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Canopy Index Evaluation for Precision Management in an Intensive Olive Orchard

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Abstract: The evaluation of the canopy in orchard cultivation is a key aspect for the main cultivation techniques, such as pruning, thinning, harvesting, production and improved fruit quality. The possibility of having a periodic screening of the state of development of the vegetation can be of practical support to growers. Research on the application of precision agriculture has provided tools for reading and interpreting crops, and the resulting information is potentially useful. Many of the systems under study provide after monitoring information processing systems that reduce the timeliness of intervention. Especially in intensive systems such as olive groves, knowing the precise intervention points is often essential. In the present work, a multi-parameter instrument was used for field monitoring on the agricultural tractor to analyse the canopy. The system allows measuring various indicators such as height and density of the canopy and the temperature and humidity of the ambient air and at the leaf level. The first evaluation of the data made it possible to identify areas with greater vegetative concentration and greater or lesser development. The system made it possible to identify with good approximation the homogeneous areas, based on the Canopy Index (CI) evaluation to be subjected to subsequent and specific management efforts, dividing them into low, ordinary, and high vegetative growth. The results highlight the possibility of directly combining operators able to intervene with the same passage, selecting based on differences in growth, typical varietal specificities, and areas of deficient development or that are affected by plant diseases, confirming the objective of defining the areas of the orchard that require different management and workload techniques.

Keywords: precision farming; simulation model; sensors; automation

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1. Introduction

In recent decades, various possibilities for the remote monitoring of agricultural production have been developed based on data acquisition from orbiting satellites, aircraft, and drones. Many remote sensing and canopy evaluation experiences occurred in vineyards [1]; however, many studies were also carried out in orchards focusing, above all, on the production phase and increased fruit production [2–5]. In this respect, even if limited to pome and stone fruits, the investigations focused on the grouping of fruits in the plant, single branches, the solar exposure, and the growth rate of the fruits [6].

Orchard management consists of a series of tasks that require mental concentration and physical commitment following the various types of interventions that, in turn, result from the different cultivated species, the pedoclimatic and plant conditions, the age, and the fruit load and positioning in the plant.

The advantages of intensive cultivation have long been known for improving management and facilitating the introduction of technology [7]. In olive growing and other fruit tree cultivation systems, the pruning effort is second only to thinning and harvesting in terms of cost (mechanical pruning versus manual pruning efficiency is more than 20 times. It generally accounts for about 20–30% of annual cultivation costs) [8]. The olive harvesting costs were monitored in different training systems and plant densities starting from traditional systems [9]; however, what makes pruning a critical crop phase is the inherent danger pruners undergo independently from adopted safety measures (e.g., falling height risk, hand/machine cutting system). Tombesi et al. [10] studied the effort that pruners must sustain when working in an olive tree grove with vase-shaped plants, 5 $\times$ 5 m spaced. Comparing five teams of well-trained pruners equipped with a chain saw, chain pruner, lopper, and pneumatic pruning shears with and without an extension pole, it was observed that the working capacity was 16–23 trees h^{-1} and that when more massive and more numerous cuts are necessary, the less tiring working equipment consisted of a chain saw coupled with a pneumatic pruning shear. A preventive screening on the canopy could replace the traditional monitoring of the entire grove (made of generic and repetitive evaluations on the plant crowns), providing pruners and other operators with helpful information about where and to what extent to intervene.

In olive tree groves, especially in high-density cropping systems, the varieties and agronomic techniques are the most critical factors that affect fruit production and plant adaptation to the mechanical operation until harvest [11]. In open field conditions, the need for specific mechanical pruning starts from the 6th year of planting to be repeated every year. Medium-low vigour cultivars (Spanish and Greek) showed good adaptability to mechanical and manual prunings without yield impairment. On the contrary, medium-high vigour cultivars (both new and belonging to the Italian tradition) require mechanical hand pruning to control the canopy size, but this operation can severely impair their yield production constancy level. [11,12]. It follows that pruning could represent one of the many cultivation operations that most benefits from remote management of the canopy.

