Assessment of the spatiotemporal variability of trees status in an olive orchard through multispectral drone images

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Abstract

Precision Agriculture (PA) is a management strategy based on Information and Communication Technologies (ICT) used to assist management decisions with the aim to increase productivity, to reduce labor time and inputs needed, to improve benefits and to protect the environment. Techniques related to PA were initially used to monitor status of annual crops and they were recently adopted on fruit trees. Nevertheless, PA is still in its initiation phase in Morocco. Given the importance of olive in the national and international levels, applying this concept in the intensive and hyper-intensive production systems would be a reliable and cost-effective approach for the assessment of orchards health and nutritional status and then make reliable decisions. With the aim to assess the potential of multi-spectral images to inform on temporal and spatial variability characterizing an olive orchard, this study was carried out in an orchard of 22 ha, in Meknes region, Morocco, planted principally with “Picholine marocaine” variety. Four Unmanned Aerial Vehicle (UAV) flights, from June to November 2020, were performed and three vegetation indices (VIs) were computed: NDVI, GNDVI and NDRE. Spatial variability was assessed using variogram, a geostatistical tool, and temporal variability was evaluated using Spearman rank correlation and relative difference methods. The three VIs showed a weak temporal and spatial stability of trees which indicate an overall unstable canopy condition related to tree physiological behavior and environmental conditions (temperature and rainfall). Additionally, the observation of a potential stress was recorded firstly by NDRE, followed by NDVI and GNDVI. Results show promising perspectives of using remote sensing techniques to assess olive trees status and therefore support farmers in orchards management. Such challenge requires more in-depth work to develop in house models correlating VIs to agronomical parameters.

Key words: Precision Agriculture, Vegetation indices, NDVI, GNDVI, NDRE, Olive, Morocco

Evaluation de la variabilité spatiotemporelle dans un verger d'olivier à travers des images multispectrales prises par un drone

Résumé

L'agriculture de précision (AP) est un concept, basé sur les technologies de l'information et de communication (TIC), qui conjugue à la fois des objectifs agronomiques (amélioration du rendement et de la qualité des produits), économiques (minimisation des coûts de production) et environnementaux (meilleure utilisation des intrants). Les techniques relevant de l'AP ont été utilisées au premier abord sur les grandes cultures, mais ont été vite adoptées en arboriculture fruitière. Au Maroc, le recours à ce nouveau concept reste limité et encore moins au niveau de l'olivier. Etant donné l'importance de cette culture, tant à l'échelle nationale qu'internationale, le recours à l'AP comme moyen d'aide à la décision pour une gestion raisonnée et efficiente des vergers d'olivier; conduits en intensif et semi intensif; présente une approche prometteuse pour l'oléiculture marocaine. Le présent travail consiste à étudier le potentiel des images multispectrales pour déceler la variabilité spatiotemporelle pouvant caractériser un verger d'olivier. L'étude a été menée dans une oliveraie de 22 ha dans la région de Meknès, plantée par la variété « Picholine marocaine ». A partir des images multispectrales, prises sur 4 survols de drone (de juin à novembre), trois indices de végétation (IV) : NDVI, GNDVI et NDRE ont été dérivés. La variabilité spatiale a été évaluée à l'aide du variogramme, un outil géostatistique, alors que la variabilité temporelle a été évaluée à l'aide des méthodes de corrélation de Spearman Rank et des différences relatives. Les trois IVs ont montré une faible stabilité temporelle et spatiale au niveau du verger; une instabilité liée au comportement physiologique des arbres (la canopée particulièrement) et aux conditions environnementales (température et précipitations). En plus, la présence d'un stress potentiel a été enregistrée d'abord par le NDRE, puis par le NDVI et le GNDVI. Les résultats montrent des perspectives prometteuses d'utilisation des images multispectrales dans le cas des oliviers et invitent à un travail plus approfondi pour développer des modèles corrélant les IVs aux paramètres agronomiques qu'il serait utile de suivre.

Mots clés : Agriculture de Précision, Indices de végétation, NDVI, GNDVI, NDRE, olivier, Maroc.

تقييم التباين الزمكاني لأشجار الزيتون عن طريق الصور المتعددة الأطياف باستعمال طائرة مسيرة عن بعد

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ملخص

الزراعة الدقيقة هو مفهوم يعتمد على تقنيات المعلومات والاتصالات؛ يجمع بين أهداف زراعية (الرفع من المردودية مع تحسين الجودة)؛ أهداف اقتصادية (تقليل تكاليف الانتاج) و أهداف بيئية (استخدام أفضل للمدخلات).

تم استخدام التقنيات المتعلقة بالزراعة الدقيقة خصوصا في الزراعات الحقلية Grandes Cultures؛ ولكن سرعان ما تم تبينها في زراعة الأشجار المثمرة. يضل استعمال هذه التقنيات محدودا في المغرب؛ لاسيما على مستوى زراعة الزيتون. لكن نظرا لأهمية هذه الشجرة على الصعيدين الوطني و الدولي؛ يتبين أن التطرق و اللجوء الى الزراعة الدقيقة كوسيلة لدعم القرار و تسيير ضيعات الزيتون؛ تدبير محكم و مقاربة واعدة للنهوض بهذه الزراعة في المجالين المكثف و الشبه المكثف.

