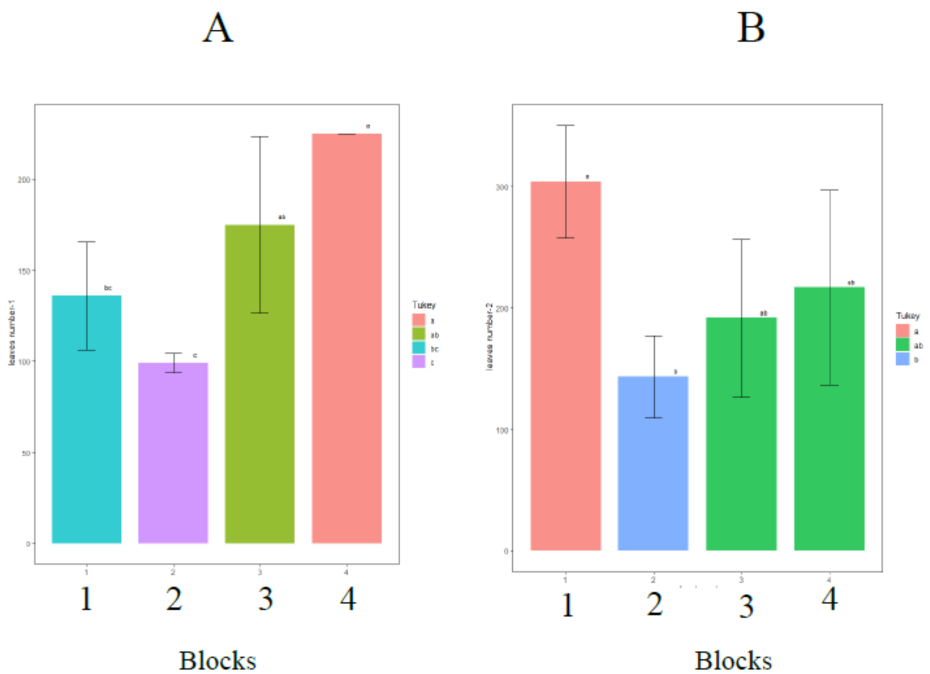


Figure 4. (A and B) presents the results of the analysis of variance (ANOVA) and Tukey's multiple comparison test for the number of leaves per vine in 2019 and 2020. The statistical significance was determined at a level of $p < 0.05$

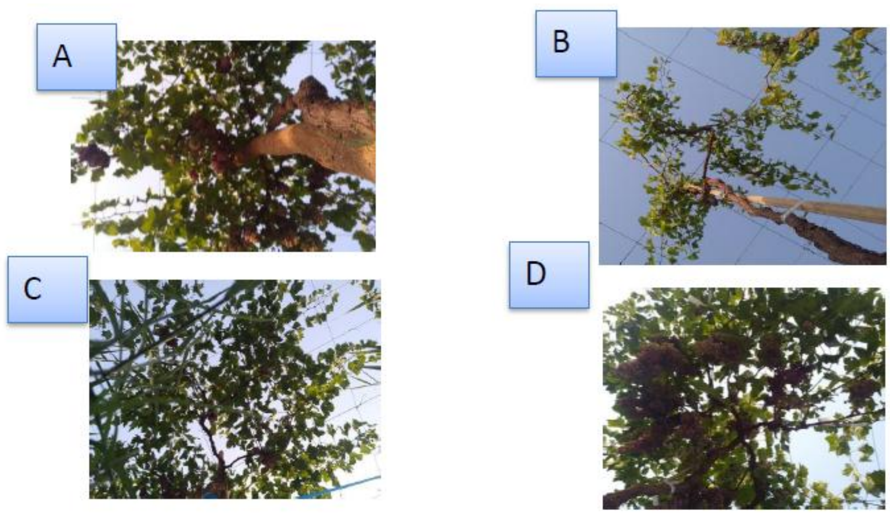


Figure 5. (A, B, C, and D) showcases the images of vineyard vegetation in four different blocks captured in 2019

At the Figure (4 and 5) first season, there are differences in the number of leaves per vine in plants between each block. It unclouded in the second season as well. The highest value in the first season and the second season, respectively was block 1, (136 and 304), and the lowest value was block 2 in the first and second seasons (99 and 134). There is a significant improvement from the second season to the first in the number of grape leaves. ANOVA, Tukey´s multiple comparison test (significant $p< 0.05$) of it is evident that there are significant differences between the blocks where the highest value was sector block 4 and the lowest was block 2. In the second season, sector block 1 was the highest. But it was the lowest in the first season. The second season was greater than the first, at the Figure (4). The study elucidated that the variation in forage growth and leaf count is attributed to environmental factors, including the specific growth conditions and soil fertility. These factors result in year-to-year, seasonal, and geographical variations, even when considering the same stage of maturity. Moreover, it was observed that higher temperatures tend to accelerate plant development while reducing leaf-to-stem ratios (Buxton, 1996).

Total chlorophyll

In Figure (6) of the first season and second seasons ANOVA, Tukey´s multiple comparison test (significant $p < 0.05$) of total chlorophyll in the first season had clear significant differences. The highest value was block 4 as the number of grapevine leaves, while the lowest was block 2. This is proportional to the number of leaves per vine in the first season. While in the second season, there weren't significant differences. The measurement of chlorophyll levels can vary among different plants and is influenced by various factors. Some studies suggested that this variation may be attributed to deficiencies in certain elements, while others associate it with the presence of diseases (Shibaeva *et al.*, 2020). There are also indications that both factors could potentially play a role (Mishra *et al.*, 2017). Additionally, research suggests that environmental conditions, such as sunlight exposure, can impact chlorophyll levels (Muñoz-Huerta *et al.*, 2013). Furthermore, studies have explored the use of remote sensing techniques to assess the nitrogen status in plants, which can provide valuable information related to chlorophyll content (Muñoz-Huerta *et al.*, 2013).

Remote sensing measurements

Normalized difference vegetation index (NDVI) (4-8)

