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Spatial distribution of water status in irrigated olive orchards by thermal imaging

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Abstract Information regarding tree water status in irrigated olive orchards is essential for managing growth to optimize yields and olive oil quality. One management practice option is to monitor or sample individual trees and use this information for orchard-scale management. This study assessed the ability of thermal imaging to provide the spatial distribution and variability of tree water status in a commercial irrigated olive orchard, and described strategies and a procedure for choosing which individual trees best represent the orchard. The study employed gradual upscaling from individual trees grown in lysimeters, through a controlled experimental field plot, to a commercial orchard. Thermal imaging of olive trees grown in lysimeters attested the sensitivity of the technique to identify mild-level water stress by correlating crown temperatures to stem water potential. Knowledgeable choice of five or ten representative trees in the experimental plot, based on the histogram distribution obtained for the entire experimental orchard, lead to successful reconstruction

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of the spatial distribution of canopy temperature, and thus of water status. Positively skewed distributions of crown temperatures found in both the field plot and commercial orchard suggested distinct patterns, where the canopy temperature of the majority of the trees was lower than the average, and a relatively small number of trees had significantly higher temperatures and suggest commercial practicality of the proposed methodology. Thermal imaging can therefore serve as a useful tool for determining representative trees that, if frequently monitored, or instrumented with continuous water status sensors, can provide important information for orchard water management.

Keywords Crop water stress index · Transpiring canopy area · Lysimeters · Geospatial analysis · Sampling strategies

Introduction

Over the last few decades, irrigation has been shown to positively affect olive (*Olea europaea*) oil yield (Gómez-Rico et al. 2006; Ben-Gal et al. 2011). This accelerated the transition of the olive oil industry from traditional rain-fed to intensively-managed irrigated orchards (Lavee 2011). However, while fruit and oil yield have been reported to be positively affected by increasing the amount of water applied, oil quality parameters, such as polyphenol concentration and free fatty acid content, were reported to be negatively affected (Gómez-Rico et al. 2006; Dag et al. 2008; Ben-Gal et al. 2011). Optimization of olive oil quality and quantity can be achieved by water management that allows conditions of mild stress during pit hardening and induces stress during the oil accumulation stage, particularly prior to harvest. Similarly, control of water stress conditions is required in high-density olive orchards where deficit irrigation is used to moderate vegetative growth and maintain a manageable canopy size (Lavee 2011; Naor et al. 2013). Monitoring and control of olive orchard water status is therefore becoming increasingly important. Scarcity of fresh water in the Mediterranean region, where olive oil production is concentrated (Vossen 2007), further heightens the need for improved water use efficiency (Ben-Gal et al. 2006).

Best management concerning water in orchards could potentially be achieved if water status of each individual tree at any given time was known. For economic reasons, this is impractical. A near optimal approach would provide continuous water status information for representative trees. Continuous water status measurement techniques e.g. dendrometers (Reineke 1932 and thereafter) or leaf turgor pressure probes (Zimmermann et al. 2008), are nowadays available at costs reasonable enough to instrument a limited number of trees. The open question is how to choose the representative trees.

Tree water status is a function of environmental conditions (climate, soil water status) and plant parameters (variety, canopy size, fruit load), and as such, can be affected by cultivation practices (tillage, weeds, irrigation method and quantity, irrigation water quality) and external biotic stress causing agents (diseases, pests). Tree water status can be evaluated by direct (e.g. stem or leaf water potential) and indirect (e.g. stomatal conductance, trunk diameter, leaf thickness) methods (Ben-Gal et al. 2009). Yet, when such information is required for the entire orchard (or a representative sample), preferably simultaneously, employing these traditional methods is not feasible due to their time and labor intensive nature, as well as due to the variability inherent to results derived from changes in climate conditions during the measurement. Naor et al. (2006) found that a representative sample of 4–8 trees of a population of 27–30 trees was required for stable average readings of stem water potential (SWP) in apple, nectarine and pear orchards, indicating that numerous measurements are required to evaluate the average of entire orchards.