تهدف الدراسة الحالية الى التحقق من فعالية الصور المتعددة الأطياف في الكشف عن التباين الذي قد تتحلى به الضيعة نفسها بين مختلف أرجائها و تهدف كذلك الى الكشف عن التباين الذي تعرفه الضيعة من فترة زمنية الى أخرى. أجريت الدراسة الحالية في ضيعة زيتون مساحتها 22 ha بنواحي مدينة مكناس؛ تتسم بزراعة صنف ''Picholine Marocaine'' و تم استنباط ثلاث مؤشرات للغطاء النباتي(IVS) : GNDVI, NDVI و NDRE من خلال الصور الملتقطة إبان 4 تحليقات لطائرة بدون طيار من يونيو إلى نونبر. أبانت النتائج عن التباين المكاني الذي تتميز به الضيعة عن طريق أداة جيوإحصائية **المتغير Variogramme** وكذا عن التباين الزماني باستخدام Spearman Rank و الفروق النسبية. يرجع تباين مؤشرات الغطاء النباتي و عدم استقرارها الى السلوك الفيزيولوجي للأشجار (الجزء المخضر خصوصا) و الظروف البيئية (حرارة و تساقطات). ولقد أظهرت النتائج وجود إجهاد Stress بالضيعة؛ أبان عنه في بادئ الأمر مؤشر NDRE؛ يليه مؤشر NDVI ثم GNDVI. أخيرا؛ تنم هذه النتائج عن الآفاق المتعددة للصور المتعددة اللأطياف في تسيير ضيعات الزيتون وتدعو الى العمل للربط بين مؤشرات الغطاء النباتي وبعض المؤشرات الزراعية التي يجدر اتباعها.

الكلمات المفتاحية: الزراعة الدقيقة, مؤشرات الغطاء النباتي, NDVI , GNDVI, NDRE, الزيتون ، المغرب.

Introduction

Precision Agriculture (PA) is a management strategy based on Information and Communication Technologies (ICT) that gathers, processes and analyzes temporal and spatial variability and combines it with agronomic information to support management decisions in order to improve benefits (Stafford, 2000). It enables to know precisely what parameters are needed for healthy crop and where and when they will be supplied. To achieve this, the acquisition and processing of a large amount of data related to crop health remain the main steps (Shafi et al., 2019). One of PA technologies that has been widely used to monitor crops' health in the last two decades is remote sensing (Shafi et al., 2019). For this purpose, special cameras are used to capture georeferenced images of a specific area using several platforms. These latter can be airborne-based, satellite-based and Unmanned Aerial Vehicle (UAV)-based (Rudd et al., 2017). Each platform has its own coverage range, which is determined by three factors: (i) Ground Sampling Distance (GSD) which is computed in terms of spatial resolution, (ii) data collection rate or frequency and (iii) average distance between the object and sensor (Rudd et al., 2017). For some tasks, ground-based platforms are needed for acquiring low altitude imagery with frequent coverage for dynamic phenomena. They offer portability, flexibility and controllability (Huang et al., 2016).

Images obtained by satellite platforms cover large area but they are expensive in the case of high spatial resolution images, strictly fixed time schedule (data cannot be collected at critical timings) and highly sensitive to weather conditions (Rudd et al., 2017). Comparatively, the revisit time with airborne platforms can be changed in any time. However, they are still expensive and their coverage area is much smaller than satellite-based ones and relatively greater than the UAV platforms. Finally, UAV platforms represent an alternative to satellite and airborne platforms (Shafi et al., 2019) and are considered as the most suitable platforms for scanning the terrain, especially for PA, due to their high spatial resolution.

Remote sensing-based indices provide information on the crops requirements in terms of nutrients and water (Jovanovic et al., 2020), assess the vegetation health status and the crop growth and permit yield investigation through various phenological stages (Sakamoto et al., 2013). Vegetation indices (VIs) have been developed by combining the remote sensing data and the reflectance of monitored surfaces within different wavebands, mainly visible (green and red), Near Infrared (NIR) and Red-edge. These indices are considering the information related to the absorbance/reflectance of plants pigments (such as chlorophyll, carotenoids, anthocyanins…). In fact, Chlorophyll absorbs strongly in red (650–700 nm) and blue (400–500 nm) spectral regions with a maximum reflectance in green wavelengths (560 nm) (Croft et al., 2017). The red-edge spectral region covers the wavelength range between red band absorption maxima to the NIR shoulder (690– 750 nm) and has been identified as being particularly sensitive to changes in chlorophyll content (Curran et al., 1990, Xie et al., 2018).