The Council for Agricultural Research and Economics (CREA), between the end of 2019 and spring 2020, carried out some tests with a multi-parameter sensor mounted on an agricultural tractor ordinarily used for the primary cultivation operations. The tests aimed to monitor and highlight the different vegetative phases of an intensive olive tree grove to characterize the canopy and identify which specific and point-like areas of the row undergo progressive vegetative development, flowering, fruit set, and ripening to provide helpful information to olive growers.

2. Materials and Methods

2.1. Crop Survey

The test occurred on a 0.95-hectare surface within an olive grove of 1.85 hectares located in Agugliano (Ancona, Italy) in a high-density olive orchard (1250 trees ha^{-1}, 4.0 m $\times$ 2.0 m) planted in 2011 at the experimental farm of the Polytechnic University of Marche, Italy (43°32′55.57″ N, 13°21′52.69″ E, 85 m a.s.l.). The experimental orchard aims to evaluate the attitude of several local, national, and international olive varieties grown in an intensive growing system in specific pedoclimatic conditions. Initially trained as a central leader, the tree canopy was afterwards flattened according to a hedgerow, removing long branches toward the interrow.

The soil is with a clay prevalence, grassed between the rows and mechanically managed for weed control along the row. The orchard management relies on an agroecological approach with integrated pest management. Fertilization and complementary irrigation are supplied according to seasonal requirements.

The climatic data source are the Centro Agrometeo ASSAM by the weather station of the University of Polytechnic of Marche located in the experimental University farm of

Agugliano (An) from which the data of the temperature, rainfall, and rainy events were extrapolated. In the monitored period, the environmental conditions are recorded from five months first of winter passage and one month after the summer test in June.

The screening tests were carried out at two different vegetation steps: in December 2019, after fruit harvesting, and in June 2020, when plants were in the complete vegetative phase.

2.2. Multiparametric Sensor

The Proximal sensors used for the tests consisted of two RGB optical matrix imaging sensors (mounted on the left and right of the tractor) and the related algorithm, called Canopyct [13], whose output is the Canopy Index (CI): a dimensionless number ranging between 0 and 1000 directly correlatable to physically based variables such as LAI (Leaf Area Index) and TRV (Tree Row Volume).

The multiparametric sensor (Figure 1) works in the RGB colour space in the respective bands of 500, 600, and 690 nm, weighing less than 1000g, with a power supply at 12v, protection level IP68, the possibility of dedicated connection or CAN-BUS, with sampling frequency 1–20 Hz, a distance of reading from 25 to 300 cm of positioning with a reading window of 60° from 60 to 250cm. In addition to the CI, it measures environmental temperature, leaf temperature, relative humidity, and distance from 30 to 150 cm using an ultrasound system.

Figure 1. Image of the modular measuring system adopted in the test. The system is easy to install in any type of tractor in the front or rear position and able to increase the survey frequency as needed.

The sensor can also perform the real-time control of variable rate technology machines: in this case, the sensor acquisitions can modulate the intensity of the intervention of the operating machine (e.g., sprayer, trimmer, defoliator) placed on the rear of the tractor itself. Such monitoring may occur using previously acquired data and real-time acquisitions: the sensors' range of acquisition embraces a width of up to 20 m transversely to the direction of advancement of the tractor. The CI readings are insensitive to the differences in the illumination of the vegetated wall (e.g., presence/absence of clouds, height, and angle of the sun, shading). The Canopyct algorithm processes the acquisitions from the two RGB imaging sensors: for each sensor, after calculating the Hue (H), Saturation (S), and Brightness (L) coordinates of each pixel of the image from its R, G, and B components, the software calculates a linear combination of R, G, B, H, S, and L of any pixel and compress the data into a single dimension. The acquisition system provided for a reading of the data with a frequency of 1 Hz.

2.3. Methodology

Therefore, the collected values had an interval of about one meter, with a variability caused by the small variations of the forward speed. The continuity of the values over the entire surface was obtained by applying the processing by interpolation with the kriging method, developing the krige function of the gstat package of the R software on the collected dataset.