To overcome these limitations, alternative methods that have the ability to provide instantaneous, spatially distributed, information are desirable. The canopy temperature of single trees can be determined using thermal imaging, provided that the spatial resolution of the acquired images is adequate (Berni et al. 2009), and has been proven reliable for measuring water status of oil olive trees (Sepulcre-Canto et al. 2006, 2009; Ben-Gal et al. 2009). However, the applicability of the technique for olive trees was tested mainly on two extreme water status conditions, i.e. acute water stress versus well watered trees, but not for the mild levels of water stress expected to be desirable for production of high quality oil. The first objective of this study was therefore to test the sensitivity of the thermal imaging technique to identify mild level water stress in oil olive trees.

Thermal imaging provides the crown temperature, and thus the water status, of each of the trees within the scene. However, for practical water management applications, thermal images at spatial resolution that allows identification of individual trees are required at high temporal resolution (i.e. 1–2 days). As yet, such information is unavailable. Alternatively, the spatially distributed temperature field, based on data regarding each individual tree within an orchard, can be used in combination with geographical information systems (GIS) to provide the framework required for applying spatial analysis (e.g. Bellvert et al. 2012). Such spatial statistical information can be utilized to characterize the properties of the orchard and identify representative trees. These trees can be repeatedly sampled, measured or monitored with instrumentation including continuous water status sensors to provide representative information regarding the orchard water status to managers.

An important and powerful spatial analysis method is spatial interpolation, which, based on a set of limited sample points, computes values for an entire surface. This enables modeling of the spatial distribution of a phenomenon at locations where no sampling is available (Lloyd 2010). Together with the interpolation information, descriptive a-spatial statistics (i.e. using the spatially distributed data without consideration of the specific location of the values) provide a summary of the distribution. The frequency histogram is a statistic summarizing the distribution of a dataset providing its minimum, maximum, mean, median and skewness. Combined with GIS methodology, which can locate the trees that are associated with certain data values in the database on a map, a histogram-based method can be used in order to connect between the a-spatial distribution of the data values and their spatial distribution.

Choice of the representative trees, selected from the histogram, depends on criteria most important to the farmer. If information on the overall status of the orchard is sought, individual trees will be selected to represent the entire histogram distribution (an overall distribution strategy). If there is need to assess the water status of the median values (neglecting the edges of the histogram), selection of trees will focus on the median area of the distribution (a median based strategy). Lastly, if the driest and wettest trees are of interest, monitored trees will be selected from the tails of the distribution (a tails based strategy).

The potential of utilizing sporadically available spatially distributed information for each tree in the orchard to choose the representative trees that, when frequently measured, will provide the representative water status of the entire orchard is presented.

Materials and methods

Three experimental sites, representing different spatial scales, were employed in this study: a collection of single tree lysimeters, an experimental field plot, and a commercial orchard.

The fully automated weighing-drainage lysimeters allowed closure of water mass balance of individual trees and served as a base for comparison with thermal imaging. Canopy temperature distribution was determined in the experimental field plot using images of groups of trees and in the commercial orchard using a single aerial image. Results from both were evaluated as potential management tools.