Many studies reported that VIs such as, NDVI (Normalized Difference Vegetation Index; Rouse et al., 1974), GNDVI (Green Normalized Difference Vegetation Index; Gitelson et al., 1996) and NDRE (Normalized difference red edge index; Horler et al., 1983) are highly correlated to many features. NDVI, the most common spectral indice used in the crop studies, is an important data source for many applications, such as the estimation of vegetation photosynthetic activity (Myneni et al., 2002), detection of vegetation phenology (Zhang et al., 2007, Cao et al., 2018,) and classification of land cover (Friedl et al., 2002). GNDVI coupled to NDVI were correlated to Chlorophyll and Nitrogen content (Bell et al., 2004) whereas the NDRE was reported as an efficient index for early stress detection in comparison with NDVI and GNDVI (Eitel et al. 2011). Moreover, VIs provide consistent spatial and temporal information on global vegetation conditions (Solano et al., 2010). They permit, as has been demonstrated in many studies, the distinction of healthy or unhealthy portions of a cultivated field without any ground radiometric measures (Candiago et al., 2015, Blanco et al., 2020).

In this sense, the present study aims to explore the potential of multispectral images for monitoring the physical features of an olive orchard without referring to agronomical parameters. Although PA has been mostly used for row crops such as corn and wheat (Lee et al., 2010), the technology has been adopted recently for other crops including fruit trees such as olive species (Jorge et al., 2019, Caruso et al., 2019). In Morocco, with about 1.2 Mha, olive represents more than 55% of Morocco's current fruit tree orchards and has a prominent socioeconomic role. The three major production systems conducted in Morocco are the traditional, intensive and hyper-intensive ones. The adoption of PA technologies would be a fast, reliable and cost effective approach in olive orchards, especially in the intensive and hyper-intensive production systems, for precision farming applications and monitoring.

This study focuses on three VIs (NDVI, GNDVI and NDRE) with the following objectives: (i) assess their potential to provide information on the current status of the orchard, (ii) assess the temporal and spatial variability characterizing the orchard over one season and (iii) produce a variability map to reveal the stable and unstable parts/trees of the studied orchard. Finally, the perspectives and implications of using multispectral images and VIs as a monitoring tool in olive orchards are discussed.

Material and Methods

Study area

The studied orchard, similar to the most Moroccan intensive olive groves, is located at Ras Jerry (Meknes province, Morocco, 33°45'37.4"N and 5°41'28.9"W; Fig. 1). It is a commercial irrigated orchard in full production, with an area of 22 ha and a plant spacing pattern of 6 × 5 m (average density: 333 trees/ha). The region is characterized by a Mediterranean continental climate with notable thermal and rainfall oscillations (Fig. 2). Its altitude varies from almost 632 m to 649 m above the sea level. The orchard is cultivated by two inter-compatible varieties: 'Picholine marocaine' and 'Picholine de Languedoc', with a ratio of 9:1, to guarantee a good fruit set.

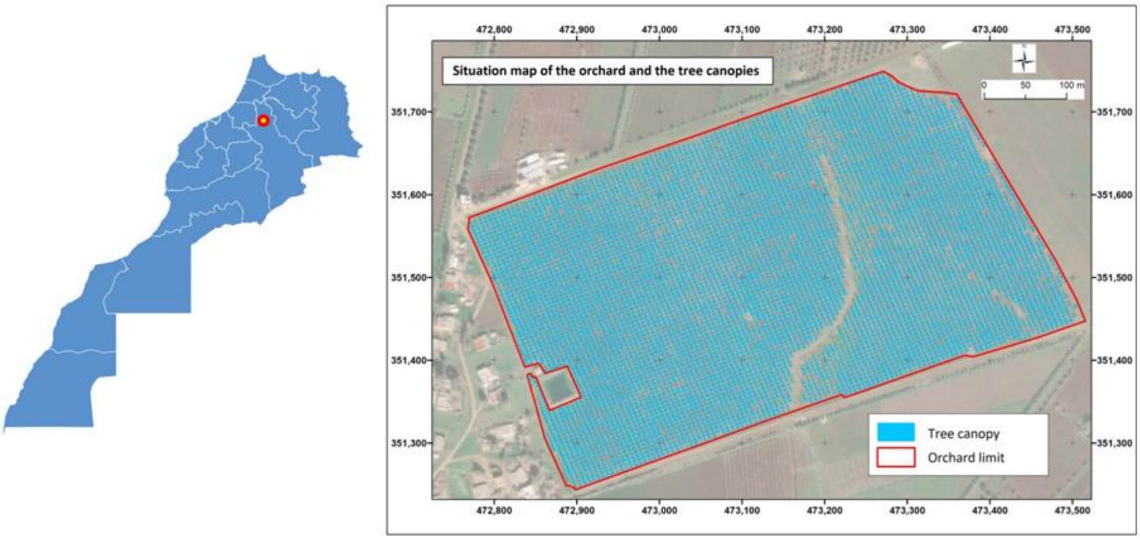


Figure 1: Location of the olive farm: the aerial view with trees vectorization.