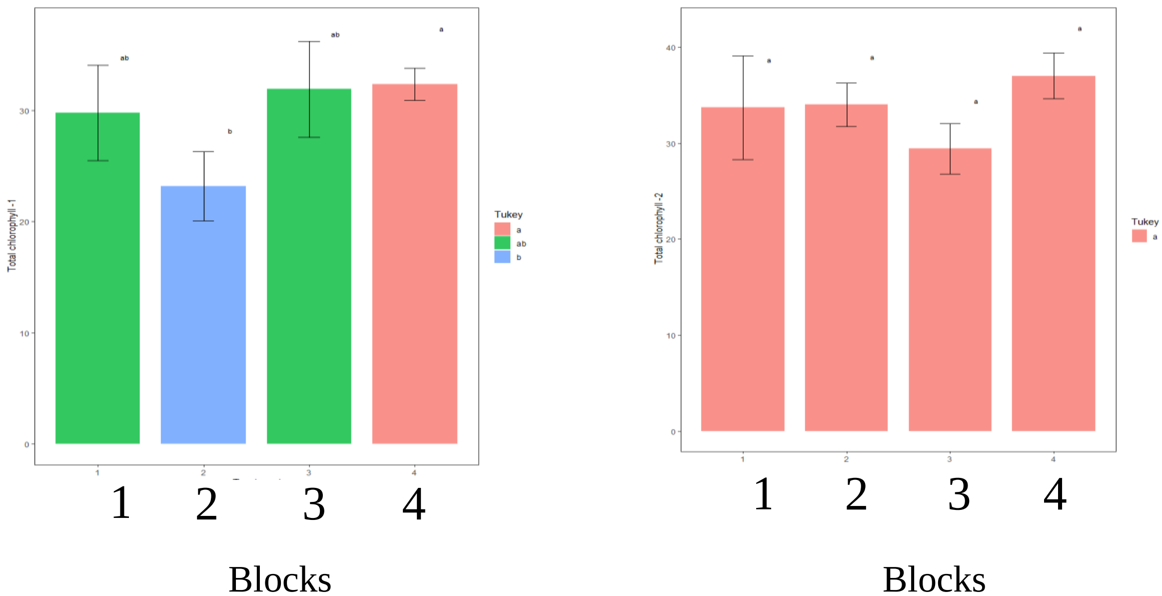


Figure 6. (A and B) demonstrates the analysis of variance (ANOVA) and Tukey's multiple comparison test for total chlorophyll levels in 2019 and 2020. The significance level was set at $p < 0.05$

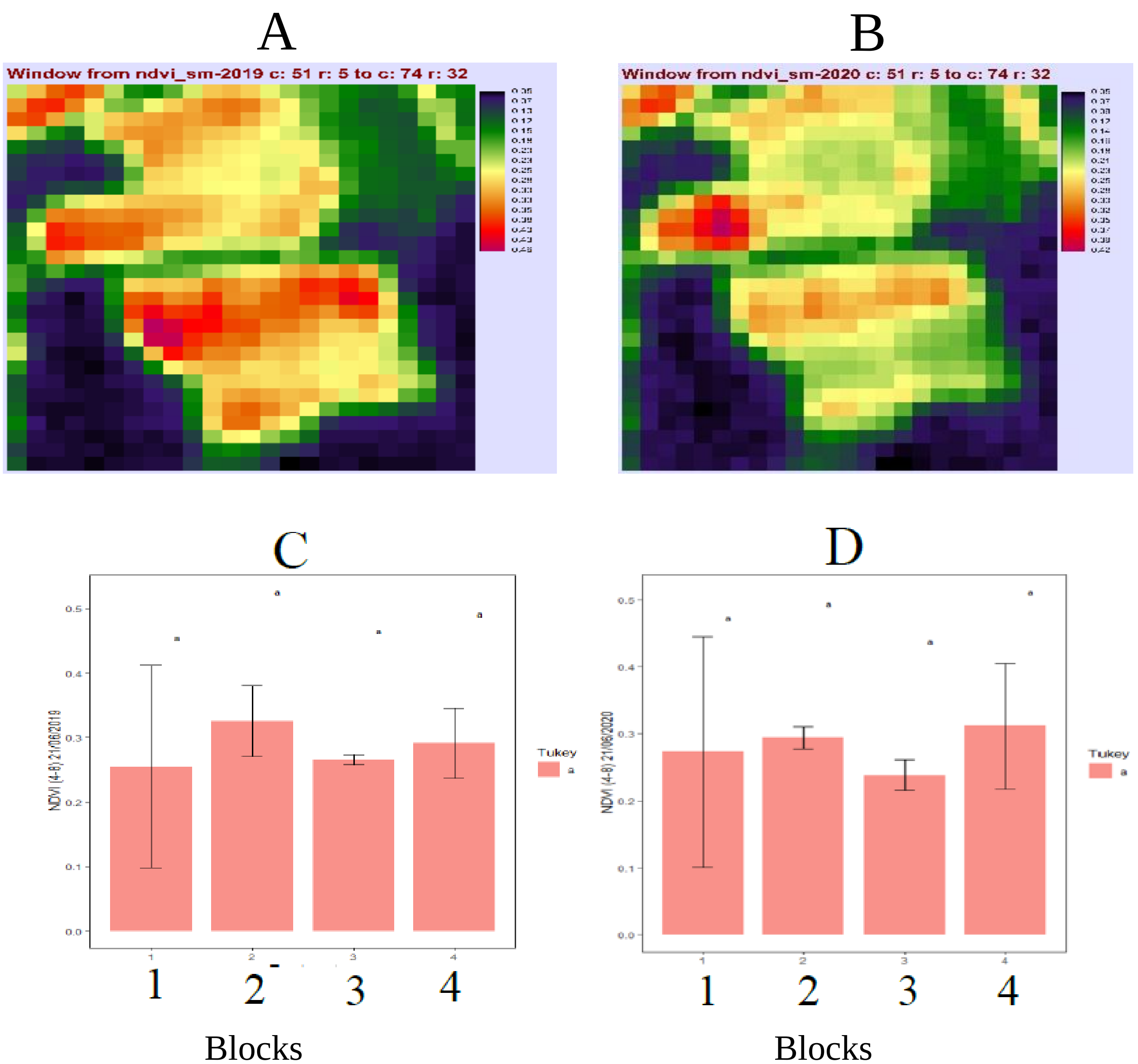


Figure 7. Consists of four images. In Figure 7 (A and B), the ANOVA and Tukey's multiple comparison test results for the NDVI (Normalized Difference Vegetation Index) at four different blocks are depicted. The significance level was set at $p < 0.05$, indicating statistically significant differences in the NDVI values among the blocks. (C and D), the NDVI images of the same area captured in 2019 and 2020 are shown. These images visually represent the distribution and intensity of vegetation based on the NDVI values for the respective years

In the first and second seasons, as shown in Figure, (7), it can be observed that ANOVA, Tukey´s multiple comparison test (significant p< 0.05) of NDVI (4-8). There are no significant differences between the different regions for the first and second seasons. The studies concluded that NDVI is effective in monitoring changes over large areas when using modern farming methods and farmers with a high degree of technology (Perez-Flores *et al.*, 2019).

N ormalized difference vegetation index red edge (NDVI) red edge (5-6)

