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Remote Sensing for Sustainable Pistachio Cultivation and Improved Quality Traits Evaluation through Thermal and Non-Thermal UAV Vegetation Indices

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Featured Application: Pistachio orchard management using remote sensing with UAVs.

Abstract: Pistachio (*Pistacia vera* L.) has earned recognition as a significant crop due to its unique nutrient composition and its adaptability to the growing threat of climate change. Consequently, the utilization of remote sensing techniques for non-invasive pistachio monitoring has become critically important. This research was conducted in two pistachio orchards located in Spain, aiming to assess the effectiveness of vegetation indices (VIs) in estimating nut yield and quality under various irrigation conditions. To this end, high-resolution multispectral and thermal imagery were gathered using a Micasense ALTUM sensor carried by a DJI Inspire 2 drone in order to calculate the NDRE (normalized difference red edge index), GNDVI (green normalized difference vegetation index), NDVI (normalized difference vegetation index), and CWSI (crop water stress index). Each orchard underwent two flights at distinct growth stages, totaling four flights. In June, NDRE-carbohydrates ($r = 0.78$) and CWSI-oleic ($r = 0.77$) showed the highest correlations, while in September, CWSI-carbohydrates ($r = 0.62$) and NDVI-iron ($r = 0.54$) Despite NDVI's limitations due to saturation effects, all VIs had significant yield and quality correlations, with GNDVI proving most effective in both flights. CWSI correlated considerably on both dates in terms of several quality parameters (carbohydrate percentage, magnesium, iron, and fatty acids, namely palmitoyl, stearic, oleic, and linoleic), surpassing non-thermal indices. Finally, it is important to consider the impact of environmental factors, such as the location of the sun, when interpreting the CWSI, as it modifies the temperature distribution pattern within the canopy. This study supports the viability of remote sensing and vegetation indices as potential tools for enhancing the management of pistachio orchards.

Keywords: CWSI; drone; GNDVI; irrigation; multispectral; NDRE; NDVI; nut quality; *Pistacia vera*; LWIR

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1. Introduction

Pistachios (*Pistacia vera* L.) have emerged as some of the most nutritionally rich nuts, distinguished by a protein, essential amino acids, vitamins, and mineral ratio surpassing that of many other frequently consumed nuts [1]; these nuts have been shown to contain an array of nutrients including protein, fiber, monounsaturated fatty acids, minerals, vitamins, carotenoids, phenolic acids, flavonoids, and anthocyanins, all of which contribute to the antioxidant and anti-inflammatory properties of pistachio [2]. Incorporating pistachios into the diet has been associated with various health benefits since the consumption of nuts, pistachios included, positively impacts a range of health outcomes. Pistachio nuts are nutrient-dense and possess a unique nutrient profile, with a lower fat and energy content compared to other nuts and a higher concentration of specific vitamins, minerals, phytosterols, and antioxidants [3]. Furthermore, pistachios can be consumed raw but they can also be utilized in derived products of interest to the food industry [4]. Therefore, in the context of increasing global demand for nutritious and sustainable food sources in recent years, the pistachio has garnered significant interest due to these aforementioned attributes.

On the other hand, from an agronomical perspective, pistachios show great promise for addressing the challenges of climate change. Climate change signifies a process of altering global climatic patterns on Earth. According to the latest report from the Intergovernmental Panel on Climate Change (IPCC) of the United Nations (UN) published in 2022 [5], our planetary climate system is undergoing a notable global warming trend, underscored by increased surface air and sea temperatures, which have on average risen by 0.87 °C since the pre-industrial era up to the decade between 2006 and 2015. This report accentuates the persistent rise in temperatures, which is causing increasingly frequent heatwaves and potentially leading to a higher frequency and severity of intense precipitation events globally. Paradoxically, this trend is anticipated to be accompanied by a higher incidence of drought in certain regions, such as the Mediterranean, intensifying plant water stress, increased agricultural water usage, and decreased water availability [6].

The pistachio tree is recognized for its significant drought resilience and its ability to maintain photosynthesis even under low leaf water potential [7], showing impressive adaptability to challenging environmental conditions and water scarcity [8,9]. An additional challenge is that reduction in soil water content usually leads to increased salinity [10]; however, pistachios are known for their salinity resistance, albeit only to a certain degree, because moderate salinity does not hinder the initial growth of these trees but elevated salinity levels and extended exposure can be detrimental [11]. Depending on the rootstock used, responses can vary based on different stress resistance mechanisms, thus underscoring the importance of rootstock selection in mitigating environmental conditions and enhancing crop performance [12–14]. Given the potential for a wide array of symptoms, it is important to have tools that allow for the swift and accurate analysis of crop status and early symptom onset.

With the remarkable advancements in multispectral and thermal or LWIR (long wave infrared) imaging technology, there are new and exciting prospects for precision agriculture. Such imaging technologies allow for the acquisition of precise spectral and temperature data about crops, thereby aiding in agricultural management through informed decision-making processes. A popular method in agriculture for leveraging multispectral images is to calculate vegetation indices (VIs), which are the algebraic combinations of the numerous information bands provided by the images. The normalized difference vegetation index, or NDVI [15], is a well-known VI widely utilized for monitoring woody crops [16–18] due to its direct correlation with the vegetation present in the field [19]. Additional VIs, such as the green normalized difference vegetation index, GNDVI [20]; the normalized difference red edge index, NDRE [21]; and the crop water stress index, CWSI [22,23], have proven beneficial in precision agriculture [24–26]. The CWSI, in particular, which relies on thermal imagery, provides a comprehensive approach to understanding crop water usage and stress, identifying temperature variations within and between crop canopies, and offering critical insights into plant transpiration rates and potential irrigation-related problems [27–29].

Several studies have centered on imaging techniques in relation to pistachios. For instance, Mohammadi-Moghaddam et al. [30] created models based on Vis/NIR hyperspectral imaging and multivariate analysis for predicting the moisture content and textural features of pistachio kernels roasted under different conditions. Bonifazi et al. [31] assessed different multivariate classification methods applied to shortwave infrared range (SWIR: 1000–2500 nm) hyperspectral images for identifying contaminants in edible pistachio products. Eksi-Kocak et al. [32] developed a rapid, nondestructive technique to detect green pea adulteration in pistachio nut granules using Raman hyperspectral imaging, principal component analysis, and partial least squares regression, and Singh et al. [33] were able to distinguish between two types of pistachios (Kirmizi and Siirt) commonly grown in Turkey, using imagery and convolutional neural networks. However, the majority of these studies concentrate on post-harvest fruits, showing a knowledge gap regarding the use of images for managing pistachio cultivation in the field.

Only a few studies have demonstrated the potential of using images for managing pistachio crops in the field. For instance, Jacygrad et al. [34] exploited the power of Unmanned Aerial Vehicles (UAVs) to capture the seasonal changes of pistachio tree crowns in a pistachio orchard, providing valuable insights into tree characteristics. Vélez et al. [35] developed an innovative method that leverages the shadows cast by the canopies of pistachio trees to estimate their volume in a cost-effective manner. In a similar vein, Barajas et al. [36] validated the effectiveness of NDVI as a reliable tool for identifying the vigor of pistachio trees. Testi et al. [37] found that CWSI served as a sensitive indicator of water stress in pistachio trees, highlighting clear differences between well-irrigated and deficit-irrigated trees. Moreover, Bellvert et al. [38] utilized NDVI data derived from Landsat-8 to compute various coefficients linked to pistachio water use, revealing distinct seasonal variations. While these studies have significantly progressed the field and explored the potential of imaging technologies in pistachio crop management, there still exists an evident gap in establishing a robust link between such imagery and two critical aspects of pistachio cultivation: yield and nut quality.

Therefore, the novel contribution of the present study lies in exploring the relationship between multispectral and thermal images and the most important agronomic and quality parameters for pistachio cultivation. The focus of this work centers on harnessing the potential of UAV-based remote sensing that employs thermal and multispectral imaging technologies, with the aim of optimizing pistachio crop management, emphasizing three key factors: irrigation, yield, and quality. Intending to foster sustainable and efficient agricultural approaches in pistachio cultivation, this study strives to highlight the relationships between remote sensing techniques and the agronomic factors and quality features of pistachios.