Afterwards, there is the creation of a thematic map: the instantaneous acquisitions of the RGB sensors undergo a grouping technique that classifies each pixel of the image as belonging to the vegetation or not following a statistical data processing algorithm based on a "two-class" implementation of the Jenks Natural Breaks classification method [14]. Finally, the CI results from the following formula:

$$\text{CI} = \text{Npixvegetation}/\text{Npixtotal} \times 100 \tag{1}$$

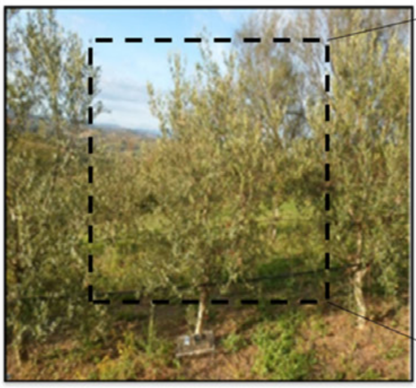
where:

Npixvegetation = is the total number of pixels of the image classified as "vegetation";
Npixtotal = is the total number of pixels in the image.

The overall CI for a single position results from the average of the left and right acquisitions. Applying different intelligence data filtering techniques to the collected data removes the readings unrelated to the crop.

Before the acquisition tests with the proximal sensors, each plant of the olive grove was characterized based on geographic coordinates, size (i.e., the linear width—m—measured with a meter from one end to the other of each plant) and the capturing of a frontal photograph on the row (two pictures, one for each side).

The collected data underwent statistical processing with the software R [15] through the "raster" function of the "raster" package [16]. A regular grid of geo-localized points was prepared to extract the CI values from each of the 16 rasters obtained during field reading. It was, therefore, possible to obtain for each plant a matrix of values having 16 rows and 11 columns (Figure 2).



C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	
195	195	235	235	235	235	241	254	253	253	238	R 16
158	195	195	195	222	235	254	254	253	242	231	R 15
150	158	195	228	235	245	254	253	240	240	230	R 14
158	195	195	228	248	254	249	240	240	233	228	R 13
202	235	254	253	253	247	240	240	231	231	231	R 12
253	253	253	242	240	240	240	240	240	240	240	R 11
251	240	240	240	240	240	240	240	240	240	251	R 10
240	240	240	240	240	247	253	253	253	253	251	R 9
253	253	253	253	254	254	254	254	254	238	228	R 8
254	254	254	238	235	215	195	195	150	150	140	R 7
251	238	235	235	208	173	150	150	88	88	47	R 6
235	235	235	202	195	173	129	88	26	26	26	R 5
150	150	150	98	88	57	26	26	26	26	26	R 4
188	150	150	98	88	88	26	26	26	26	26	R 3
253	254	235	235	208	173	129	88	88	36	26	R 2
215	218	231	231	237	240	254	254	235	202	137	R 1

Figure 2. Example of CI acquisition. The dashed square in the left picture represents the "focus" of the sensors. The numerical matrix on the right shows the organization of the acquired CIs (16 rows and 11 columns).

The calculation of the difference in canopy index from June 2020 to December 2019 allowed for the assessment of the dynamic of the canopy zone in the considered period in each position of the orchard and in any row at single plant level, calculated as follows:

$$\Delta CI = CI_{\text{June 2020}} - CI_{\text{December 2019}} \tag{2}$$

where:

$\text{CI}_{\text{June 2020}}$ = canopy index on June 2020
$\text{CI}_{\text{Dec. 2019}}$ = canopy index on December 2019

The resulting dataset underwent processing with an Excel spreadsheet and Minitab 17 software to point out the variability of the various rows of CIs and define the setpoints useful to establish which canopy zones are subjected to the most extreme variations. Such discrimination was achieved by determining for each row of the matrix the interquartile range (IQR) and pointing out the values deserving much attention.

Data analysis foresaw a two-step process. In the first step, all the calculated ΔCIs underwent basic data processing to depict the variability (box plots) and establish the percentiles. Then, in a second phase, the percentiles were georeferenced.

3. Results and Discussion

3.1. Environmental Data

Weather conditions were typical of the region, with average temperatures progressively decreasing from August 2019 to January 2020, while remaining, in the following summer, lower than the previous year. Concerning rainfall in the period of August–December 2019 and of January–June 2020, there was a significant reduction in rainfall almost equal to rainy events (days), going from over 150 mm to 105 mm (Figure 3). The winter was rainy in the first period, favouring the storage of water in the deep layer of soil, but significant rainfall reduction in the spring may have reduced the initial vegetative phase of the olive plants.