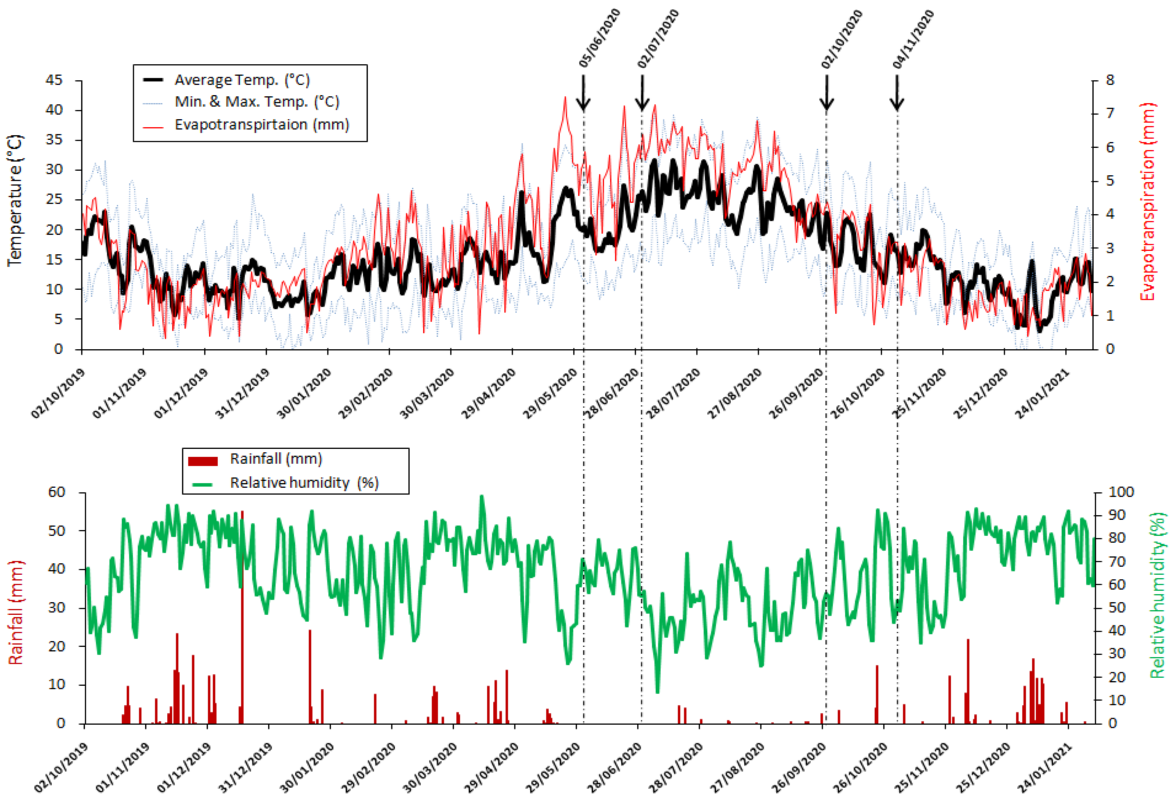


Figure 2: Daily Variation of temperature, rainfall, relative humidity and evapotranspiration during two successive years (2019 and 2020).

Imagery data acquisition

Aerial imaging was conducted using a fixed-wing A300 UAV (SOWIT, France). Images were taken with a multispectral Parrot Sequoia + camera (SenseFly SA, Switzerland) installed on the UAV. The sensing device is capable of capturing information in four different spectral bands within the visible and the infrared spectrum: Green (550nm ± 40nm), Red (660nm ± 40nm), Red edge (735nm ± 10nm) and Near Infrared (790nm ± 40nm). To cover the entire study area, more than 1000 georeferenced images were captured for each of the four spectral bands to elaborate a mosaic of orthorectified images using the Agisoft Metashape photogrammetry software (Agisoft LLC, Russia). Four flights were made during 2020, corresponding to different phenological stages of olive tree (BBCH scales, Sanz-Cortes et al., 2002): 5th of June (around 30% of fruit size ; S73), 2nd of July (pit hardening ; S75), 2nd of October (S81, beginning of fruit coloring) and 4th of November (S85, increasing specific fruit coloring). Concerning radiometry, it is important to note that the four flights occurred under the same atmospheric conditions (clear sky conditions), at the same time, at the same flight altitude; 60m above ground level; with an airspeed of 15m/s and a ground spatial resolution of 12 cm. Furthermore, the images used in the study were provided as raster layers with derived digital numbers. The digital numbers are of float type with a 32-bit depth.

Image processing methods

The georeferenced orthorectified multispectral images (Geotiff) of the four time series were used to assess the orchard variability through the spectral signature of vegetation. Hence, three vegetation indices (VI) were derived: NDVI, GNDVI and NDRE. The raster layers of the three VI were computed using the Raster calculator tool implemented in ArcGIS software (ESRI, Redlands, Ca, USA) using the following equations:

NDVI = (NIR - Red) / (NIR + Red)
GNDVI = (NIR - Green) / (NIR + Green)
NDRE = (NIR – RedEdge) / (NIR + RedEdge)

Additionally, the ArcGIS software was used to vectorize canopies by applying the natural breaks of Jenks classification to the first flight's NDVI pixel values, using one threshold and three iterations. Two clusters have been differentiated: tree pixels and non-tree pixels. Jenks classification was applied to NDVI raster layer for its correlation to chlorophyll content, which helps to set the difference between the canopy and the surrounding areas, including artefacts due to small weeds and other spontaneous vegetation. For the four flights, the canopy vector layer was used to extract the average values corresponding to the three VIs, using zonal statistics tool implemented in ArcGIS software.