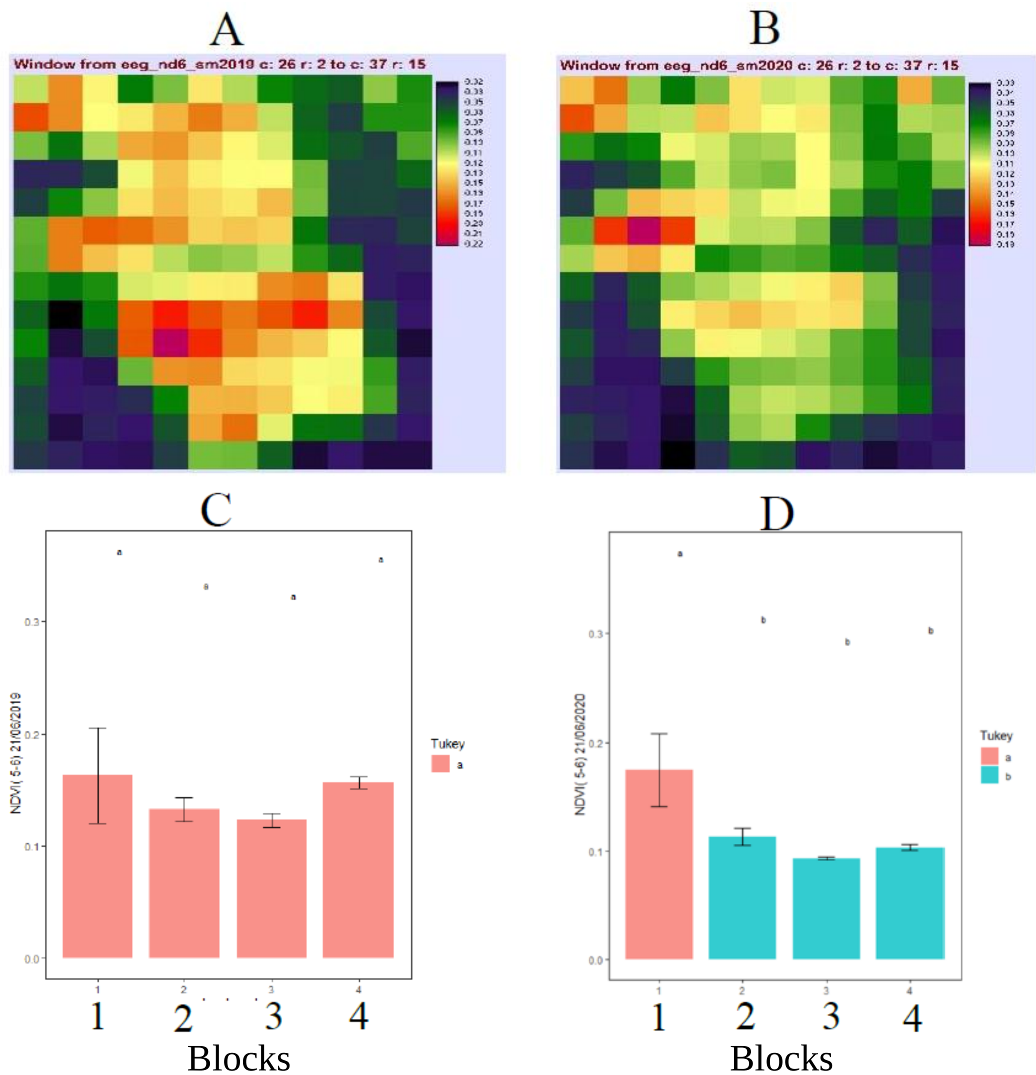


Figure 8. (A and B) illustrates the ANOVA, Tukey´s multiple comparison test (significant p< 0.05) of NDVI (5-6) at 4 blocks and (C and D) (NDVI image in same area at 2019 and 2020

Figure (8), provides a visual representation of results from the first and second seasons ANOVA, Tukey´s multiple comparison test clarify that there are no significant differences between the different regions in the first season. While, in the second season, the difference appears in a form between block 1 and the rest of the others regions. Multi-Spectral Instrument (MSI) has been found to be more sensitive to NDVI red edge (5-6) in monitoring changes in plants than NDVI (4-8), despite the differences in spatial resolution. Studies utilizing NDVI measurements play a crucial role in monitoring changes in vegetation health and identifying areas of potential concern, such as drought, disease outbreaks, or invasive species infestations (Vélez *et al.*, 2020). NDVI provides valuable insights into the overall health and condition of vegetation cover. However, in the specific study mentioned (Cogato *et al.*, 2019), the effectiveness of NDVI was found to be weak, which could be attributed to the limited size of the study area (Cogato *et al.*, 2019). It is important to note that while this particular study may have reported weak efficiency of NDVI for monitoring vegetation health.

Normalized difference vegetation index red edge (NDVI) (5-7) and (5-8a)

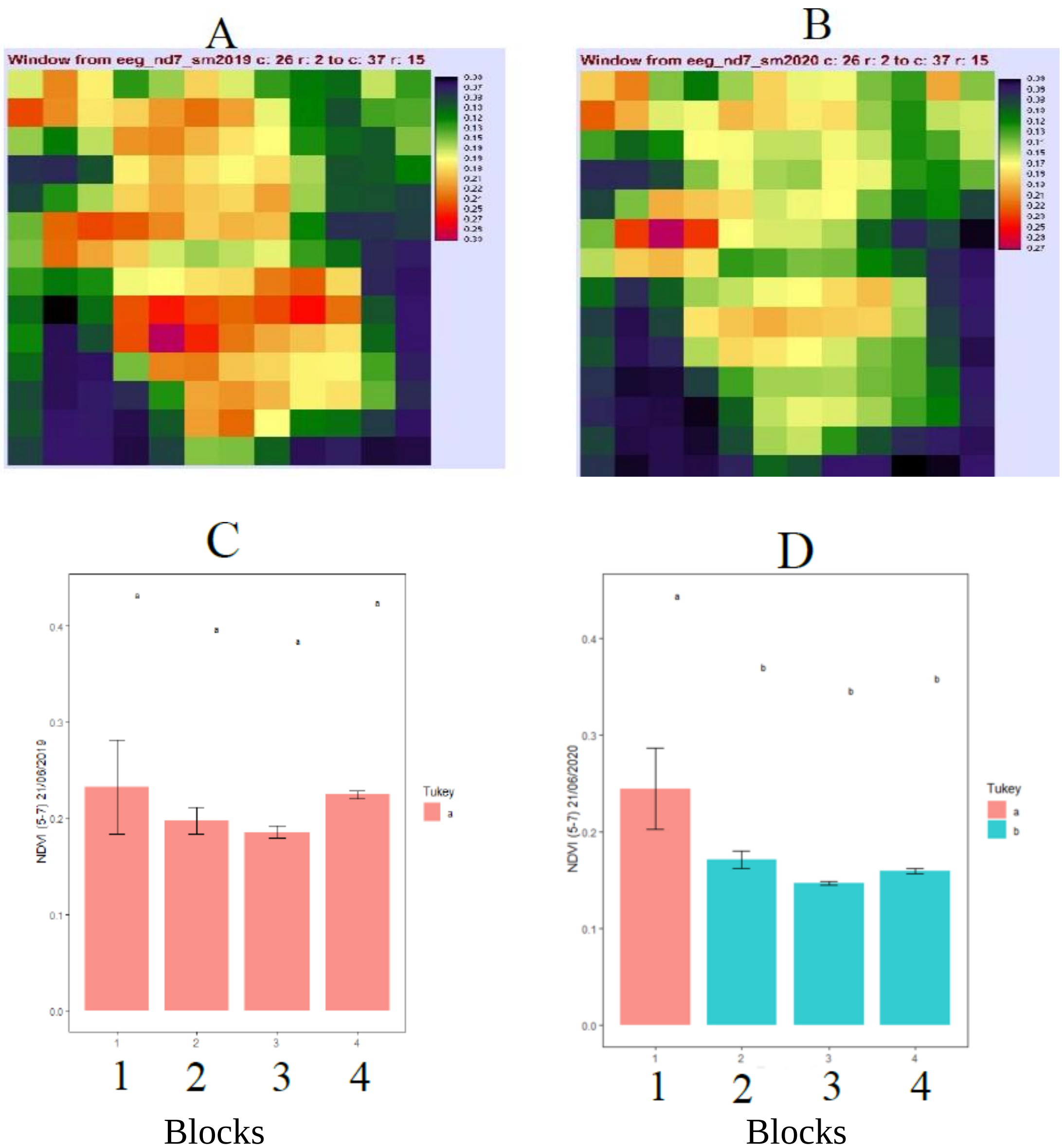


Figure 9. (A and B) NDVI image in same area at2019 and 2020 and (C and D) illustrates the ANOVA, Tukey´s multiple comparison test (significant $p < 0.05$) of NDVI (5-7) at 4 blocks