Lysimeters

Single 2-year old (cv. Barnea) olive trees were planted in fifteen 2.5 m^3 volume free-standing weighing lysimeters at the Gilat Research Center in the northwestern Negev, Israel (31°20′N, 34°40′E) in June 2008. A full description of the lysimeters is detailed in Ben-Gal et al. (2010). The lysimeters facilitated calculation of daily actual water consumption according to $ET = I - D - \Delta W$; where ET is evapotranspiration; I is irrigation; D is drainage and ΔW is change in soil water. The units of all water balance components were mass (kg) and easily convertible to volume (L). There was no rainfall during the experimental period (July–August 2010). The trees were irrigated daily, with quantities always exceeding (by ~20 %) the previous day's ET rates as calculated from the weight data of the lysimeters (ET_a). A nearby weather station provided daily reference ET, (ET_o) (FAO Penman-Monteith; Allen et al. 1998). On 9 August 2010, gradual mild water stress was applied to the trees by ceasing irrigation for three consecutive days to deplete plant available water in the soil profile. Thereafter, water application was set to 90 % of the previous day's ET_o multiplied by a factor empirically derived for the least transpiring tree, so that all trees received the same amount of water. The factor was a 3-day average ratio of measured daily ET_a/ET_o, termed as the effective transpiring canopy area (ETCA; Ben-Gal et al. 2010). The units of ETCA are m^2 of canopy, resulting from dividing volume (m^3 of ET_a) by length (m of ET_o). To further evaluate and understand the ETCA and its relevance to trees in orchards, it was compared to tree canopy volume estimated by tree upper transect, calculated from the RGB images, multiplied by measured tree height. The different ETCA under uniform deficit irrigation, and therefore uniform uptake amounts, resulted in varying stress levels, represented by the difference in ETCA between the initial conditions before stress was applied and the conditions during thermal imaging after moderate stress had been developed (Fig. 1). The deficit irrigation ranged between 90 and 45 % of each tree's expected potential daily uptake if sufficient water had been available. Thermal imaging was carried out 4 days after the 90 % ET_o irrigation was initiated.

Thermal images of tree crowns were acquired on 19 August 2010 at 13:30, the time at which the foliage exhibited the highest temperature of the day (Ben-Gal et al. 2010) with an uncooled infrared thermal camera. The camera (ThermaCAM model SC2000, FLIR Systems, Meer, Belgium) has a 320 × 240 pixel microbolometer sensor, sensitive in the spectral range 7.5–13 nm, and a lens with an angular field of view of 24°. The thermal camera, together with an RGB camera looking at the same target and shooting simultaneously, was mounted on a truck-crane about 30-m above surface. The canopy height was ~5 m, so that the linear field of view of the thermal camera at the canopy level was 11 × 11 m, with spatial resolution of 3.3 cm. This resolution enabled discrimination between leaves and soil and selection of pixels that contained sunlit leaves. Crown temperatures were assessed based on an area that included canopy only, excluding the canopy edge, where the pixel was a mixture of leaves and soil surface. Thermal images were processed with digital image processing tools using ThermaCamExplorer software (FLIR Systems, Sweden) and Adobe Photoshop 7.0 software (Adobe Inc.). Simultaneously, SWP was assessed using a Scholander-type pressure chamber (M. R. C. Arimad, Personal

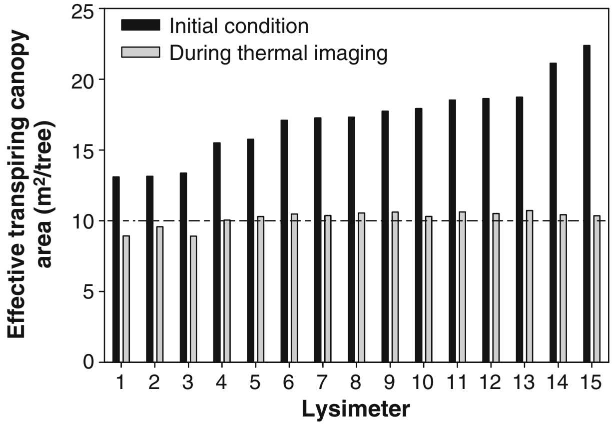


Fig. 1 ETCA prior to (initial) and during the thermal imaging

Communication Holon, Israel) according to Gucci et al. (1997) on single west-facing shoulder height stems with five to seven new growth leaves that had been covered prior to 07:00 h on the day of measurements. Three stems were measured from each tree between 12:00 and 13:30 h.