2. Materials and Methods

2.1. Study Site and Plant Material

In 2022, the experimental trials were conducted in two separate pistachio orchards located in Valladolid, region of Castilla y León, Spain (Figure 1). The orchards were located in two different areas located in the south of the province, "Moraleja de las Panaderas" and "La Seca", respectively.

The planting material utilized in the experimental trials included both 7-year-old and 15-year-old pistachio plants of the cv. Kerman variety, one of the most common female cultivars, known for its high-quality nuts and adaptability to various environmental conditions [2]. These plants were grafted onto the UCB rootstock, a *P. atlantica* × *P. integerrima* hybrid, and the experimental orchards were arranged in a 7 × 6 m triangular planting pattern, featuring NE–SW orientation, which optimizes sunlight exposure and promotes the efficient use of available resources. The variety used as male was cv. Peter. As part of the standard crop management practices in this region, weeds, insect pests, and diseases were controlled by applying the recommenced agrochemicals to avoid yield limitations.

2.2. Irrigation Treatments

The pistachio trees in this study (Figure 2) were subjected to two distinct irrigation treatments during their vegetative cycle. The higher irrigation treatment (H) administered 50% more water compared to the control treatment (C). At the "La Seca" location, the trees underwent irrigation from January to October 2022, utilizing a computer-controlled drip irrigation system. This system allowed for precise adjustments to the duration of each irrigation episode, ensuring the accurate regulation of water quantities. Throughout 2022, the total volume of irrigation water supplied to the trees in "La Seca" was 2.750 m^3 ha^{-1} for the control treatment (C) and 4.660 m^3 ha^{-1} for the higher treatment (H).

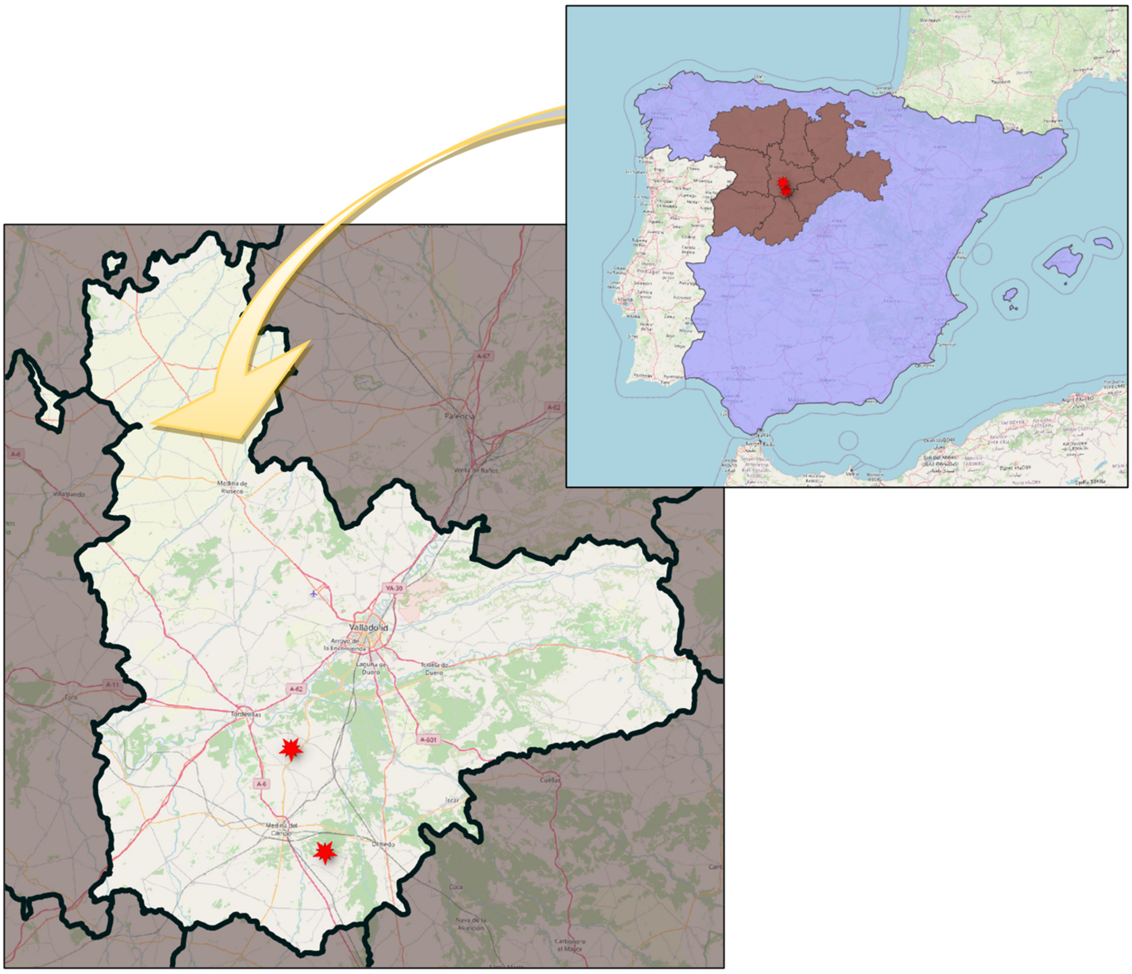

Figure 1. The geographic location of pistachio groves in “Moraleja de las Panaderas” and “La Seca” (red stars), situated within Valladolid, in the “Castilla y León” region, Spain.

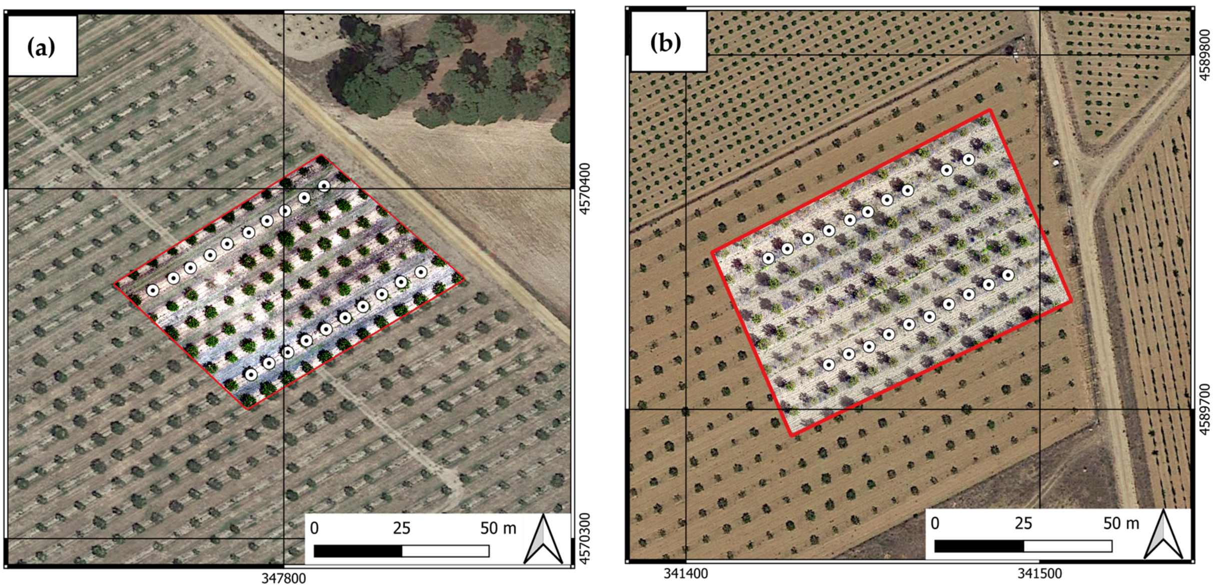

Figure 2. Location of pistachio trees in each designated plot. (**a**) “Moraleja de las Panaderas”. (**b**) “La Seca”. Coordinates in CRS ETRS89/UTM zone 30N.