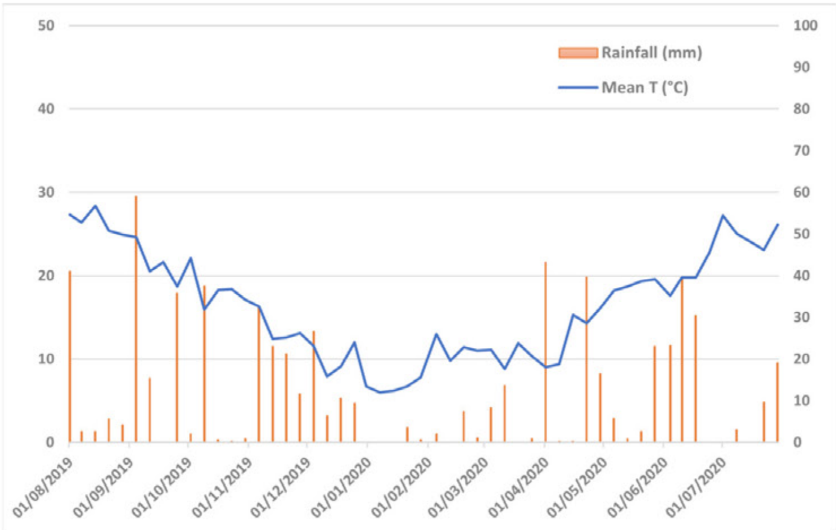


Figure 3. Environmental conditions in the intensive olive orchards.

3.2. Crop Data

The tree height, the longitudinal (along the row) and transversal (perpendicular to the row) diameters of the canopy, the height of the first branch from the soil, and the trunk cross sectional area (TCSA) at 200 mm from the ground were measured in July 2019 and the average values ± standard deviation were 3.23 ± 0.35, 2.24 ± 0.36, 1.71 ± 0.23, 0.67 ± 0.21 m, and 6752.42 ± 2512.15 squares mm, respectively.

The resulting ΔCI dataset ranged from −228 to +228. Of course, each row of data has its pattern of variation as it refers to specific plant heights. This analysis aims to point out which plants eight shall undergo visual inspection: the distribution of the ΔCIs points out any potential increase (ΔCI > 0) or decrease (ΔCI < 0) of biomass.

The IQR is the range of the middle 50% of the ΔCI distribution that the outliers can hardly ever influence, resulting in a robust measure of the occurred variability

Figure 4 points out such variation. For each row of data, it is observed that the difference between the two canopy conditions is not always positive. For some rows, particularly, i.e., R10 to R14, the IQR relies entirely on the negative part, meaning that such canopy fractions decreased in the considered period. However, some other rows of ΔC is have their IQR above or predominantly above zero (i.e., R2 and R3), meaning that a more intense vegetative activity or redistribution occurred.