Experimental field plot and commercial orchard

In the experimental field plot, thermal images of 86 tree crowns were taken from above a 0.2 ha mature non-bearing olive orchard (cv. Leccino), located nearby the lysimeter field, between 11:30 and 12:45 h on 7 October 2010 with the same thermal camera. A week prior to imaging, mild water stress was applied to the orchard by adjusting the irrigation amounts to obtain average SWP values of −0.2 MPa. The imaging setup was similar to the one described in the lysimeters study. Four overall images, encompassing 22 tree crowns each, were taken from 32-m above ground. The imaging procedure spanned over an hour, during which changes in environmental conditions were evident.

As temporal changes in environmental conditions (mainly solar radiation, wind speed, air temperature and humidity) affect crown temperature, acquisition of thermal imagery of an orchard is suggested to be performed in a single shot. Otherwise, canopy temperature should be normalized to account for these changes. Normalizing the actual crown temperatures to high- and low-boundaries, and calculating the crop water stress index (CWSI) is an established way to account for changes in atmospheric conditions (CWSI; Idso et al. 1981; Jackson et al. 1981, 1988; Jones 1992, 1999). The canopy temperature was accordingly normalized to an empirical CWSI (Irmak et al. 2000; Ben-Gal et al. 2009), such that

$$\mathrm{CWSI} = \frac{T_\mathrm{C} - T_\mathrm{wet}}{T_\mathrm{dry} - T_\mathrm{wet}} \tag{1}$$

in which T_wet is the temperature of a leaf transpiring at the maximum potential rate and T_dry is the temperature of a non-transpiring leaf. According to the empirical approach (Cohen et al. 2005; Grant et al. 2007; Moller et al. 2007), T_dry was set to 5 °C greater than air temperature (Jackson 1982), and T_wet was determined based on measurements of a wet artificial reference surface captured by the thermal image. The T_C was defined as the average crown temperature of each individual tree.

Computation of the CWSI required continuous measurements of meteorological information. Global radiation, wind speed, air temperature and relative humidity were measured at 2-m above ground by a meteorological station positioned in an open field ~50 m from the field plot. The sampling rate was 0.1 Hz, and 1-min averages were recorded by a data acquisition system (CR10X, Campbell Scientific Inc., UT, USA). SWP was assessed for ten trees chosen randomly from five blocks representing different zones in the field plot, using the procedure described above.

In order to visually examine how well the selected trees reproduce the spatial variability of crown temperature in the orchard, a spatial interpolation method was applied. Note that spatial interpolation is generally applied to continuous (not discrete) data. While the temperature associated with the tree crowns represents a continuous phenomenon, the tree crowns do not cover the entire surface, and thus may be referred to as discrete data in terms of their spatial extent. The interpolation was nevertheless performed on the crown temperature, and the results represent the spatial variation as if the tree crowns would have covered the entire area. Since the soil background was of no relevance, in this case, and interpolations were not used in order to simulate or extract values in un-sampled locations, the approach was considered to be valid.

An inverse distance weighted (IDW) interpolation method was used to represent the spatial variability in CWSI values, applying a power of two to the weighing function. It was selected over alternative methods due to its suitability for cases of sufficient and evenly distributed data in reference to spatial variation (Lloyd 2010) and since, among the tested options, it performed best [lowest root mean square error (RMSE)]. A histogram built from the mean crown temperature of each of the 86 trees was built, based on which several strategies for data sampling were examined to optimize the locations for sampling or deployment of water status sensors. Each strategy was evaluated for five and ten samples and the selected samples (individual trees) were examined in their spatial context to assess their ability to represent the spatial variability in orchard crown temperatures. For each sampling strategy, selection of samples was done using the querying capabilities of the GIS system. For example, in the tails-based strategy, since only two trees meet the criteria of being the tails (min and max values), additional trees were selected based on the threshold defined by the number of sensors, i.e. the five or ten highest and lowest values. The same process was applied to the median value, by selecting the five or ten trees with data values that are closest to the median.