Observing Figure. (9 and 10) in relation to the first and second seasons ANOVA, Tukey´s multiple comparison test, there are no significant differences between the different regions of the first season. In the second season, the difference appears in a form between block 1 and the rest of the regions normalized difference vegetation index red edge (NDVI) (5-8a) and (NDVI) (5-7) .It also represents that, no significant differences between the different regions of the first season. In the second season, the difference appears in a form between block 1 and the rest of the others blocks. Multi-Spectral Instrument (MSI) has been found to be more sensitive to NDVI red edge in monitoring changes in plants than NDVI (4-8), despite the differences in spatial resolution. The results demonstrated that the red-edge band indices outperformed the broadband indices, (Imran *et al.*, 2020).

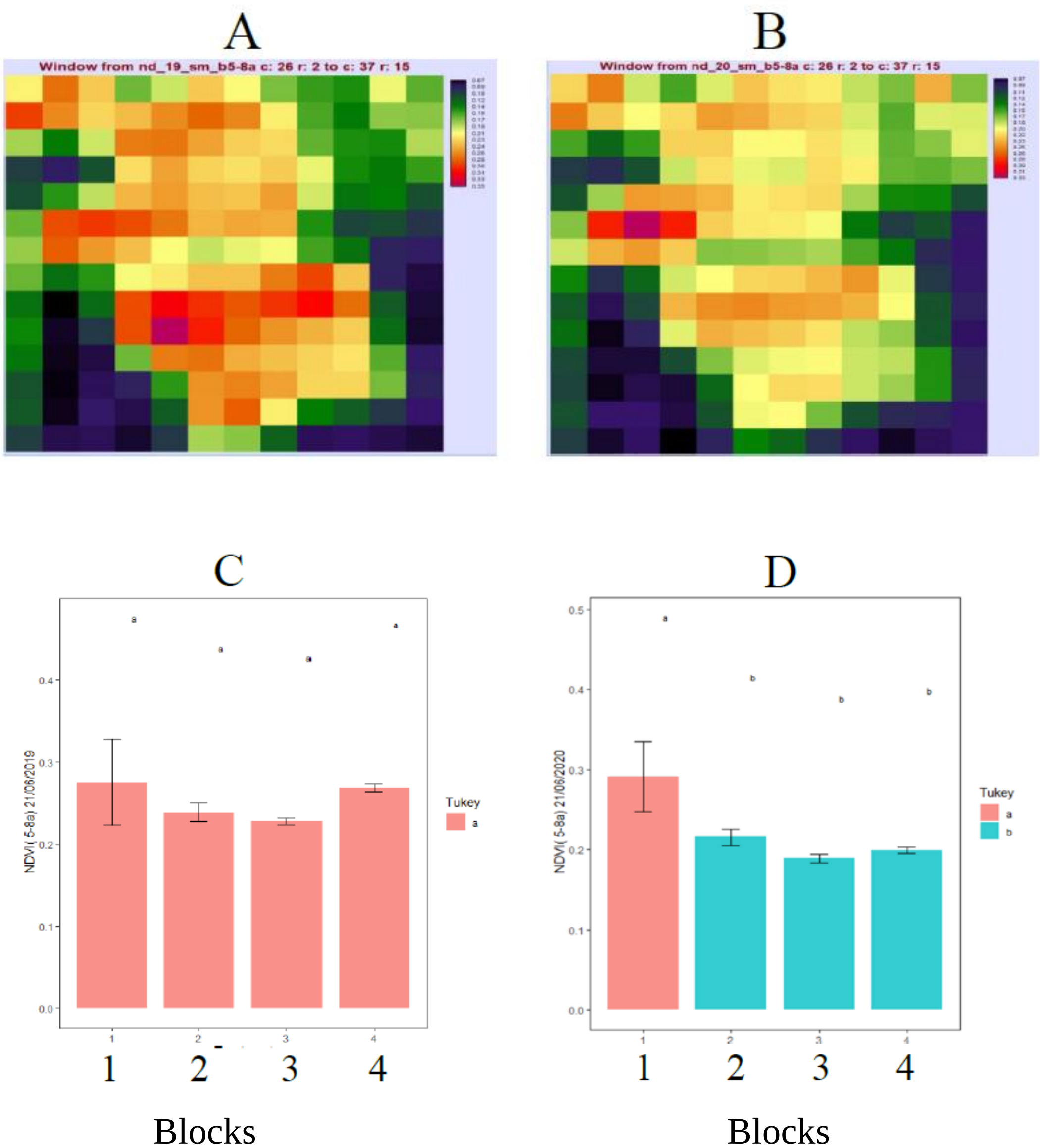


Figure 10. (A and B) NDVI image in same area at 2019 and 2020 and (C and D) illustrates the ANOVA, Tukey´s multiple comparison test (significant p< 0.05) of NDVI (5-8a) at 4 blocks

VV band Sentinel-1

The graphical illustration in Figure (11) visually captures the unique aspects and variations of the first and second seasons show that. ANOVA, Tukey´s multiple comparison test (significant p<0.05) of There are no significant differences between the different regions of the first season. In the second season, the difference appears in a form between block 1 and the rest of the others blocks. Sentinel-1 (VV) and Multi-Spectral Instrument (MSI) has been found to be more sensitive to NDVI red edge in monitoring changes in plants than NDVI (4-8), despite the differences in spatial resolution. The radar satellite Sentinel-1 showed similar sensitivity in detecting changes compared to the observations obtained from the red edge of NDVI, although there was an inverse relationship. This highlights the importance of Sentinel-1, as it provides high spatial accuracy and the ability to capture data even in the presence of cloud cover. Furthermore, it is worth noting that the capabilities of NDVI (bands 4-8) were found to be at their minimum in this context (Vreugdenhil *et al.*, 2018).