On the other hand, in "Moraleja", the trees received irrigation water from May to October, with the control treatment (C) amounting to 844 $m^3\ ha^{-1}$ and the higher treatment (H) receiving 1.161 $m^3\ ha^{-1}$ of water. This controlled variation in water supply enabled the introduction of variability to examine the effects of different irrigation levels on the growth and productivity of the pistachio trees.

2.3. Image Acquisition and Processing

Throughout the growing season, a total of four drone flights were conducted, with two flights in each of the selected orchards, in order to gather comprehensive multispectral and thermal imaging data. The initial flight was conducted on 24th June (DOY 175, Flight 1), capturing images during the growth stages of the pistachio nuts (F1–F2 stages), corresponding to when the mesocarp started to turn yellow, while the subsequent flight took place on 7th September (DOY 275, Flight 2), providing valuable information on the progression of plant growth and nut maturity during the later stages of the season (M stage). All flights were planned and executed automatically at 30 m above the ground level and 2 m/s speed, under optimal weather conditions, on windless and sunny days with minimal cloud cover (1 okta cloud conditions). This settings delivered a ground resolution of 1.29 cm/pixel for the thermal and the multispectral imagery. The UAS system (Figure 3) employed for data acquisition was composed of a UAV DJI Inspire 2 (DJI, Shenzhen, Guangdong, China, Table 1), which was equipped with a Micasense ALTUM multispectral camera (AgEagle Sensor Systems Inc., Wichita, KS, USA, Table 2).

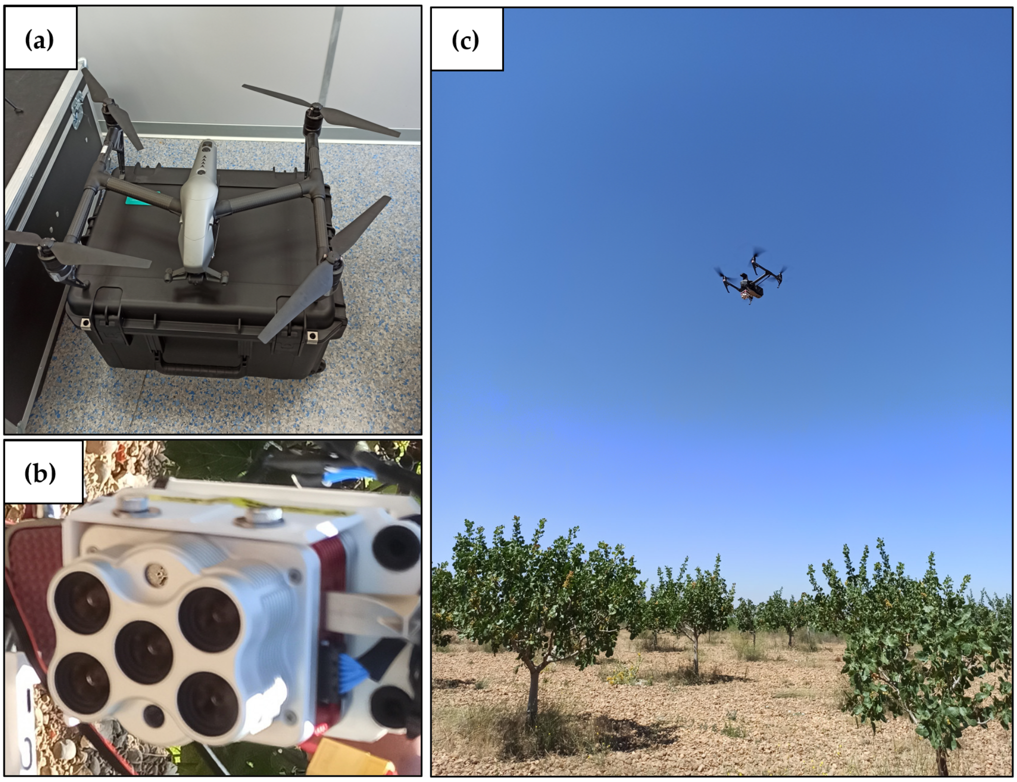

Figure 3. UAS system model employed for data acquisition. (**a**) UAV DJI Inspire 2 drone. (**b**) Micasense ALTUM multispectral camera. (**c**) UAS flying over the pistachio orchard.

Table 1. Detailed technical specifications of DJI Inspire 2 drone.

Maximum Take-off Weight and Maximum Speed	9.37 lbs (4250 g), 58 mph (94 kph)
GPS Hovering Accuracy	±1.64 feet (0.5 m) vertically, ±4.92 feet (1.5 m) horizontally
Maximum Flight Time	Approximately 27 min
Remote Controller Model	GL6D10A
Operating Frequencies	2.400–2.483 GHz, 5.725–5.850 GHz
Maximum Transmitting Distance	2.2 miles (3.5 km) under CE regulations
Battery Capacity, Voltage, Capacity, Power	Model TB50, 4280 mAh, 22.8 V, 97.58 Wh, 180 W

Table 2. Detailed technical specifications of the sensor model Micasense ALTUM. FOV: field of View. GSD: ground sample distance.

Dimensions, Weight	(8.20 × 6.70 × 6.75) cm length width and height, 357 g
Pixel Size Multispectral and Thermal Sensor	3.45 μm and 12 μm
Multispectral Resolution, Aspect Ratio	2064 × 1544 pixels (3.2 MP × 5 imagers), 4:3
Thermal Resolution	160 × 120 pixels (0.01 K)
Multispectral and Thermal Focal Length	8 mm and 1.77 mm
Multispectral and Thermal FOV	48° × 36.8° and 57° × 44.3°
GSD at 60 m Altitude	Multispectral: 2.6 cm, Thermal: 41 cm
Spectral Bands: Multispectral and Thermal Cameras	Blue (475 nm), Green (560 nm), Red (668 nm), Red Edge (717 nm), Near Infrared (842 nm) and LWIR (11 μm)
Spectral Bandwidth: Multispectral and Thermal Cameras	Blue (32 nm), Green (27 nm), Red (14 nm), Red Edge (12 nm), Near Infrared (57 nm) and LWIR (6 μm)
Bit Depth	Multispectral: 12-bit, Thermal: 14-bit
Thermal Sensitivity, Thermal Accuracy	Less than 50 mK, +/− 5 K

Moreover, to ensure enhanced geometric accuracy during the image mosaicking process, a set of five ground control points (GCPs) was employed, positioned in the field utilizing a highly precise JAVAD Triumph-2 real-time kinematic (RTK) GNSS system.

The acquired images were processed using Agisoft Metashape Professional software (v1.7.6, Agisoft LLC, St. Petersburg, Russia), adhering to the manufacturer's recommended guidelines. Initially, ground control points (GCPs) were identified within the images to optimize camera positions, orientation data, and enhance orthophoto accuracy. Subsequently, calibrated reflectance panel images were located to adjust image data based on the reflectance values supplied by Micasense. A high-quality dense point cloud was then generated, preserving the original resolution of the raw images without downscaling.

A digital surface model (DSM) was created using the comprehensive dense point cloud. This was followed by the automatic classification of ground points, which relied exclusively on these points to generate the digital terrain model (DTM). Then, these two layers were employed to calculate the canopy height model (CHM) in order to distinguish the pistachio tree crowns from the background.

A total of four orthophotos with six spectral bands were created from these flights and they were subsequently used to calculate a range of the VIs (Table 3), offering valuable insights into the vigor and overall productivity of the pistachio plants under investigation. These indices can aid in identifying the status of the vegetation and patterns and trends in plant growth [19,39], as well as detecting potential issues related to water stress, nutrient deficiencies, or disease [40–43]. The calculation of the CWSI, the thermal-based VI calculated in this study, was conducted in accordance with the established methodology of [44]. This method involved segmenting the tree canopies from the background by utilizing the CHM and, following this, temperature histograms were computed specifically using pixels derived from pure pistachio vegetation.

Table 3. Vegetation indices (VIs) employed in this work. *R*, reflectance in the red (660 nm); *NIR*, near-infrared (760 nm); *RE*, red edge (around 715 nm); T_l, average canopy temperature acquired using the UAV thermal imagery after removal of ground pixels; T_{wet}, lower canopy temperature; T_{dry}, temperature of the upper limit of the canopy.