Data analysis

To assess the spatial and temporal variability in the studied orchard, the average values corresponding to the three VIs (NDVI, GNDVI and NDRE) were computed for each olive tree through the four flights. Hence, the spatial heterogeneity was assessed using geostatistical method of variogram (Curran, 1988; Oliver et al., 2005). ArcGIS was used to compute and model the twelve variograms permitting to compare between all parameters. The structured fraction (spatial structure) of the datasets was determined using the complement to 100 of the Nugget to Sill Ratio percent. The temporal stability was determined globally using the non-parametric Kruskal-Wallis test (Rodrigez-Moreno and Bullock, 2014) and Spearman rank correlation and locally, for each tree, using the relative differences methods (Vachaud et al., 1985, Douaik et al., 2006).

Results

Spatial variability

Table 1 highlights the parameters derived from twelve variograms, where very high Nugget to Sill Ratio (NSR) values are reported. It shows the spatial structure that characterizes trees in the studied orchard for each flight. The NDVI spatial structure values vary from 37.2 to 4% with a moderate spatial structure recorded in the first flight. For GNDVI, the spatial structure varies from 29.9 to 4.4% with a weak spatial structure recorded in the third flight. Finally, for the NDRE, the spatial structure varies from 12.9 to 8.1%. Its decrease is noted in the fourth flight. Therefore, all the indices are characterized by a weak spatial structure, with structured fractions ranging from 2.9% to 37.2%. This indicates the weak structure of the VIs for the four flights, which reports no apparent spatial pattern of the orchard trees vigor throughout the study period. Figure 3 represents the variograms for the first and the third flights corresponding respectively to NDVI and GNDVI representing the most and the least structured indices.

Table 1: Variogram models and parameters for the VIs: NDVI, GNDVI and NDRE

Index	Flight	Model*	Range	Nugget	Partial Sill	Total Sill	NSR* (%)	Spatial Structure (%)
NDVI	1	E	87	0,00108	0,00064	0,00172	62,8	37,2
	2	S	23	0,00408	0,00025	0,00433	94,1	5,9
	3	E	523	0,00274	0,00011	0,00285	96,0	4,0
	4	E	135	0,00256	0,00015	0,00271	94,6	5,4
GNDVI	1	E	163	0,00047	0,00020	0,00067	70,1	29,9
	2	S	26	0,00083	0,00005	0,00088	94,5	5,5
	3	E	732	0,00126	0,00004	0,00130	97,1	2,9
	4	S	106	0,00139	0,00006	0,00145	95,6	4,4
NDRE	1	S	535	0,00020	0,00003	0,00023	87,1	12,9
	2	E	13	0,00022	0,00004	0,00026	84,2	15,8
	3	S	8	0,00021	0,00004	0,00025	83,0	17,0
	4	E	315	0,00027	0,00002	0,00029	91,9	8,1

* *E: Exponential, S: Spherical, NSR: Nugget to Sill Ratio*

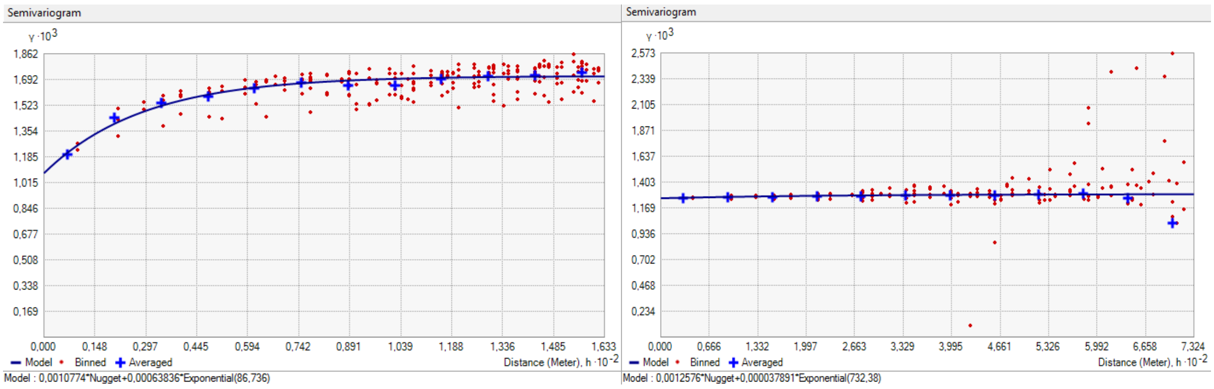


Figure 3: Experimental and fitted variograms for NDVI (left) and GNDVI (right) corresponding to the first and the third flights.