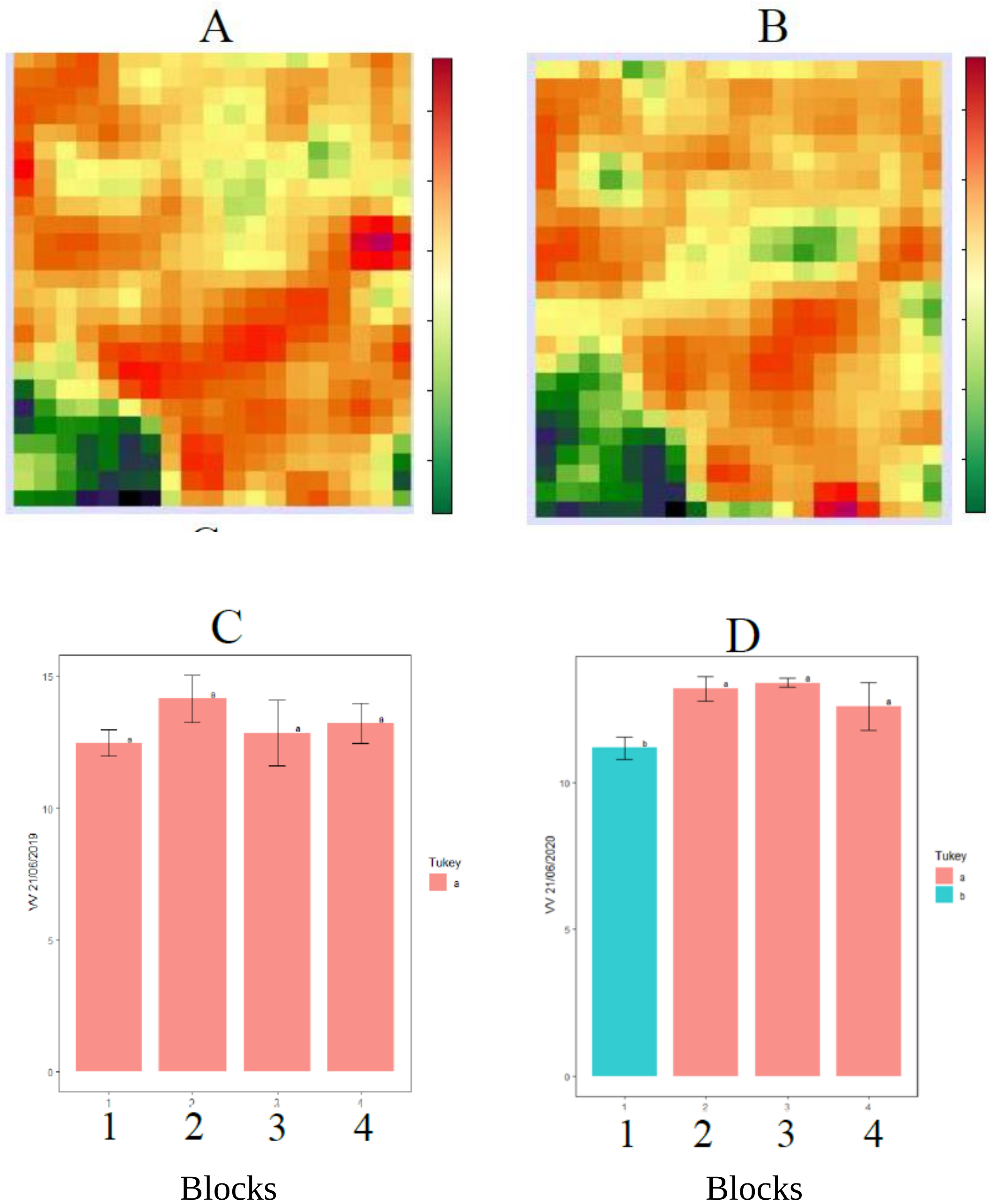


Figure. 11. (A and B) (VV image in same area at 2019 and 2020 and (C and D) illustrates the ANOVA, Tukey´s multiple comparison test (significant p< 0.05) of VV at 4 blocks

Numerous studies have investigated the accuracy of using radar data from the Sentinel-1 satellite for assessing vegetative growth. For example (Vreugdenhil *et al.,* 2018) significant amount of the variability with 87% for corn and 63% for winter cereals, indicating the potential of Sentinel-1 data for estimating vegetative growth, (Vreugdenhil *et al.*, 2018).

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Regression analysis between field and satellite measurements

Regression analysis relationship between number of leaves in the first and the second seasons among types of NDVI and VH band and VV band Sentinel-1 measured from satellite images.