Interpolations were evaluated for their spatial accuracy by visually comparing the interpolations to the original 86 sample interpolation and by computing the RMSE of the interpolations. The RMSE was calculated by comparing between the values extracted from the interpolations at each of the 86 tree locations and the measured CWSI values.

In a 13 ha commercial orchard of mature olive (cv. Barnea) trees, located near Revadim, Israel (centered at 31°44′55″N 34°51′05″E) airborne thermal images were taken at 13:00 on 29 August 2010 using the same thermal camera. Crown temperature of two sections of adjacent 500 trees (total 1 000 trees), representative of the orchard, were used to generate crown temperature histograms.

Results and discussion

Canopy temperature as a detector of water status

Quantification of ET_a, ET_o and their derivation, ETCA, was facilitated by the lysimeters and the onsite weather station. The ETCA, prior to the experiment when water was not limiting to the trees, strongly corresponded with canopy volume determined by multiplying cross sectional cover by tree height (Fig. 2). Tree volumes ranged from less than 20 to more than 45 m^3 while ETCA ranged from 13 to almost 23 m^2. In spite of the fact that the trees in the lysimeters were at the same physiological phase and exposed to similar environmental conditions, they varied significantly in canopy size and tree-scale water consumption. This variability cannot be explained by climate, soil type, pest control, tree variety, fruit load or water application management, as these were all uniform throughout the three year growing period of the trees. Therefore, natural biological variability, micro conditions due to relative placement, and possible variability in pruning, were assumed to be the operative parameters leading to canopy size differences and tree water uptake.

Following reduction of irrigation for all trees according to 90 % of the smallest (least uptake under optimum conditions) tree, uptake became equivalent to water applied and ETCA was similar for all the trees (Fig. 1). At this point, the differences in tree volume were expected to produce varied stress levels between the trees, with larger trees experiencing relatively greater stress. To evaluate this and to further assess that tree size was the dominant reason for differences in water uptake, direct measurements of SWP, considered as a bench mark of water status measure in trees (Jones 2007), were plotted against the pre-stress ETCA (Fig. 3a). A significant positive correlation was observed ($r^2 = 0.65$, $P < 0.001$). The scattering of data was attributed to the temporal changes in atmospheric conditions during the SWP measurements: solar radiation decreased continually from 900 to 650 W m^{-2}, and wind speed fluctuated between 4.5 and 6.5 m s^{-1}. The SWP ranging from −1.1 to −1.6 MPa (Fig. 3a) is considered high and representative of fairly well watered olive trees. Ben-Gal et al. (2009) showed a range from −2.0 to −4.0 MPa for well watered to severely deficit irrigated cv. Barnea olive trees, measured in September. In a separate study in the same lysimeters, baseline midday SWP was around −1.2 to −1.4 MPa and decreased to less than −3.0 MPa under extreme drought stress (Ben-Gal et al. 2010). Similar to SWP, crown temperatures were related to ETCA (Fig. 3b, $r^2 = 0.64$, $P < 0.001$), with a range of around 2 °C, demonstrating the ability of the thermal imaging technique to identify mild variations in water stress in olive oil trees.

Water status distribution

Histograms of CWSI and of canopy temperature for the tree population in the field plot and the two 500-tree sections of the commercial orchard, respectively, are presented in Fig. 4.