Temporal variability

The nonparametric Kruskal-Wallis test showed significant differences between the four flights for the three VIs. Moreover, it showed significant differences between all pairs of flights, indicating lack of temporal pattern. In addition, the Spearman rank correlation coefficients were all below 0.06, confirming the Kruskal-Wallis test results. The local temporal stability, as derived using the relative differences method, is shown in Fig. 4 (temporal stability maps). Due to the abrupt decline of NDVI during the second flight period, this index recorded the least temporal stability with 6.6% of stable trees (455 trees from a total of 6907). Moreover, the most stable index was GNDVI with 7.8% of stable trees (538 trees) followed by NDRE recording a temporal stability of 7.2% (494 trees). These rates show a weak temporal stability for the three indices, which indicated an overall unstable canopy conditions. Otherwise, taking into account the spatial relationship in the indices evolution pattern, stable trees are not the same considering the three VIs, except for 96 trees (21% of orchard's trees); most of them are located towards the West side of the orchard, with an important density at the Southwest part.

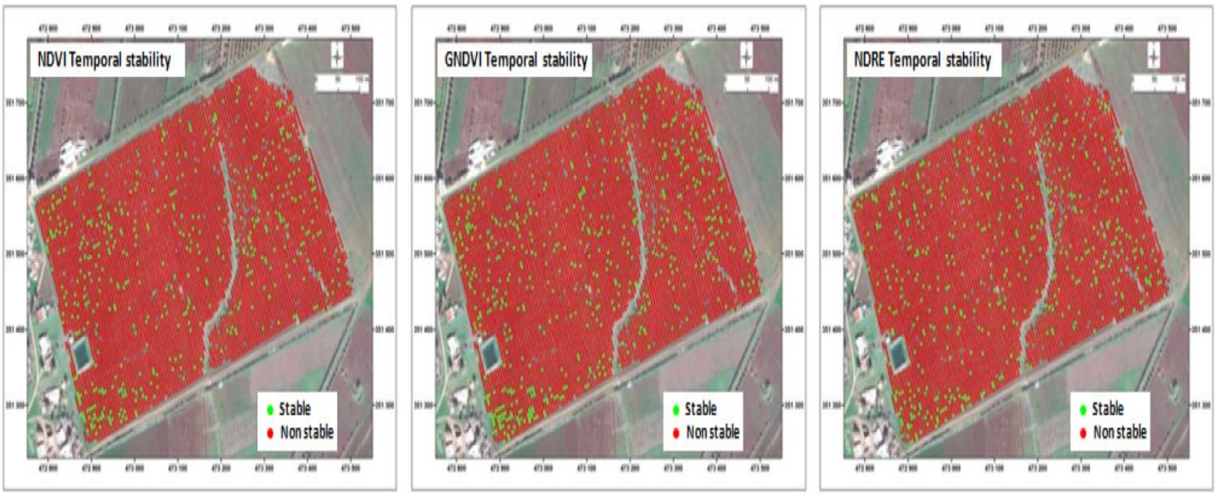
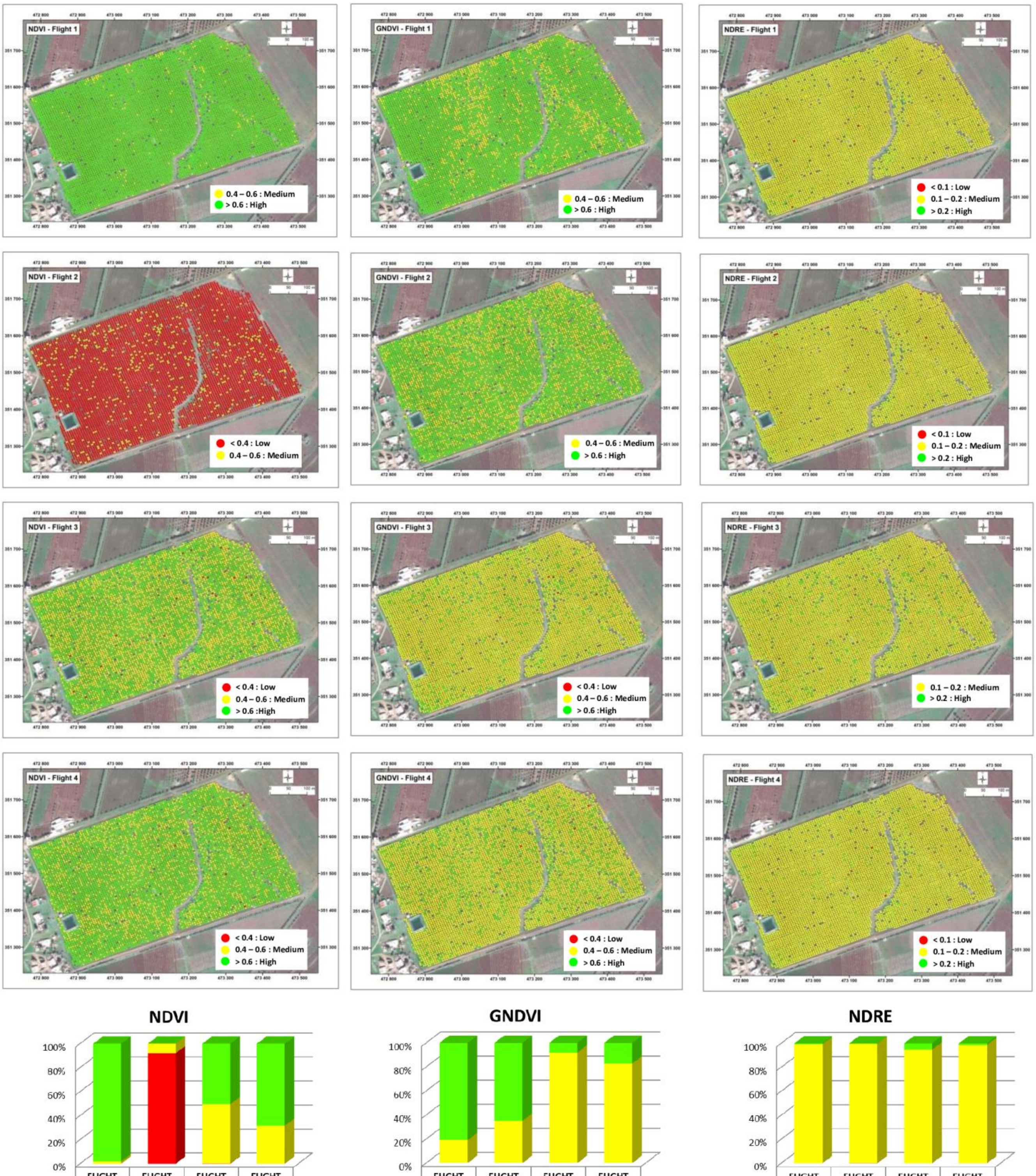