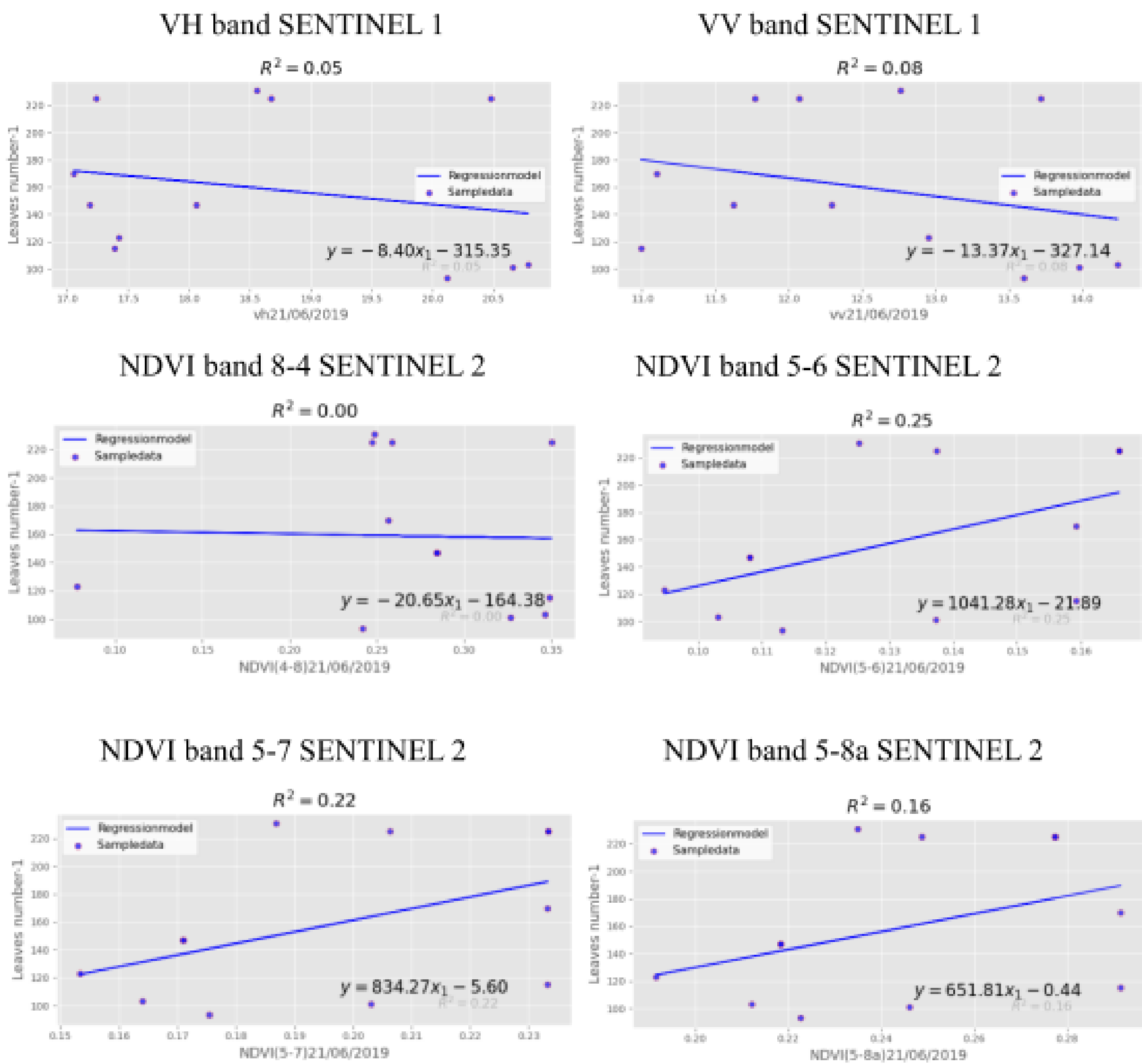

Figure 12. Simple linear regression relationship between Leaves number Season 1

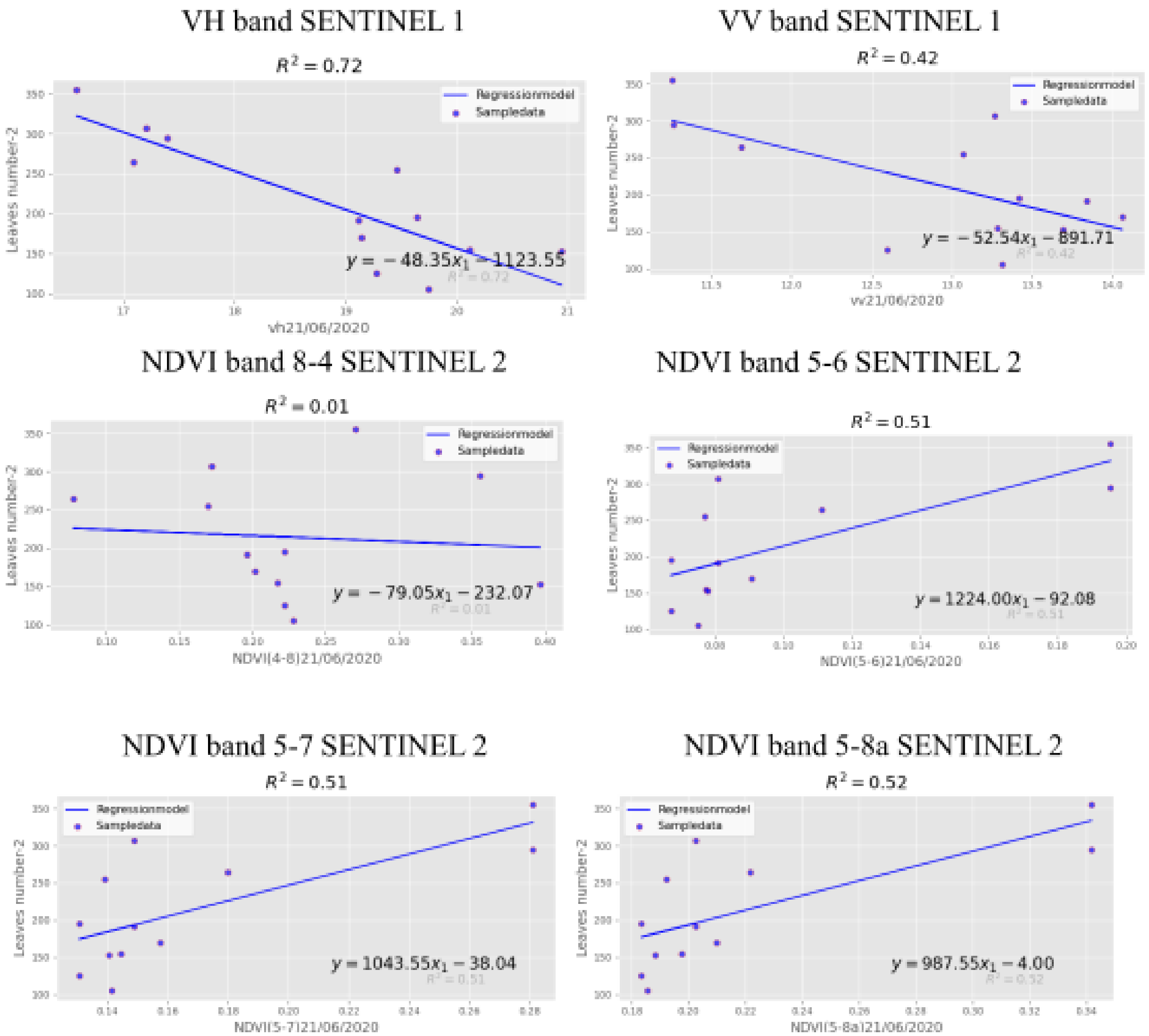

Figure 13. Simple linear regression relationship between Leaves number Season 2

Based on the analysis presented in Figures (12 and 13), the relationship between the number of leaves in the first and second seasons can be observed in relation to various vegetation indices and radar bands. In Figure (12), the highest values were observed for NDVI (5-6), (5-7), and (5-8a) during the first season, indicating strong relationships (R^2 =0. 25, R^2 = 0.22, and R^2 = 0.16, respectively) between these indices and the number of leaves. Figure (13) illustrates the simple linear regression relationships between the number of leaves in the second season and the VH and VV bands of Sentinel-1, as well as the NDVI bands 8-4, 5-6, 5-7, and 5-8a of Sentinel-2. The R^2 values for these relationships were 0.72, 0.42, 0.51, 0.51, and 0.52, respectively. This indicates higher relationships between the number of leaves and these variables during the second season. The VH band had the highest correlation. NDVI (4-8) had a lower sensitivity and strength compared to the other sensors, possibly due to the influence of a higher number of leaves in the second season and the specific characteristics of the area. Furthermore, the regression analysis indicates that the values of NDVI (5-6), NDVI (5-7), and NDVI (5-8a) from Sentinel-2, as well as the VH and VV bands from Sentinel-1, have higher regression relationships compared to NDVI (8-4). This implies that these variables provide better predictive power for understanding the relationship between the number of leaves and the seasons, as depicted in Figures (12 and 13). The accuracy improved in the second season as compared to the first season, possibly due to an increase in the number of vine leaves. The relationships between the data, whether obtained through radar or multispectral means, were also more apparent in the second season. Research studies have shown that while the radar satellite Sentinel-1 has low sensitivity in monitoring changes, it can still support the findings presented in the research. For example, essential for regional crop monitoring and accurate management rice (Yang *et al.*, 2021). Sentinel-1 has gained extensive usage in monitoring crop meteorological disasters and assessing losses, specifically for detecting frost damage in grapes (Li *et al.*, 2021), and drought monitoring (Mendes *et al.*, 2021). The widespread utilization of Sentinel-1 radar data highlights its potential in detecting changes and monitoring various fields. Supporting decision-making processes in diverse domains. There are no significant differences between the different regions of the first season. In the second season, the difference appears in a form between regions A and the rest of the others regions.

Regression analysis relationship between total chlorophyll in the first and the second seasons among types of NDVI and VH band and VV band Sentinel-1 measured from satellite images.