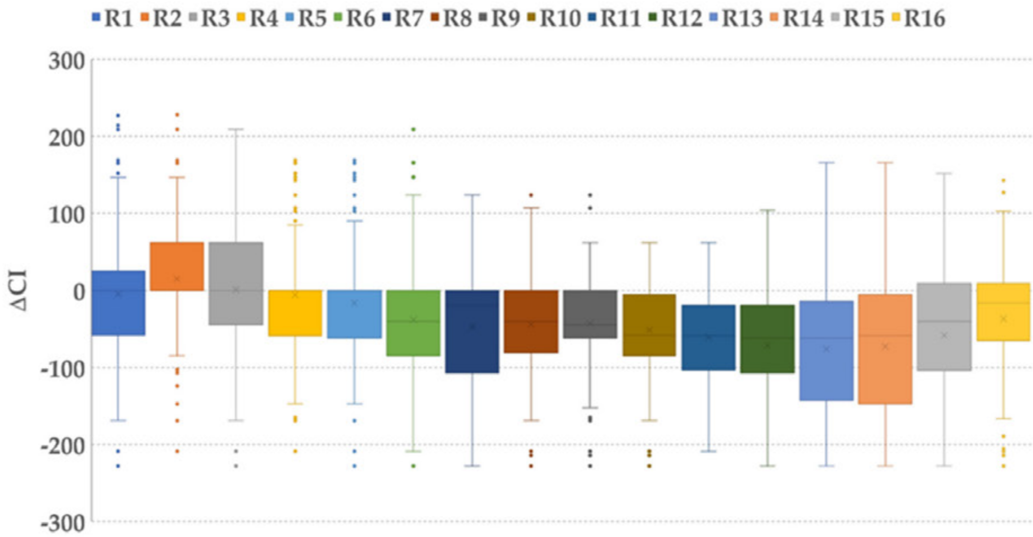


Figure 4. Box plots representation of the ΔCI is obtained in each row (from 1 to 16) of the orchard.

The quantiles analysis also provided useful hints to assess the threshold above which the observed variation shall be considered non suspected (Figure 4).

3.3. Data Analisys

In a normal distribution of data such as that sampled here, the biased observations lie outside the IQR. However, based on all the observations, ΔCI values between −60 and +4 (representing 55% of the observations) provide average canopy growth information. The canopy modifies according to the weight increase for the fruits and the branches' ordinary growth rate. Here the 30th and the 85th percentile represent the thresholds above or below which the information deriving from ΔCI calculation brings to alert it allows to identify the points of the plant characterized by more remarkable vegetative growth resulting from either more young leaves and branches (e.g., requiring pruning) or more scarce or damaged plant sectors (e.g., the rise of a pest attack) (Figure 5).

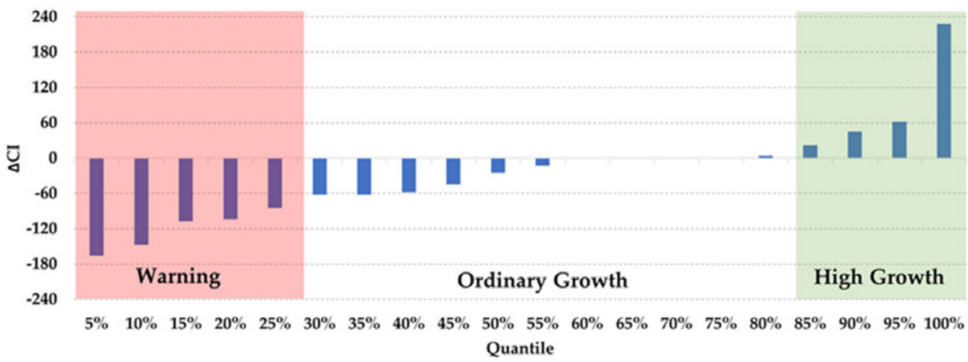


Figure 5. Representation of the percentiles of all the ΔCI values and positioning of threshold alert for low and higth growing.

Warning for excessive growth, not only pruning even just vegetative not fruit discrimination.

As explained above, each matrix of 9 columns and 16 rows represents a plant (144 acquisitions overall). It is possible to convert numerical data into percentages using the following criteria:

If $\Delta CI < -62$ = warning low growth (W)
If $-62 < \Delta CI < 45$ = ordinary growth (O)
If $\Delta CI > 45$ = warning high growth (P)

For each plant, the frequencies' percentages can be calculated and represented graphically (Figure 6).