Vegetation Index	Formula	Measure	References
Normalized Difference Vegetation Index (NDVI)	$= \frac{(NIR-R)}{(NIR+R)}$ (1)	Quantity, quality, and development of vegetation	[15]
Green Normalized Difference Vegetation Index (GNDVI)	$= \frac{(NIR-Green)}{(NIR+Green)}$ (2)	Water and nitrogen consumption	[20]
Normalized Difference Red Edge Index (NDRE)	$= \frac{(NIR-RE)}{(NIR+RE)}$ (3)	Measuring the amount of chlorophyll	[21]
Crop Water Stress Index (CWSI)	$= \frac{T_l-T_{wet}}{T_{dry}-T_{wet}}$ (4)	Relative transpiration rate	[22,23,45]

2.4. Harvest Assessment and Nutritional Analysis

At maturity, a total of twenty trees, ten per irrigation treatment and location, were harvested (October 2022). Several agronomic and quality parameters were determined at harvest: fresh weight per tree (Yield_FW, kg tree^{-1}), number of bunches per tree (Bunch, bunch tree^{-1}), and average bunch weight (Yield_raw, kg tree^{-1}). Thereafter, the samples were peeled and dried for 24 h at 60 °C to avoid mycotoxin contamination and weighed again to obtain the dry weight (Yield_DW, kg tree^{-1}). The size was determined as the number of pistachios present in one ounce (commercial caliber, 28.35 g). The percentage of open husk, closed husk, and empty nuts was also determined (Split, Non_Split, and Blank) and the weight of open husk, closed husk, and empty nuts per tree (DW_split, DW_non_split and DW_blank, kg tree^{-1}) were calculated at a representative subsample of twenty five nuts.

Regarding nutritional quality, the numerous parameters of a sample of pistachio nuts collected from the studied trees were evaluated in the physicochemical laboratory of the 'Instituto Tecnológico Agrario de Castilla y León'. On the one hand, the fiber (g 100 g^{-1}) was calculated using the enzymatic–gravimetric method via sequential enzymatic digestion with α-amylase, protease, and amyloglucosidase, and the fat content (Fat, g 100 g^{-1}) was obtained through petroleum ether extraction using the Ankom sealed bag system. On the other hand, the protein content (PROT, g 100 g^{-1}) was calculated from nitrogen quantification (Dumas combustion method) by multiplying the value obtained with the coefficient 6.25 [46], and the carbohydrates content (CBH, g 100 g^{-1}) was determined through the difference of other major components (CBH = 100 − Ash-Humidity-PROT-Fat), in which ash and humidity content were determined gravimetrically.

Furthermore, macro and micronutrients, such as calcium (Ca, mg kg^{-1}), magnesium (Mg, mg kg^{-1}), phosphorus (P, mg kg^{-1}), potassium (K, mg kg^{-1}), sodium (Na, mg kg^{-1}), iron (Fe, mg kg^{-1}), and zinc (Zn, mg kg^{-1}), were determined. To that end, in the ETHOUS UP microwave digestion system (Milestone, Sorisole, Italy), 500 mg of dry material was digested at 200 °C in a Teflon container. The solutions were then cooled to room temperature and diluted. To conclude, the nutrient content was measured using an Agilent Technologies Varian 720-ES inductively coupled plasma-optical emission spectrometer (ICP-OES; Santa Clara, CA, USA).

Finally, after acid digestion via dry route, several fatty acids expressed by percentage were measured, including palmitic, palmitoyl, stearic, oleic, linoleic, and linolenic, through gas chromatography with a flame ionization detector (GC-FID).

2.5. Image, Statistical, and Data Analyses

The data obtained from the study underwent a comprehensive analysis to identify potential relationships between variables and gain a deeper understanding of the factors affecting pistachio quality and yield under different irrigation treatments.

To perform this tasks, QGIS software (version 3.22.X, QGIS developer team 2022) facilitated the processing and visualization of remote sensing data, while the R software (version 4.3.X, R Foundation for Statistical Computing, R Core Team 2019, Vienna, Austria) facilitated image, statistical analysis, and data manipulation. The integration of these software applications and packages enabled the robust and efficient analysis of the complex data collected during the study.

The analyses involved several R packages, including *raster* and *rgdal*, which were sourced from the Comprehensive R Archive Network (CRAN). The packages *factoextra* and *FactoMineR* were used to extract and visualize the multivariate data analyses (PCA, principal component analysis), which essentially convert a set of potentially correlated variables into a smaller, orthogonal set of "principal components". These principal components are calculated in such a way that the first few retain most of the variation present in all the original variables.

A correlation matrix based on Spearman's correlation was employed to evaluate these relationships using the function *cor()* and was visualized using the package *corrplot*. In addition, with some of the most correlated variables, linear regressions were carried out in order to examine their relationship with the function *ggplot()* in depth and were visualized with the packages *ggplot2* and *ggpmisc.* The abbreviations for each trait used in the figures are described above.

3. Results

First, we conducted a visual inspection of the generated VIs maps obtained through remote sensing (CWSI, NDVI, NDRE, and GNDVI), aiming to gain insights into the patterns and relationships among the examined VIs (Figure 4).

Upon examining the CWSI values, it was observed that the vegetation values ranged from 0 to 1 and higher values were present on the south and east sides of the canopy crowns, due to the position of the sun. On the other hand, when analyzing the non-thermal-based VIs, the values ranged from 0.5 to 1 and an interesting observation across all maps was the positive relationship between the canopy size and the values of NDVI, NDRE, and GNDVI. In contrast, NDRE values were not as high, and there was greater variability within each canopy crown compared to NDVI. GNDVI, on the other hand, exhibited a pattern similar to NDRE, indicating that both indices capture comparable information about the overall vegetation growth.

In our study, we employed principal component analysis (PCA, Figure 5) as a statistical technique to both reduce the dimensionality of our data and investigate inherent trends and relationships. Thus, the first component accounted for 33.8% of the total variability within the data set, which is a substantial proportion, considering it is just one of many potential components. Meanwhile, the second component contributed to explaining a further 21.2% of the total variability. Cumulatively, these two components alone were able to reveal more than half (approximately 55%) of the total variability within the data set. The visual representation of this PCA reveals clusters that distinguish between different treatments and geographical locations, showing that the data did not differ according to irrigation treatments (Figure 5a) but did differ according to plot location (Figure 5b).