In Figure (14), the highest R^2 value of 0.15 was observed for NDVI (4-8), indicating a strong relationship with chlorophyll and other variables during the first season

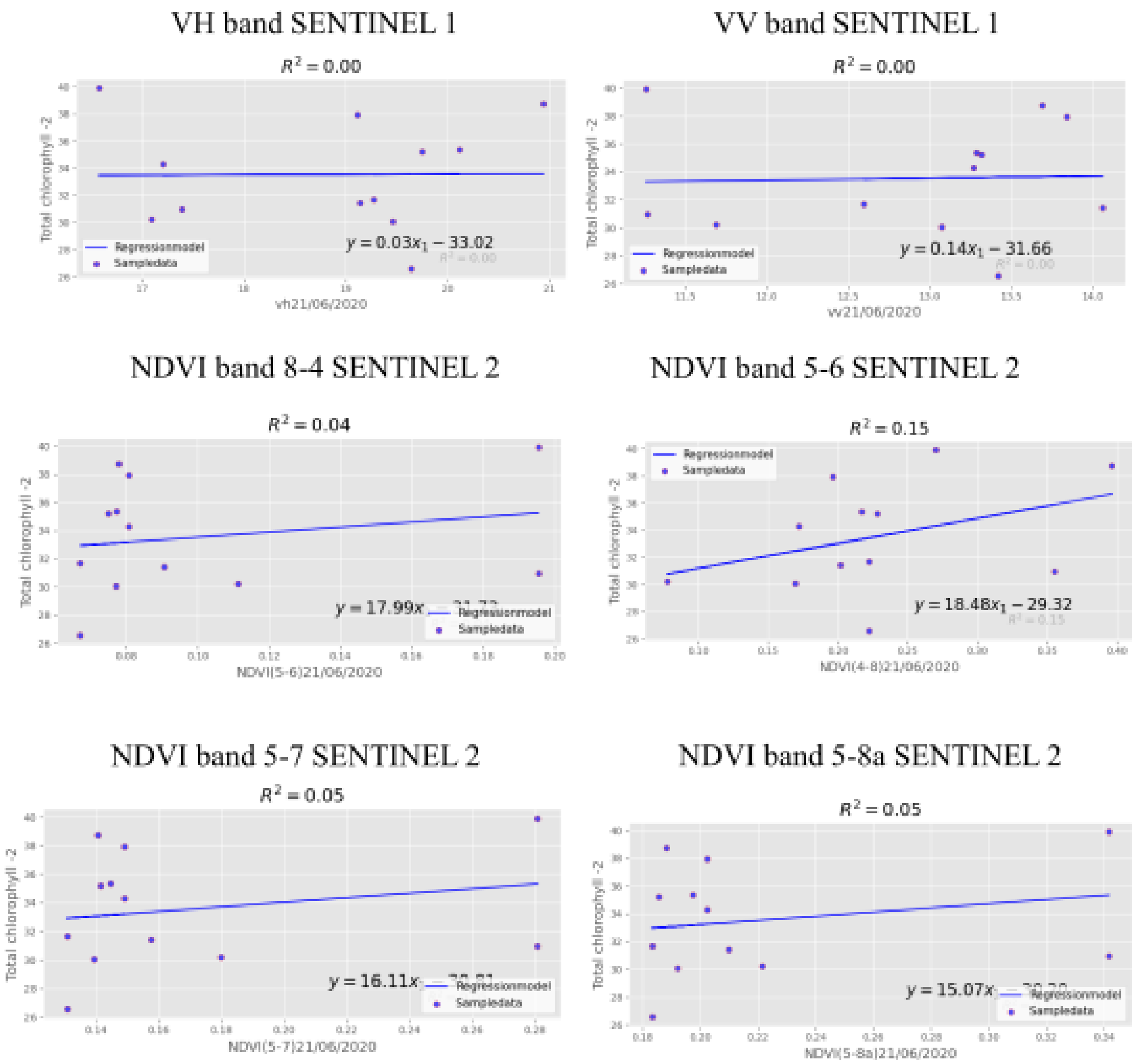

Figure 14. Simple linear regression relationship between Total chlorophyll Season 2

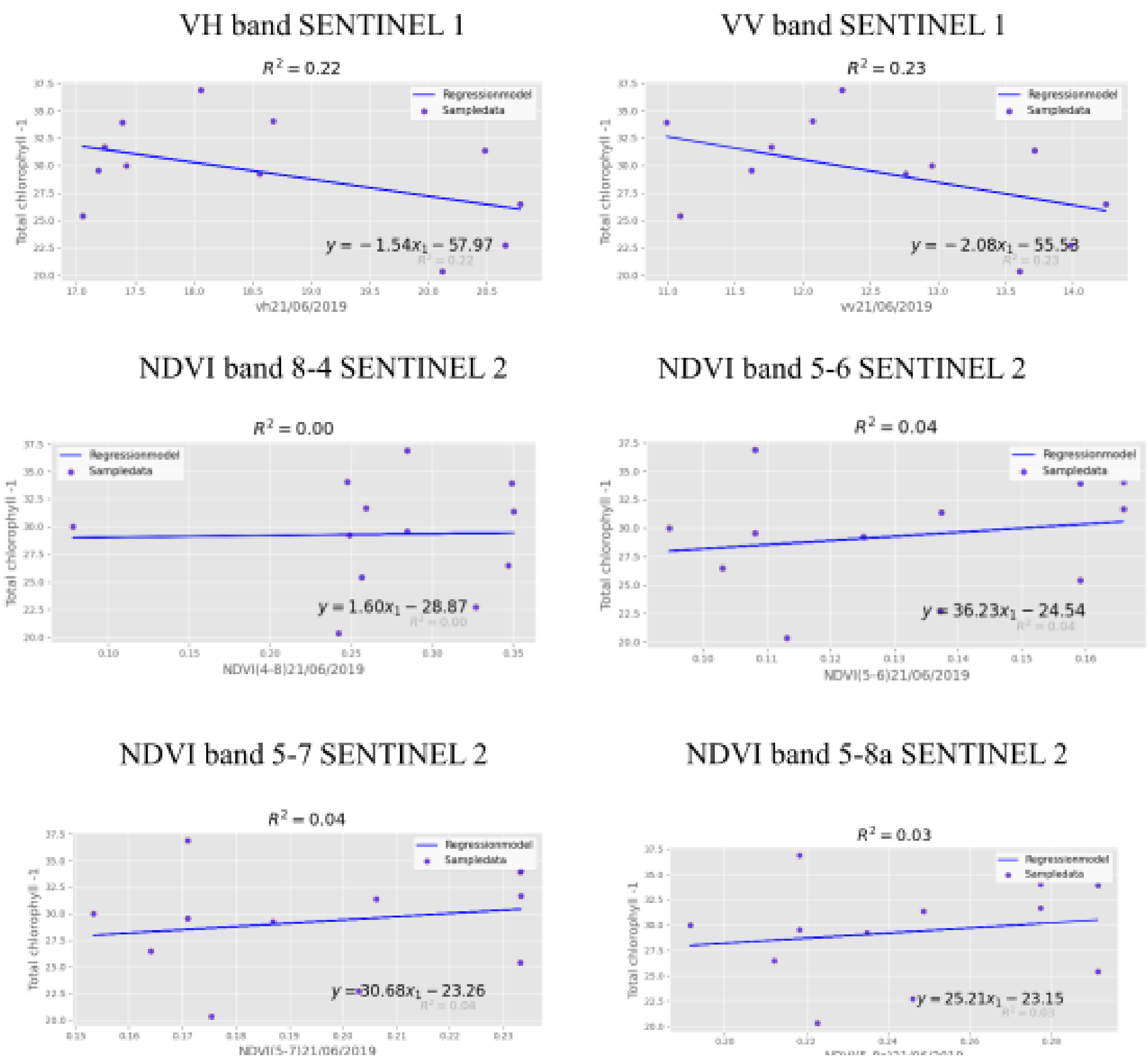

Figure 15. Simple linear regression relationship between total chlorophyll Season 1