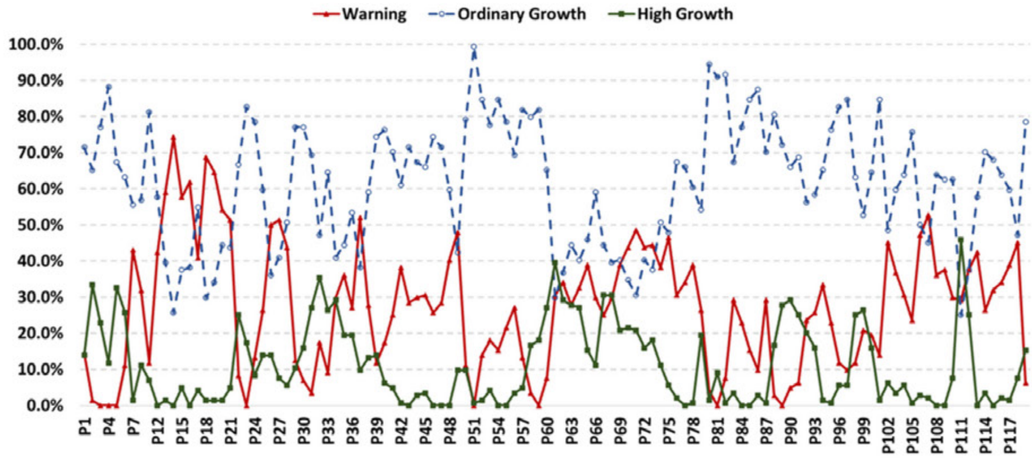


Figure 6. Percentages of ordinary growth (dashed blue), high growth (green), and warning situations (red) in the monitored orchard. The x-axis reports the labels of the plants.

Such a chart shows that, throughout the olive grove, the ordinary growth situation is generally widespread. However, some critical zones need attention where a loss of canopy index occurred (e.g., some predominantly peripheral areas), highlighting some risks for future production.

The system allows the precise identification of ordinary, high, and low vegetative areas that can support the operator in choosing the specific areas of intervention for fruit growing management. Spanish experiences, the most known reference areas for intensive olive growing, have already characterized the water needs and management [17,18] of intensive olive groves. Some cultivation operations substantially impact production costs, and various authors have noted their impact on various fruit species [19]. CREA has already carried out experiences on regulating the fruiting load monitoring both flowers and fruits [20] if it should be particularly uneven in the detected canopy for precision chose of intervention orchards area. In other orchard studies [21], remote sensing solutions exist for monitoring fruit growing as a function of specific fruit load. There are several and available alternatives of remote and proximity systems to detect canopy uniformity and distribution [22]; however, the possibility of having them installed on the machine that ordinarily performs the work allows for the constant updating of the situation as a result of performing periodic passages inside the olive grove.

In the present work, thinking only in terms of ΔCI, it is also necessary to pay attention to the different shade of the plant parts expecially in term of leaves between December, that is, almost at the end of the vegetative season with more old leaves, and June of the following year in which the young leaves can be read with different canopies, for which further and specific investigation is required. Similar considerations can be made for the branches and apical parts of the same.

The areas defined with the specific CI value, framed in one of the three areas (low, medium, and high), after precise geolocation, required an in-depth study for a better characterization of the pixel (Figure 7).

Figure 7. Detail of an in-depth area for CI evaluation where branches, young leaves, and fruit are integrated.

Once the aspects to be highlighted have been defined with sufficiently detailed criteria, artificial neural network (ANN) approach methodologies could be applied aimed not only at the identification of two classes of pixel (vegetation and non-vegetation), but also of further, progressively more specific physiological aspects as already experimented in the definition of the periods of thinning intervention for the evaluation of the forces of detachment of fruits [23].

Such information can also be transformed into a KML layer and added to any map rendering software (e.g., Google Earth), providing immediate information to farmers on the critical zones' location for more investigation.

The resulting graphic representation (Figure 8) helps identify the most critical areas in this case study. Both warheads signal warnings could be attributed, for example, to the poor effect of pesticide treatments, poor fertilizer distribution (e.g., when starting the spreading), and transverse cold currents passages are all aspects that are to be investigated but which, avoiding the generalized control of the plot, can be summarized in a few monitoring areas. Similar considerations could apply to the left side of the plot, where other criticalities are highlighted.

The study of the canopy index, on the one hand, allows to precisely identify the areas with greater or lower vigor; on the other, it markedly signals the problems linked to identifying the correct causes of this diversity. Since the causes are multiple and of different intensity, the analysis of these aspects deserves in-depth studies such as to recommend self-learning systems (with support of artificial intelligence) that can always better characterize defined index ranges from 1 to 1000, which can also progressively indicate the most probable cause in term of agronomic aspects and technical level. This aspect can show different interpretation possibilities of the canopy index (CI) not directly linked to different plant parts.