Figure 4: Temporal stability maps of the NDVI (left), GNDVI (center) and NDRE (right) indices.

Overall, Fig. 5 shows the evolution of the orchard vegetation indices through the study period. The NDVI evolution shows an abrupt decrease at the second flight, revealing a severe stress that affected 92% of the trees, while the remaining trees recorded medium values. The NDVI then showed a positive evolution through the third and fourth flights, with a rough decline of low values, and medium values reaching 49% and 31% respectively in favor of high values reaching 51% and 68% respectively. The stress of the second flight period affected GNDVI values at later stages, where high values rate declined from 81% (flight 1) to 65% (flight 2) before dropping to 8% (flight 3) in favor of medium values then slightly increasing to 17% at the fourth flight. The NDRE index followed a similar pattern to GNDVI in response to the flight 2 period stress, with the dominance of medium values (+90%) through the four flights period.



NDVI

	FLIGHT 1	FLIGHT 2	FLIGHT 3	FLIGHT 4
HIGH	6747	0	3479	4719
MEDIUM	131	548	3409	2184
LOW	0	6360	19	5

GNDVI

	FLIGHT 1	FLIGHT 2	FLIGHT 3	FLIGHT 4
HIGH	5588	4479	557	1185
MEDIUM	1320	2429	6347	5720
LOW	0	0	3	3

NDRE

	FLIGHT 1	FLIGHT 2	FLIGHT 3	FLIGHT 4
HIGH	41	16	360	87
MEDIUM	6864	6884	6548	6819
LOW	3	8	0	2

Figure 5: Evolution of the vegetation indices through the four flights.

Discussion

For decision-making in managing olive farms, it is of great interest to know the spatial and temporal variability within an orchard. In this study, we used multispectral images (Green, Red, Red-Edge and NIR) of high spatial resolution (12 cm/pixel) to compare between three widely used VIs (NDVI, GNDVI and NDRE) and reveal which one can bring valuable information on the status of olive trees. Previous studies showed the importance of using VIs to exhibit the spatial variability and either the temporal one in a cultivated field and also to distinguish between healthy and unhealthy portions of a cultivated field without referring to agronomic measures (Candiago et al., 2015; Blanco et al., 2020). Some studies conducted on olive trees revealed that spectral data could be used to predict the relative water content and leaf water potential as an indicator of water stress (Camoglu et al., 2013) and to estimate biophysical and geometrical parameters of olive trees under different irrigation regimes (Caruso et al., 2019). Using a multispectral camera, Matese et al. (2013) mapped the wine vigor of a vineyard based on NDVI index. Agüera et al. (2011) measured sunflower nitrogen status with a microdrone and compared those measurements with data collected from a ground-based platform. It was also attested that the high-resolution of UAV images represent a fast, reliable, and economic resource in crop assessment for precision farming applications (Candiago et al., 2015). So, in this study we highlighted the evolution of three VIs (NDVI, GNDVI and NDRE) through one season and compared between them to assess the status of an olive orchard, considering two levels: the spatial variability and the temporal one. This variability is expressed by fluctuations of VIs in response to the spectral signature of vegetation through 4 successive flights. In fact, the fluctuations of VIs could be explained by photosynthesis rate among physiological stages of the olive tree and the reflectance of leaf pigments, especially chlorophyll a & b and probably carotenoids (Ritz et al., 2000, Croft and Chen, 2017).