Figure (15) depicts the relationship between chlorophyll and various variables. During the second season, VH and VV had R^2 values of 0.22 and 0.23, respectively, which were the highest values. In the first season, VV exhibited the highest value. Figure (14) shows the simple linear regression relationship between total chlorophyll in the second season and NDVI band 5-8a from Sentinel-2, along with the VH and VV bands from Sentinel-1, NDVI band 8-4, NDVI band 5-6, NDVI band 5-7 from sentinel 2, and NDVI band 5-8a. Figure (15) demonstrates the results of regression analysis, indicating that the VH and VV bands from Sentinel-1 have the highest values among the other variables. The study revealed that a higher number of plant leaves corresponded to a stronger relationship, which was observed in both the first and second seasons. Furthermore, the study suggested that NDVI (5-6) had higher accuracy but lower resolution compared to NDVI (4-8), likely due to differences in the wavelengths used. However, regarding chlorophyll, the results were inconclusive in both seasons, possibly due to the lack of discernible differences, despite previous studies confirming the existence of a relationship. The results for chlorophyll were inconclusive in both seasons, which could be attributed to the lack of differences observed. This is despite previous studies confirming the relationship between chlorophyll and vine health. Studies have investigated the relationship between remote sensing and chlorophyll using satellite data. For example, (Zhen *et al.*, 2021) developed a chlorophyll content retrieval model using remote sensing data from the Sentinel-2 satellite in mangrove forests. The value of the Sentinel-2 can support more sustainable wheat crop management practices (Revill *et* *al.,* 2019). The application of artificial intelligence in agriculture through remote sensing offers promising opportunities. Integrating crop simulation models with remote sensing has already shown its value in providing insights into crop development and projected productivity. Additionally, satellite remote sensing has proven to be an effective tool for monitoring chlorophyll content in vegetation, which further enhances the capabilities of remote sensing in agricultural applications (Hatfield *et al.,* 2019). This study introduces a wheat modeling approach that utilizes Sentinel-2 data to estimate and predict wheat yield. The developed model versions demonstrate their effectiveness in accurately predicting wheat yield. Specifically designed for durum wheat, this yield prediction model holds significant potential as a valuable tool for stakeholders involved in the wheat industry, including dealers, traders, and pasta food companies (Li *et al.,* 2019). The studies have reached the conclusion that VV (Vertical Vertical) and VH (Vertical Horizontal) polarizations, along with NDVI red edge (5-6), are more effective in monitoring changes in plants compared to NDVI (4-8).

In conclusion, the study demonstrated the effectiveness of using satellite data to accurately monitor leaf changes in grapevines. By analyzing specific bands such as VH and VV in Sentinel-1 and NDVI bands 8-4, 5-6, 5-7, and 5-8a in Sentinel-2, the researchers established significant relationships with leaf changes, as indicated by the R^2values of 0.72, 0.42, 0.51, 0.51, and 0.52, respectively. However, when assessing chlorophyll levels, the accuracy was comparatively lower. These findings emphasize the high precision of satellite technology in monitoring vegetative growth in grapevines and underscore the importance of further developing techniques to improve the monitoring and analysis of chlorophyll levels. By addressing this limitation, future applications of pressing agriculture can be enhanced, leading to more efficient and targeted grape cultivation practices.

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الملخص العربي

الكشف عن التباين وتحليل خصائص الغطاء النباتي شجيرات العنب باستخدام بيانات الاستشعار عن بعد بالأقمار الصناعية في أسوان، مصر

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تمثل الزراعة قطاعًا كثيف العمالة ، وتلعب دورًا حاسمًا في ضمان الأمن الغذائي.وقد أثر التطور العلمي السريع على مختلف المجالات ، بما في ذلك الزراعة ، مع تأثيرات كبيرة على علوم الوراثة وعلوم النبات والدراسات البيئية وأبحاث المناخ وإدارة الأراضي والآلات والتكنولوجيا والاستشعار عن بعد. وقد أدت هذه التطورات إلى تحسين إدارة الموارد ، مما أدى إلى الحد من الأزمات الغذائية والمجاعات. كان تركيز الدراسة على استخدام صور الأقمار الصناعية لرصد التغيرات علي شجيرات العنب ، وتحديداً باستخدام الاقمار Sentinel 1 و Sentinel٢ .

اجريت التجربة في مزرعة عنب صنف فليم سيدلس ، والمطعمة على اصل Freedom ، في مزرعة خاصة تقع في قرية بلانه في أسوان. كانت الإحداثيات المحددة للموقع (٢٤,٣٦٦٠٧ درجة شمالًا و ٣٢,٩٨٧٢٨٣ درجة و غربًا خط عرض ٢٤,٣٦٣٧٥ وخط طول ٣٢,٩٧٥٦١). تم إجراء التجربة خلال موسمي النمو ٢٠١٩ و ٢٠٢٠. كانت شجيرات العنب تبلغ من العمر ثلاث سنوات في بداية التجربة ، وكانت منزرعة على مسافة ١,٠ متر بين الشجيرات و ١,٥ متر بين الصفوف.نظام الري المتبع هو الري بالتنقيط والتسميد كان من خلاله. وأجريت قياسات الغطاء النباتي الحقلية ، بما في ذلك تقييم مستويات الكلوروفيل الكلية وعد الأوراق. تم إجراء قياسات الإستشعار عن بعد باستخدام الأقمار الصناعيةsentinel 1 و sentinel 2 و باستخدام برنامج معالجة البيانات Idrisi. تم التحليل الإحصائي للبيانات بعدة برامج وأدوات منها Google Earth Engine و Python و Google Colab و Wekeo ، تم إستخدام تحليل الإنحدار لفحص العلاقات بين المتغيرات. بالإضافة إلى ذلك ، تم إجراء تحليل المقارنة المعنويه للمتوسطات Tukey باستخدام برنامح R.

أكدت الدراسة فعالية هذه الأقمار الصناعية في مراقبة تغيرات الأوراق بدقة من خلال تحليل نطاقات VH و VV لـ sentinel 1 ، بالإضافة إلى نطاقات(NDVI 8-4) و (NDVI 5-6) و (NDVI 5-7) و (NDVI 5-8a) من sentinel 2. أظهرت الدراسة نتائج معنوية بين نطاقات موجات الأقمار الصناعية وعدد الأوراق حيث كانت قيم R^2ذات دلالة تبلغ ٠,٧٢ و ٠,٤٢ و ٠,٥١ و ٠,٥١ و ٠,٥٢ على التوالي. ومع ذلك ، لوحظ إنخفاض دقة قياس الكلوروفيل. تسلط هذه النتائج الضوء على الدقة العالية للأقمار الصناعية في مراقبة التغيرات في النمو الخضري لشجيرات العنب وتؤكد على أهمية تطوير تقنيات محسنة لرصد وتحليل الكلوروفيل.مع التوصية باستخدام دلائل نباتية أخري وإختيار الأعلي قيمة ومعنوية مع بعض التحليلات المعملية للأوراق خاصة العناصر الكبرى والصغرى حتي يمكن تطبيقها في عمليات الزراعة الدقيقة precision agricultutre مما يساعد في الحصول أعلي انتاجية ممكنة بإستخدام اكثر من صورة للأقمار الصناعية وتحليلها ببرامج الكمبيوتر المتخصصة المختلفة.