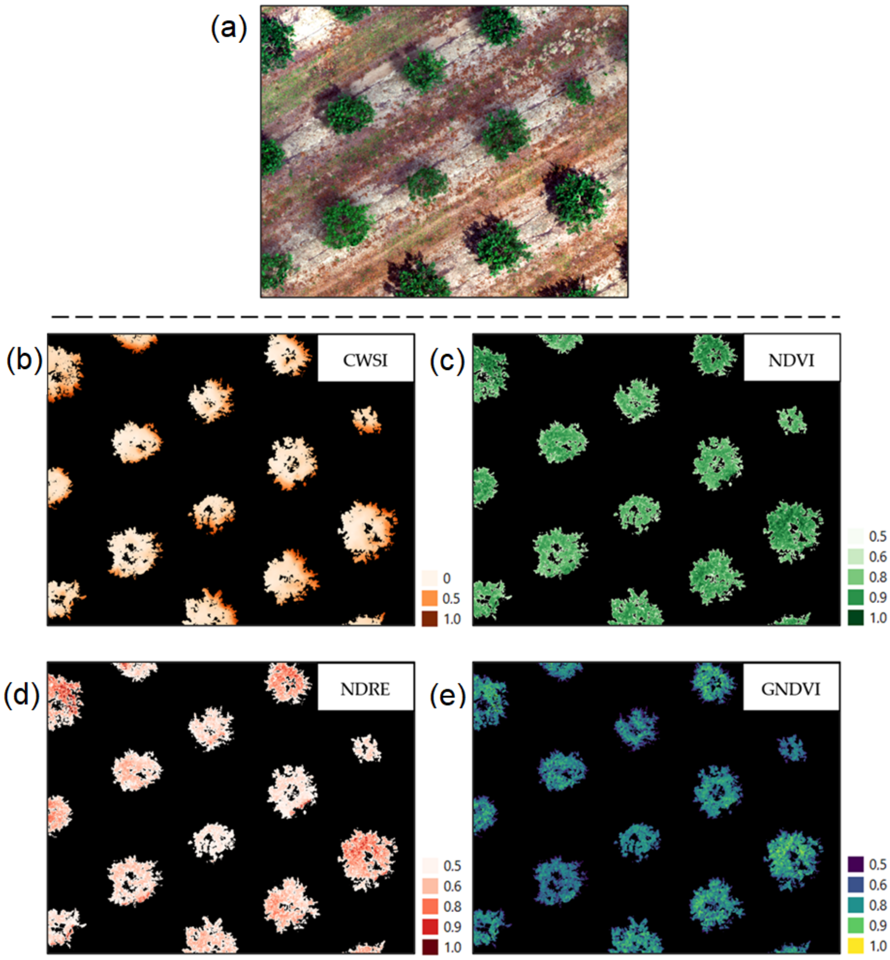

Figure 4. Maps of the pistachio orchard. Top: (**a**) orthomosaic, providing a detailed visual overview. Bottom: vegetation indices, including (**b**) CWSI (crop water stress index), (**c**) NDVI (normalized difference vegetation index), (**d**) NDRE (normalized difference red edge), and (**e**) GNDVI (green normalized difference vegetation index).

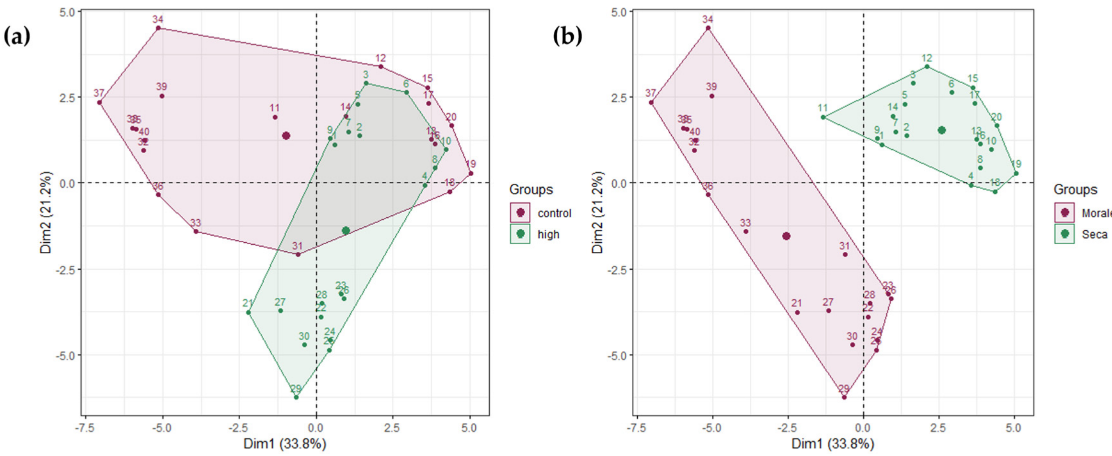

Figure 5. Principal component analysis (PCA) grouping the differences between (**a**) irrigation treatments and (**b**) plot location based on the vegetation indices, agronomic parameters, and nut quality at harvest. Two locations ("Moraleja" and "La Seca") under two different irrigation treatments (control vs. high levels).

In a further exploration of our data, Figure 6 presents a biplot of the principal component analysis (PCA), where variables are grouped based on two different factors: irrigation and location. Upon conducting this biplot analysis, contrary to our observations from the previous figure, we noticed a distinct difference in treatment due to the irrigation applied in "Moraleja" plot. However, the "La Seca" plot maintained its consistent pattern, showing no discernible differences in relation to the irrigation.

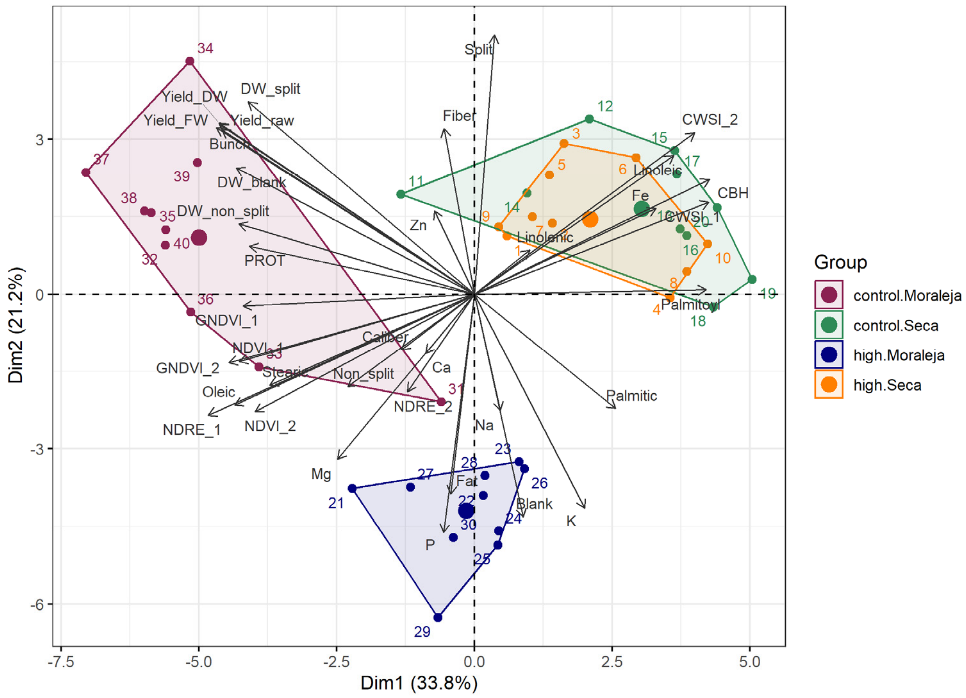

Figure 6. Principal component analysis (PCA) of vegetation indices, including CWSI (crop water stress index), NDRE (normalized difference red edge), NDVI (normalized difference vegetation index), and GNDVI (green normalized difference vegetation index) at two different time points (June and September). Agronomic parameters include fresh and dry fruit weight per tree (Yield_FW and Yield_DW), number of bunches (Bunch) per tree, and average bunch weight (Yield_raw). The commercial caliber, the percentage of open husk, closed husk, and empty nuts (Caliber, Split, Non_Split, and Blank) and the weight of open husk, closed husk, and empty nuts per tree (DW_split, DW_non_split and DW_blank). Regarding quality, fiber, fat (Fat), carbohydrates (CBH), protein (PROT), calcium (Ca), magnesium (Mg), phosphorus (P), potassium (K), sodium (Na), iron (Fe), zinc (Zn) and several fatty acids (palmitic, palmitoyl, stearic, oleic, and linoleic) are included. Data collected from two locations ("Moraleja" and "La Seca") and their interaction with the different irrigation treatments are applied.

Turning our attention to the VIs, we observed that the NDVI in June correlates with control irrigation in "Moraleja". This index exhibited a close relationship with the GNDVI in June and September, as well as the caliber and certain fatty acids, such as oleic and stearic. Meanwhile, the NDVI in September was also associated with control irrigation, but here, the NDVI demonstrated a stronger correlation with the NDRE in June, as well as with the percentage of non-split nuts. Moreover, it maintained the relationship of June with the commercial size, oleic and stearic. In addition, NDRE in September correlated with calcium and magnesium content.

On another note, both the CWSI in June and September were related to both control and high irrigation in "La Seca". The CWSI in June was more associated with carbohydrate levels and iron content, whereas the CWSI in September was correlated with linolenic and linoleic. The high irrigation treatment applied in "Moraleja" did not seem to correlate with any vegetation index.