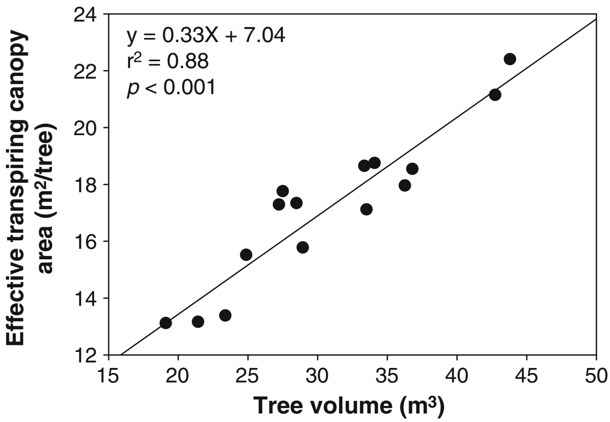


Fig. 2 Tree volume versus initial ETCA

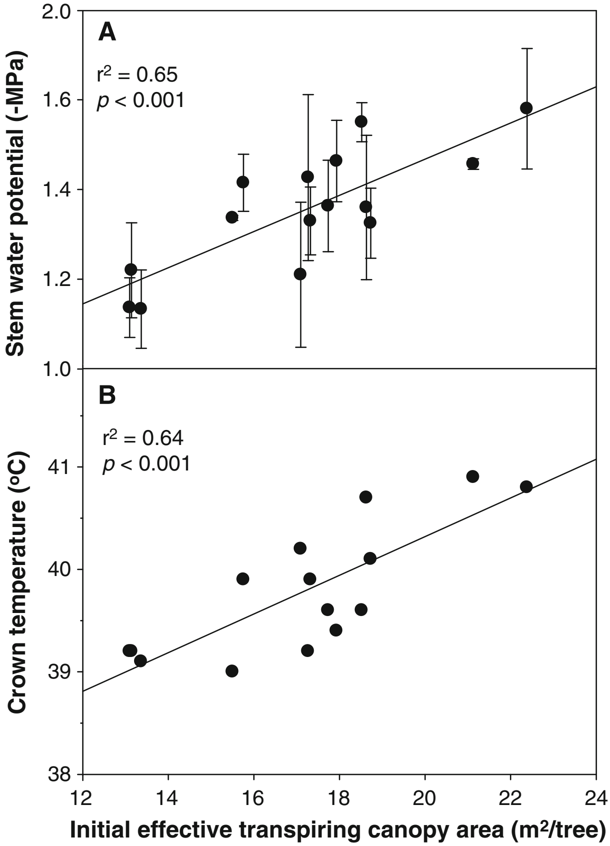


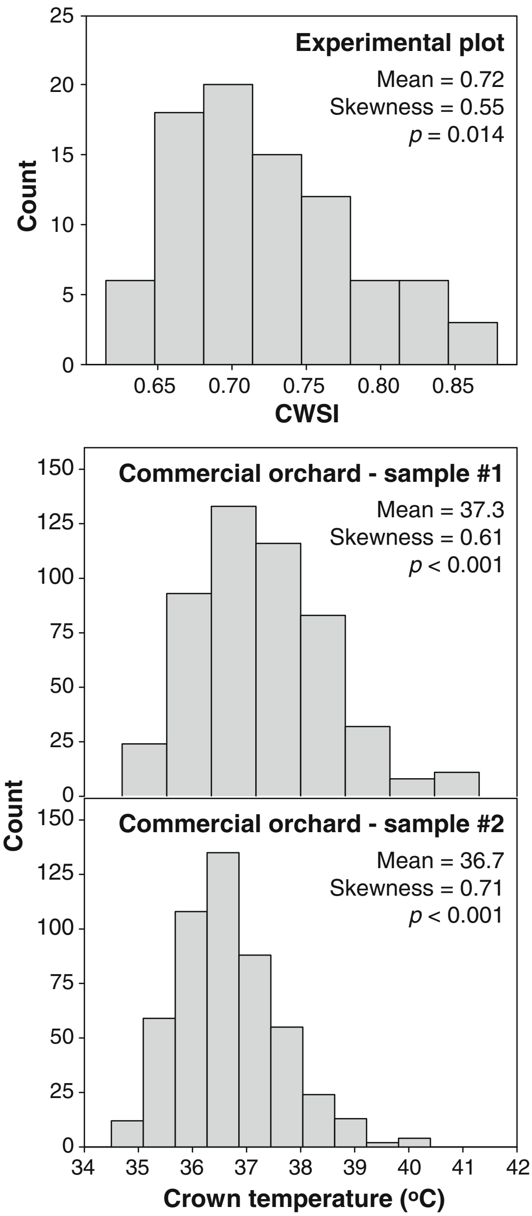
Fig. 3 SWP (**a**) and crown temperature (**b**) versus initial ETCA