The oscillation of NDVI would be referred to the leaf chlorophyll and nitrogen contents. At first, the first flight, occurring in June, showed the status of the orchard (globally in a good condition; 6747 trees with high NDVI; Fig. 5). Gamon et al. (1995) reported that the NDVI is correlated with peak springtime canopy photosynthetic rates in evergreens, which is in agreement with our results. This flight coincides also with the growing season in which chlorophyll content increases in leaves explaining the high value recorded for NDVI in June (Wong and Gamon, 2015). After one month, the NDVI values showed an abrupt decrease, revealing a severe stress that affected 92% of the trees, while the remaining trees recorded medium values. This observation could be owed to the increase of temperatures between the two flights and any water supply in this period (Fig. 2). As reported by Camoglu et al. (2013), there is a close relationship between water related indices (such as leaf water potential and relative water content) and NDVI index. Otherwise, pigments in the leaves change according to the amount of water (Arji and Arzani, 2008; Sikaoui et al., 2014) resulting in change of reflectance characteristics in the visible and NIR spectrum (Camoglu et al., 2013). Finally, the NDVI showed a positive evolution through the third and fourth flights, with a rough

decline of low values, and medium values reaching 49% and 31% respectively in favor of high values reaching 51% and 68%, respectively. The chlorophylls might have been increased by enhanced leaves moisture and improved growth conditions resulting from rainfall events during September and October (Fig. 2; Eitel et al., 2011).

NDRE recorded a dominance of medium values (+90%) through the four flights. Compared to the other indices, it’s the only index showing a different status of the orchard in the first flight. In fact, the red-edge spectral region, which is used to compute this VI, is more sensitive to chlorophyll content (Xie et al., 2018). Chlorophyll pigments strongly absorb in the red spectral region leading to red reflectance saturation at low levels and making the red band often unresponsive to an initial loss in chlorophyll at earlier stress stages (Carter and Knapp, 2001; Eitel et al., 2011). Previous studies argued that red-edge band information is superior to red and green band information in terms of its responsiveness to stress induced changes in chlorophyll a & b (Carter, 1993, 1998; Carter and Knapp, 2001; Carter and Miller, 1994; Eitel et al., 2007, 2008, 2009, 2010). This might be partly due to the red-edge band picking up some stress induced increase in fluorescence. This indeed explains the difference noted between NDVI and NDRE in the first flight; so medium values of NDRE are owed to a medium level of chlorophyll content. We assume that the NDRE is more suitable to reveal the status of the orchard and stress. It’s important to note that it remained stable over the time.

Concerning GNDVI, high values rate declined from 81% (flight 1) to 65% (flight 2) before dropping to 8% (flight 3) in favor of medium values then slightly increasing to 17% at the fourth flight. At high chlorophyll concentration, it’s known that NDVI losses sensitivity and saturates (Cao et al., 2015). Moreover, in evergreen trees, NDVI fails to capture seasonal dynamics in photosynthetic activity measured at the leaf or the canopy level (Gamon et al., 1995). To handle this saturation phenomenon, Gitelson et al. (1996) proposed the Green NDVI (GNDVI) that considers the green instead of the red band, and found that GNDVI was much more sensitive to chlorophyll concentration and detects a wider range of chlorophyll compared to the NDVI. It has also been proven that the reflectance of NIR and green wavelengths has a strong linear correlation with chlorophyll content (Datt, 1998; 1999). Similarly, Hunt et al. (2008) stated that GNDVI tracks the ratio of photosynthetically absorbed radiation and is correlated with biomass and LAI leading to more sensitivity to chlorophyll content than NDVI (Candiago et al., 2015). Hence, the high values of GNDVI in the first and the second flights are explained by the high values of tree biomass (Hunt et al., 2008) and photosynthetic rates peaking in the winter and spring and declining in the end of summer and fall (Gamon et al., 1995). On the other hand, GNDVI Values dropped consequently to water deficiency and high temperatures during summer, decreasing in turn plant transpiration and carbon gain, which can lead to higher susceptibility to other plant stresses (Breshears et al., 2009).

Conclusion

In the present study, it seems obvious that High spatial resolution UAV multispectral images are useful for field survey. They produced precise maps for early stress occurring, showed the most stable portions of the orchard and we were also able to reveal, by using VIs, the presence of temporal and spatial variability. Several information were brought without any agronomic parameters measurements. The results showed that NDRE detected that trees are stressed earlier than the other indices. It expressed moderate chlorophyll content attributed to the need of trees in terms of nutrients and/or the occurrence of other stresses (water, pests and diseases, etc.). The use of NDRE instead of NDVI and GNDVI can be recommended to identify heterogeneities in olive orchards. It is important to note that this indice was stable over time. We assume that GNDVI is more related to the biomass and photosynthetic rates instead of leaves pigments content attested by both NDVI and NDRE with different levels. Otherwise, the temporal and spatial variability characterizing the studied orchard bring new research questions through exploring physiological parameters related to water and nutrients deficiency. Finally, results are in concordance with other studies which stated the interest of using VIs to map heterogeneities in some crops (tomatoes, sweet cherry, vineyards….) and therefore make decisions based on precise data. They show promising perspectives of using multispectral images in the case of olive trees and therefore an efficient management of orchards.

Authors contribution

The authors: S. El Iraqui; A. El Bakkali, H. El laaich and A. Douiak contributed equally to this paper. The other authors are members of the project and participated actively in this work.

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