Finally, we performed Spearman's correlation analysis (Figure 7), analyzing individually the relationships between the various VIs and the yield and quality parameters of pistachio crops. Our investigation revealed that VIs bear a considerable correlation with both the yield and quality of the pistachio harvest. Specifically, the VIs derived from the first drone flight, which correspond to the development phases of the nut (F1–F2), generally exhibited strong positive correlations with most yield and quality parameters. The exception was the percentage of split or blank nuts, which did not show a significant relationship with these early stage VIs (except for the CWSI, which showed a weak correlation).

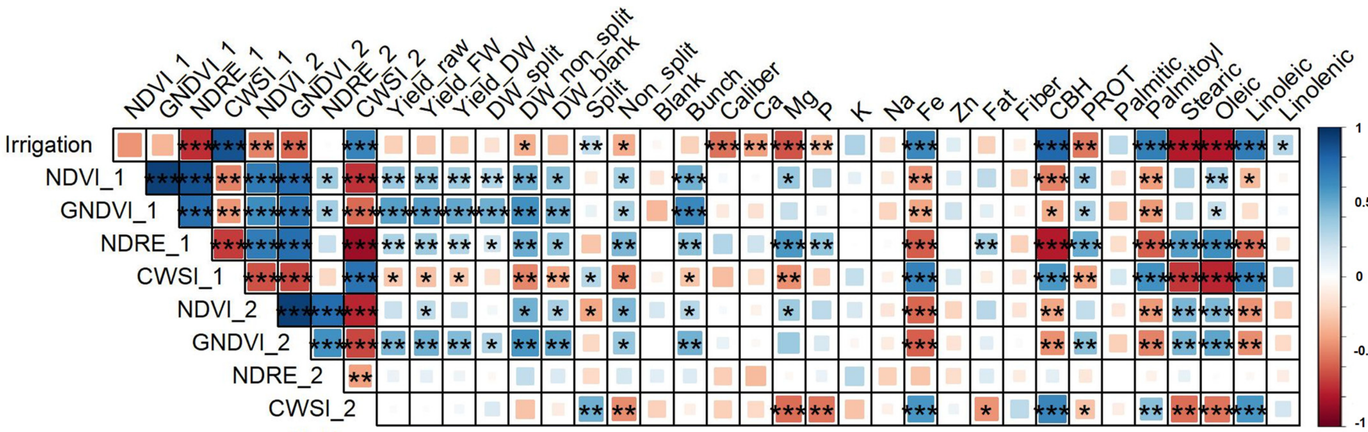

Figure 7. Spearman's correlation matrix of the irrigation conditions, agronomic, nut quality traits, and vegetation indices, considering 20 trees at two different locations in the "Castilla y León" region. Asterisks indicate significant correlations (*, $p < 0.05$, **; $p < 0.01$; ***, $p < 0.001$). Blue indicates positive correlations between two traits according to the color key and red negative correlations. Vegetation indices: CWSI (crop water stress index), NDRE (normalized difference red edge), NDVI (normalized difference vegetation index), and GNDVI (green normalized difference vegetation index) at two different time points (1, June; 2, September). Agronomic parameters: fresh and dry fruit weight per tree (Yield_FW and Yield_DW), number of bunches (Bunch) per tree, and average bunch weight (Yield_raw). The commercial caliber, percentage of open husk, closed husk, and empty nuts (Caliber, Split, Non_Split, and Blank) and the weight of open husk, closed husk, and empty nuts per tree (DW_split, DW_non_split and DW_blank). Regarding quality, fiber, fat (Fat), carbohydrates (CBH), protein (PROT), calcium (Ca), magnesium (Mg), phosphorus (P), potassium (K), sodium (Na), iron (Fe), zinc (Zn), and several fatty acids (palmitic, palmitoyl, stearic, oleic, and linoleic) are included.

Upon closer inspection, we found that non-thermal VIs demonstrated high positive correlations with yield, especially for NDVI and GNDVI. However, these indices correlated less strongly with nutritional parameters, in contrast to NDRE. CWSI displayed a similar trend to NDRE and, although the correlations with yield parameters were significant, they were weaker, and CWSI exhibited significant correlations with numerous quality and nutritional parameters, such as carbohydrate percentage, magnesium, and various fatty acids, such as stearic, oleic, and linoleic acid.

Turning to the VIs calculated from the images obtained during the second drone flight, we observed that NDRE did not show significant correlations with the pistachio traits. In general, only GNDVI showed a significantly strong correlation with agronomic and quality parameters. Nevertheless, NDVI still maintained significant correlations with certain quality parameters, such as Fe, CBH, and organic acids. CWSI did not correlate with agronomic parameters, but it still correlated with quality parameters better than non-thermal-based vegetation indices.

In addition to Spearman's correlation analysis, linear regression analyses were carried out (Figure 8) to show the strongest correlations between VIs and agronomic and quality parameters of pistachio. The highest correlations in June were found between NDRE and carbohydrates (r = 0.78), CWSI and oleic acid (r = 0.77), GNDVI and the number of bunches per tree (r = 0.62), and NDVI and carbohydrates (r = 0.52). On the other hand, the highest correlations in September were found between CWSI and carbohydrates (r = 0.62), NDVI and iron (r = 0.54), CWSI and iron (r = 0.54), and GNDVI and iron (r = 0.52).

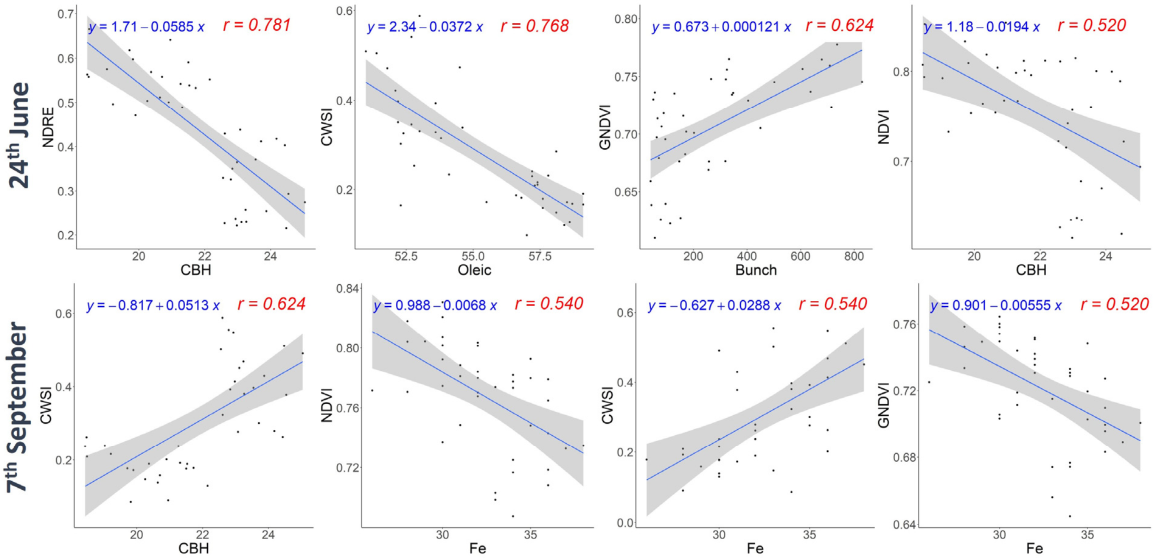

Figure 8. Linear regression analysis shows the highest correlations between vegetation indices (VIs) and agronomic and quality traits of pistachio. VIs: CWSI (crop water stress index), NDRE (normalized difference red edge), NDVI (normalized difference vegetation index), and GNDVI (green normalized difference vegetation index) at two different time points (June and September). Parameters: number of bunches (Bunch) per tree, carbohydrates (CBH), iron (Fe), and oleic fatty acid.

Finally, non-thermal-based VIs were correlated with the thermal-based VI, aiming to show the potential to estimate the CWSI values in pistachio crops (Figure 9). In this sense, the highest correlation with CWSI in June was found for NDRE and the highest correlation in September was found for NDVI. In general, the non-thermal-based VIs were more correlated with CWSI in September than in June.