Many operations of orchard management are mainly made up of the visual control of all plants, the evaluation of vegetative aspect, and intervention; generally weighted inversely to exposure order, visual control and vegetative evaluation often make up the prevalent part of the work so that by indicating the intervention areas in advance to the operators, work times can be reduced significantly. Furthermore, the progressive training of personnel in detecting the anomaly and associating the specific intervention measure and intensity level allows making all types of interventions that can be managed with this PA devices approach more and more targeted and efficient. Further investigations could be aimed at specific operations such as pruning at a further classification of the type of intervention (heavy or light, reform or production) to identify and localise the different types of intervention. Other aspects can be focused on, e.g., fertilizer distribution and localized quantity, branch addressing/bending, presence of disease or pests, and type and intensity of the problem. This additional function can be applied profitably, for example, by analyzing the location in the plant profile (height/middle/low) with characterization of the areas of greatest demand represented on the obtained maps.

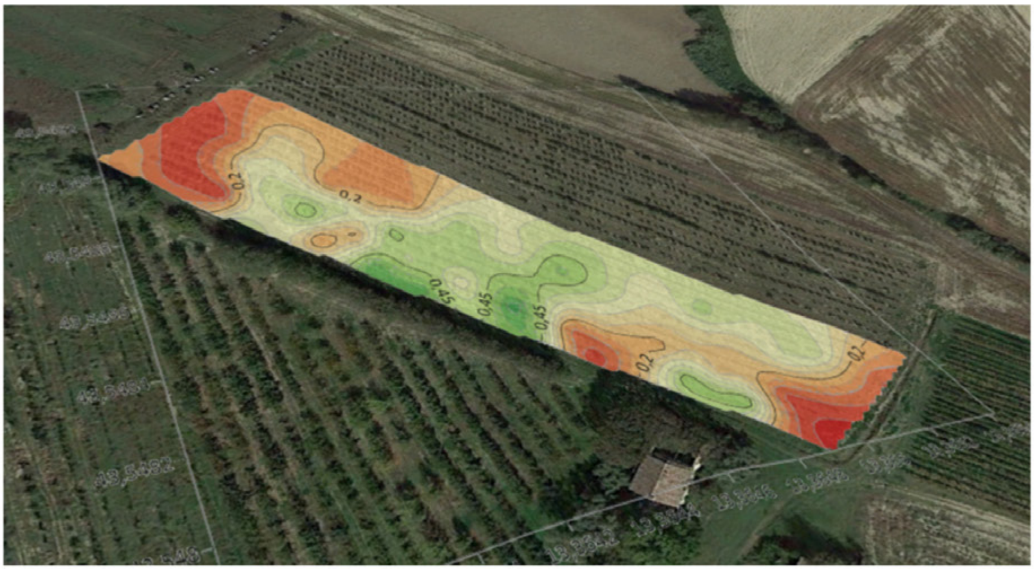


Figure 8. Graphical representation of the plants based Eg on the Pruning index: 0–5% (orange); 5–20% (greenish); 20–35% (light green); and >35% (dark green).

A limit to these considerations can be represented by the fact that by evaluating only the difference in growth in terms of canopy, even just the loss of some leaves, we can not detect differences, or if only the branch remains, we can indicate only alerts with signalling to the operator of direct verification.

Specific studies have allowed for the development, even if in other research contexts, of protocols and models for the definition of homogeneous areas through the multivariate analysis of the data obtained [24,25]. Thanks to previous experiences in forecasting modeling, the homogeneous areas defined can also be clustered by hierarchical or other algorithms developed [26–28], which can then be analyzed for specific problems or needs for intervention.

Moreover, the hyperspectral analysis of the ΔCI can point out vegetation indices able to develop novel algorithms for predicting the Leaf Area Index (LAI) of crop canopies and the remote estimation of crop chlorophyll content in the context of precision agriculture [29–31].

The possibility of obtained different homogeneity areas of the canopy requires attention above all in the definition and interpretation of spatial heterogeneity and specific correlation with crop yield [32]. In this experience, the canopy analysis is not always directly linked to olive yield but only to different growing habits.