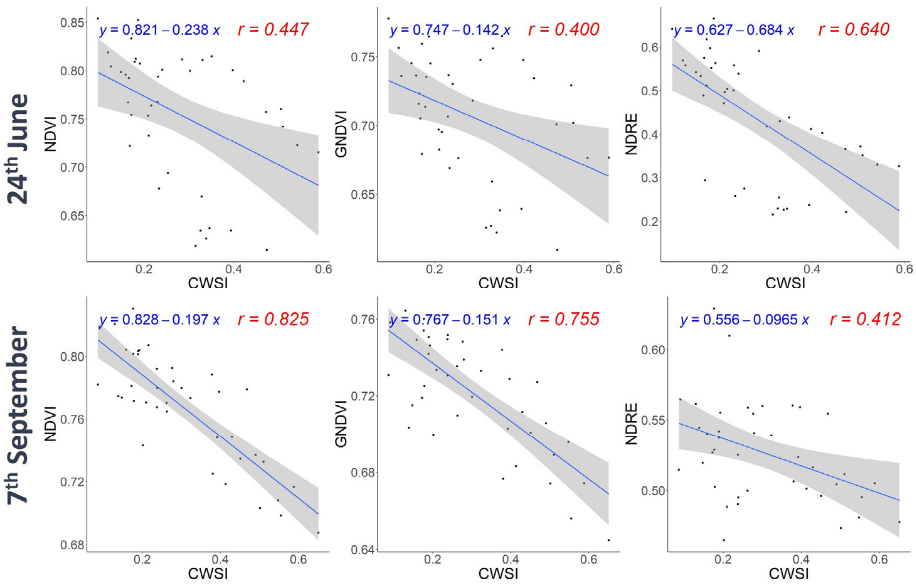

Figure 9. Linear regression analysis between thermal- and non-thermal-based vegetation indices (VIs). Thermal VI: CWSI (crop water stress index). Non-thermal VIs: NDRE (normalized difference red edge), NDVI (normalized difference vegetation index), and GNDVI (green normalized difference vegetation index) at two different time points (June and September).

4. Discussion

The domain of remote sensing is rapidly evolving and is facilitating profound crop management possibilities. Nonetheless, methods applicable to certain crops may not necessarily be suitable or effective for others, highlighting the need for designing and implementing experiments tailored to the specific crop under study. Given the recent surge in interest around pistachios, numerous researchers have started leveraging unmanned aerial vehicles (UAVs) for pistachio management, employing aerial imagery for comprehensive field oversight. In this way, Jacygrad et al. [34] used UAVs equipped with multispectral imaging to track the crown characteristics (height, size, shape, and NDVI) of pistachio trees throughout the growing season and compared UAV-derived metrics with the corresponding measurements taken in the field, highlighting the value of UAV imaging for comprehensive and real-time orchard management. Similar to our research, the study reported the highest NDVI value in June, when most trees registered between 0.9 and 1, nearing NDVI saturation. Vélez et al. [35] developed a novel, cost-effective, and rapid methodology based on segmenting RGB images and subsequently measuring the vegetation planar area along with ground shadows to estimate the canopy volume of pistachio trees by combining UAV-acquired imagery and machine learning techniques. They achieved very strong correlations with the actual canopy shape, demonstrating that is possible to effectively measure the amount of vegetation using UAV remote sensing. Unlike this study, the authors utilized spectral data solely for distinguishing soil, vegetation, and shadows, not for computing the vegetation index values of the pistachio canopies. Gonzalez-Dugo et al. [47] assessed the spatial variations in water status and irrigation requirements in a large Californian pistachio farm using high-resolution thermal imagery obtained from an unmanned aerial system, with the CWSI calculated for individual tree crowns. The authors demonstrated that CWSI, derived from this thermal imagery, is a beneficial tool for assessing the spatial variability of crop water status within a commercial pistachio orchard and can be utilized for precision irrigation. Similarly, we found a high correlation between CWSI in both dates and pistachio tree irrigation. However, this correlation was slightly lower in the CWSI of September. Moreover, the correlation existing in June between CWSI and agronomic parameters disappeared in September. This might be due to the fact that the flight that occurred in September was nearer to the harvest date. Consequently, we hypothesize that as the harvest date approaches, the relevance of CWSI in pistachio decreases, while other VIs that are not reliant on thermal information, except for NDRE, maintain their effectiveness. Related to CWSI, our study highlights the significant influence of the sun's position, emphasizing its role in illuminating specific areas of tree crowns, namely warming them and, consequently, increasing the CWSI values. This phenomenon underscores the vital importance of taking the sun's position into account when interpreting the CWSI in agricultural research due to its substantial impact on the spatial distribution of the index. The sun's position during the day is a key factor that shapes how light interacts with tree crowns and vegetation, resulting in less illuminated leaves and shadows on the ground and within the canopy [35,48], which can potentially affect the spectral information gathered from remote sensing techniques. In fact, Park et al. [49] suggest that there is a time window for accurate plant water stress mapping via CWSI–UAV thermography. Additional studies have also emphasized the role of temperature distribution in the CWSI. Camino et al. [50] highlighted that shadows cast within the crop canopy have a notable influence on the CWSI, and both the morphological characteristics of the canopy and the angle of the sun during the drone flight were identified as significant factors that alter the temperature distribution pattern within the canopy. Moreover, it is not solely the sun's position that affects the CWSI but also the presence of clouds. Cloud cover can lead to considerable variations in the amount of solar radiation reaching the crop canopy [51]. This aspect was duly considered in the design of the current study, which was conducted under clear skies.

In this study, apparently, larger canopy sizes were associated with higher values of these VIs, suggesting that more extensive canopies in Pistachio are generally healthier and more vigorous. However, the differences in NDVI values in the maps were less perceptible compared to NDRE and GNDVI. Although some similarities in the patterns were exhibited by NDVI, NDRE, and GNDVI, some notable differences were also identified. For instance, NDVI values were consistently high and close to 1 across all canopy crowns, suggesting a strong and uniform presence of healthy vegetation but also the saturation effect already observed by other authors [52], which commonly shows up at high biomass levels [53] and can limit the ability of NDVI to discriminate subtle differences in vegetation among larger canopies.

Furthermore, all VIs in June exhibited a strong correlation with yield parameters and a pronounced correlation with the quality parameters that was more or less observed in September, except for NDRE, confirming other authors' findings for other crops, which have also indicated that the VIs can be used to predict yield and quality parameters [54]. On the other hand, regarding nutritional values, a good relationship was observed with NDRE in June, although this association was not observed in September. Nevertheless, CWSI showed a strong correlation with thee nutritional values at both time points, especially CBH and fatty acids, which could help to identify the ideal time for harvesting [55]. However, these correlations were lower in September. In fact, as the season advanced, the connections between all VIs and pistachio yield parameters vanished, except for GNDVI. This observation suggests that the management in June is more critical than in September and, as the growth season progresses, the relationships between VIs and yield may become less pronounced or more complex. The contrasting outcomes observed in the CWSI compared to other VIs throughout the drone flights highlight the divergent behaviors between thermal-based and non-thermal-based indices. This fact exposes the importance of the different bands of the electromagnetic spectrum and emphasizes the critical importance of carefully selecting appropriate indices based on specific research objectives and data collection timing. Indices that provide valuable information at one stage of crop development may not be as informative at another stage and vice versa. This consideration is crucial for researchers utilizing remote sensing technologies in precision agriculture. For instance, based on our study findings, the CWSI appears to be particularly valuable for irrigation assessment and for the quality evaluation of pistachio crops, likely due to its relation to water stress that affects the plants.

However, non-thermal VIs are more relevant for predicting yield outcomes, probably because they are more associated with the current status of the crop. GNDVI deserves special recognition for preserving connections relatively consistently over the year. This dynamic nature, where different indices hold relevance at different stages of crop growth, emphasizes the complexity of applying remote sensing to precision agriculture. Nevertheless, thermal sensors are not always readily available due to their higher cost compared to visible light or multispectral-based sensors. Therefore, the correlations observed in this study pertaining to pistachio VIs can be interesting. In June, the index most correlated with CWSI was NDRE, while in September, NDVI showed the highest correlation, although GNDVI also demonstrated a significant correlation. These relationships were echoed in the results, as NDRE in June showed similar correlations to CWSI with respect to pistachio parameters, while NDVI and GNDVI showed comparable values in September.

On a more detailed level, the examination of VIs reveals similarities in several patterns exhibited by NDVI, NDRE, and GNDVI, which aligns with findings from other studies. These studies observed that NDVI correlated well with biomass and other agronomic parameters in crops, as did NDRE [56]. However, our research indicated that NDVI values were consistently higher and near "1" across all canopy crowns, demonstrating less variability between different tree crowns and within the same crown compared to NDRE and GNDVI. This can be attributed to the well-known NDVI disadvantage of reduced sensitivity when crop biomass exceeds a certain threshold, resulting in saturation at high biomass values [52]. Moreover, in certain circumstances, the NDVI saturation issue may be exacerbated by eliminating soil background contamination from images and concentrating solely on the canopy [57], which is often the case when working with high-resolution UAV imagery, allowing for precise tree crown segmentation, as in this study. Jorge et al. [26] also identified differences between NDVI, GNDVI, and NDRE, showing a strong correlation between NDVI and GNDVI values but not NDRE. Similar to these results, we did not find correlations for NDRE in September. These authors suggested that utilizing NDRE instead of the conventional NDVI could be particularly beneficial in detecting growth inhomogeneities in crops. These differences could be because NDRE is similar in the calculation to NDVI but incorporates a red-edge band instead of red, making it more resistant to the saturation problem inherent to NDVI and more sensitive to variations in chlorophyll content. In fact, Simic Milas et al. [58] emphasized the red-edge band's significance as a crucial spectral region for both leaf area index (LAI) and chlorophyll content, indicating that NDRE is a sensitive vegetation index for mapping both chlorophyll and LAI. Dong et al. [59] conducted a study in which they found that VIs based on the red-edge (RE) spectral band exhibit heightened sensitivity to chlorophyll content, facilitating the creation of empirical models for estimating leaf area index across a diverse range of crops. Additionally, Li et al. [60] employed four red edge-based indices (CCCI, MTCI, NDRE, and CIred edge), finding that these indices performed better across bandwidths for estimating plant nitrogen uptake compared to the NDVI for maize nitrogen status. Rehman et al. [61] discovered that using the same platform and sensor, NDRE provided measurements sensitive enough to inform nitrogen fertilizer management in their system, while NDVI was more limited in assessing nitrogen status and predicting grain yield in rice cropping systems. Conversely, Lima-Cueto et al. [62] asserted that the effectiveness of VIs that rely on the RE band is limited when it comes to accurately quantifying vegetation ground cover, as the utilization of the RE band in VIs leads to a decreased sensitivity in the quantification of vegetation ground cover. They attributed this to the unsatisfactory performance of the RE band when employed individually, observing that the RE band negatively impacts the accuracy of the VIs that incorporate it, such as the NDRE index.

Nevertheless, in our study, we identified that not only NDRE but also GNDVI showed different patterns than NDVI. Eitel et al. [63] observed similar outcomes, suggesting that the saturation of NDVI at low Chlab levels is due to its use of red reflectance, as opposed to GNDVI green reflectance and NDRE red-edge reflectance, which were less impacted by Chlab absorption. Therefore, intense Chlab absorption in the red band leads to saturation of red reflectance at lower Chlab concentrations, rendering NDVI less sensitive to Chlab fluctuations in moderate to high concentrations. This highlights a potential NDVI intrinsic limitation in detecting vegetation variations in pistachio tree orchards.

Finally, it is worth noting that Figure 5 revealed clusters that distinguish between different treatments and geographical locations. The location of the plots demonstrated a pronounced influence on the differences observed between the variables. This suggests that environmental factors related to location, such as local climate, soil composition, or micro-environmental conditions, might have a more prominent role in shaping these characteristics in pistachio trees. This insight could be instrumental in future research and management strategies, underscoring the importance of considering the specific context of each location when managing pistachio cultivation. Contrastingly, at first sight, the PCA revealed that the irrigation treatments we applied did not significantly differentiate the data points representing individual pistachio trees in our study. However, in the biplot of Figure 6, a difference is observed in the treatment due to the irrigation applied in the "Moraleja" plot, but not in the "La Seca" plot, indicating that in the second orchard, the irrigation treatment did not have a substantial impact on the characteristics we measured. This difference could be attributed to various factors, such as variations in water supply between the plots or differences in tree age [64]. This finding suggests that increasing water supply beyond a certain threshold may not result in changes in VIs. Therefore, it emphasizes the importance of optimizing water resource management practices. In fact, irrigation doses had a negative influence on the quality and nutritional parameters of the nuts, which can be observed in aspects such as non-split nuts, caliber, calcium, magnesium, potassium, and protein, as well as various fatty acids, such as stearic and oleic. On the other hand, a positive influence was observed in the case of the percentage of split nuts, iron and carbohydrate content, and certain fatty acids, such as palmitoyl, linoleic, and linolenic (Figure 7). However, analyzing the interrelationship between factors unrelated to the VIs generated by remote sensing falls outside the scope of the current paper.

The significance of this research is underscored by the fact that it represents the first established correlation between vegetation indices derived from UAV multispectral and thermal imagery and the crucial agronomic and quality parameters for pistachio cultivation. Furthermore, we found that this relationship exhibits variations throughout the year. As the quality of pistachios is notably impacted by harvest timing [2], remote sensing techniques that account for variations in VIs could aid in determining the optimal harvest time. Hence, further investigation is necessary to fully comprehend the intricate association with quality characteristics, as it appears to be more complex. Additionally, future research endeavors could greatly benefit from exploring the integration of multiple indices in time series analysis. This approach would facilitate a more comprehensive understanding of pistachio trees' yield and stress and the development of nut quality in agricultural settings.

5. Conclusions

Our research in precision agriculture utilizing UAVs with multispectral and thermal imaging during two flights (carried out in June and September, respectively) provided valuable insights into the relationship between various vegetation indices (NDVI, GNDVI, NDRE, and CWSI) and pistachio yield and quality. Notwithstanding NDVI's saturation issues, all VIs demonstrated significant correlations with yield and quality parameters, particularly during the nut development stages (F1–F2). In June, the highest correlations included NDRE and carbohydrates (r = 0.78) and CWSI and oleic acid (r = 0.77), and non-thermal VIs, especially NDVI and GNDVI, correlated well with yield but less well with nutritional aspects. In this sense, NDRE was more effective. In contrast, September's top correlations were CWSI and carbohydrates (r = 0.62) and NDVI and iron (r = 0.54), and flight imagery revealed that only GNDVI displayed a strong correlation with both agronomic and quality parameters. Notably, CWSI showed considerable correlations in both flights with quality parameters like carbohydrate percentage, magnesium, iron, and several fatty acids (palmitoyl, stearic, oleic, and linoleic), surpassing non-thermal-based vegetation indices. The different results observed in the CWSI compared to other vegetation indices highlight the usefulness of all bands of the electromagnetic spectrum caused by the divergent behaviors between temperature-based and non-temperature-based indices. Our research highlights the potential for the CWSI to be a key tool for assessing pistachio quality. The impact of environmental factors, like the sun's location, is also significantly emphasized in the study, illustrating the importance of taking these elements into account when interpreting the CWSI.

Remote sensing techniques not only revealed a significant correlation with yield parameters but also with nutritional values, specifically fatty acids. This crucial information could potentially fine-tune the timing of harvest, a critical determinant of pistachio quality. These correlations changed depending on the time of year at which the drone flight was conducted (which is linked to the phenological state of the pistachio tree) and on the vegetation index used, thus underlining the importance of devising a well-planned strategy that incorporates several aerial surveys throughout the year and investigates multiple indices for effective pistachio crop management. The complexity of these relationships requires further research, particularly integrating multiple indices in a time-series analysis to gain a more extensive understanding of yield and stress evolution in pistachio trees.

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