Other in-depth analyses may concern the canopy characterization in terms of the colour and shape analyses of foliage to individuate homogenous growing areas such as symptoms of deficiencies or excesses of mineral nutrition as demonstrated in other crops [33]. In addition, the development of systems can evaluate the effectiveness of the mechanical distribution of fertilizer and defence treatments in the field to rationalize their distribution only in the areas of actual need with improved treatment efficiency and environmental protection [34]. It can finally enhance the possibility of providing precise maps of points that require any direct-field verification to integrate an ordinary simplified technology synergy between crop and operator to benefit the precision farming applicability.

The presented work allows the easy evaluation similar to other canopy detection and analysis systems such as LIDAR with reference to the development and use of the Canopy height model (CHM) [35]. The system also has the advantage, being purely optical, of not presenting unknown and uninterpretable areas as happens with other technologies for which specific filling software of modest reliability are sometimes required as they borrow the single values from the neighbouring pixels [36].

This result can be obtained with tools directly available without external monitoring and data processing systems. The distribution of the values of the canopy index in a 1–1000 standard index is more simple than a traditional NDVI index, being able to be directly connected with lateral or rear operator machines used for other operations such as spraying and fertilization with VRT systems and with the possibility of excluding plants or rows sections for precision crop management.

The work showed the possibility of highlighting specific areas of the plot but, above all, underlined the need to investigate further the reasons capable of affecting the IC in field conditions.

4. Conclusions

The experimental activity had the main objective to characterize the canopy of an intensive olive orchard in terms of the height, density, and growing homogeneity to support the growers for orchard management in a precision agriculture approach in the RGB approach.

The prescription map obtained in two different vegetative phases for the analysis of different canopy indexes showed the main differences caused by a lack of branches, foliage density, and the presence and lack of fruits. The processing of the two consecutive maps highlighted these critical areas that require attention because a loss of the canopy index has occurred. The evaluations are conducted in terms of the differential canopy index (delta CI). The reasons for this loss, well indicated and geolocated, can be adequately investigated for olive growers also for focused specific intervention (e.g., pruning, presence of disease and pests, presence of cold damage). The distribution of the canopy obtained in the field showed that the areas individuated with the reduced thickness and other with more developed, but the correlation with fruits yield not is easy to highlight. This study, therefore, represents a helpful contribution to the verification of the possibility of the practical application of precision agriculture in new areas of interest, for example, as an olive manual pruning intervention which sees the main advantage in indicating the points and intensity of intervention and avoiding the continuous direct field control of the operators.

The presented paper allows direct and easy evaluation compared with other canopy detection without other analysis systems, such as LIDAR and the Canopy height model (CHM) methodology. The system also has the advantage of being purely optical and does not require the further interpretation of unknown pixel areas.

5. Future Work

The research activity will continue on both strands of orchards and tree crops and herbaceous/industrial crops to create periodic monitoring systems that allow researchers to study the evolution of the development/fruiting of plants and allow for targeted control operations (e.g., growing/defense interventions).

It is planned to combine operators capable of carrying out treatments aimed at the CI index detected previously on the same tractor in the same passage for orchards and tree crops.

For herbaceous/industrial crops, the installation above the tractor cabin allows, on the one hand, to record data at each crop passage and, on the other hand, to perform differentiated treatments only in the areas at or above or below specific CI values.

6. Patents

This section is not mandatory but may be added if there are patents resulting from the work reported in this manuscript.

Author Contributions: Conceptualization, A.A., E.R., M.B., C.B., E.M.L. and D.N.; methodology, A.A., E.R. and M.B.; validation, E.R., M.B., A.A. and C.B.; formal analysis, E.R., M.B. and A.A.; investigation, E.R., A.A., E.M.L., D.N. and M.B.; resources, A.A., C.B., E.M.L. and D.N.; data curation, E.R., M.B. and A.A.; writing—original draft preparation, M.B., E.R. and A.A.; writing—review and editing, A.A., E.R., M.B. and C.B.; supervision, A.A. and C.B.; project administration, A.A. and C.B.; funding acquisition, AA. All authors have read and agreed to the published version of the manuscript.

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