The positive skewness of all three distributions indicates a longer tail to the right side with a median left of the mean (Shapiro–Wilk probabilities in all distributions <0.05). This means that the canopy temperature of the majority of the trees is lower than the average, and that some trees have a temperature significantly higher than the others, stretching the histogram to the right.

Higher temperatures in individual trees or specific areas of the orchard, indicative of stress conditions, are a result of: under-application of water due to local malfunctioning of irrigation system; partial pruning; boundary effects (climatic or biotic stresses); lower soil water holding capacity due to shallower or lighter textured soil; or high fruit load. In contrast, trees with cooler canopy temperatures may indicate over-application of water due to local malfunctioning of irrigation system, over-pruning, or higher soil water holding capacity due to deeper or finer textured soil.

Based on these relationships, geospatial analysis of the thermal images can specify the location of trees representing the variability of water status of the entire orchard, which can then be monitored manually or by continuous water status sensors. This can allow confident quantification of the average water status of the entire orchard, providing high frequency, reliable information on tree water status distribution and irrigation requirement. Alternatively, this could facilitate selection of zones (and representative trees for monitoring within the zones) for precision orchard management. In either case, robust,

Fig. 4 Histograms of CWSI from field plot (**a**, $n = 86$) and of crown temperature of two subsections of a commercial orchard (**b**, **c**, $n = 500$ each)

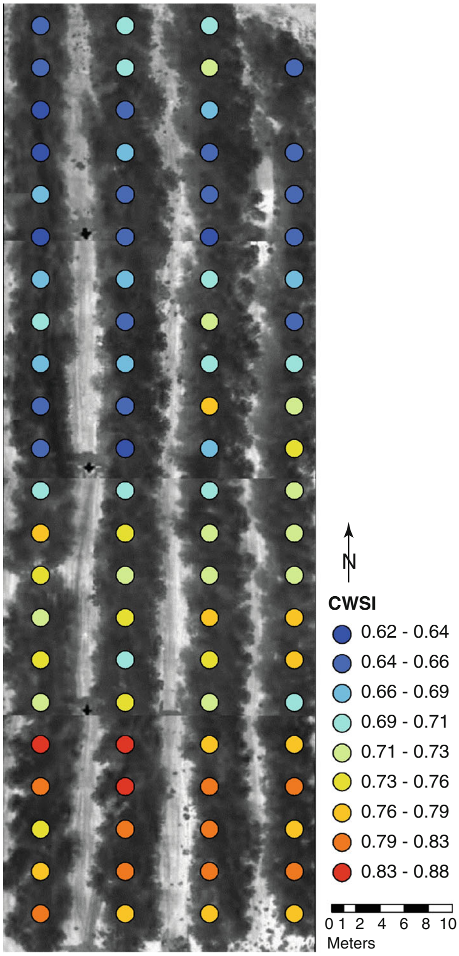


confident, representative sampling or sensors providing continuous data are expected to facilitate practical decisions regarding adjustment of water and/or fertilizer application, soil amendments for improved water holding capacity of soil, pruning and harvesting.

Geospatial analysis—choosing the representative trees

The spatial variability in CWSI values of the trees in the experimental field plot (Fig. 5) indicates two major CWSI zones of higher (at the southern part of the experimental field)

Fig. 5 Classified CWSI values overlaying the thermal mosaic of the experimental field plot



and lower (the northern part of the field) values. This pattern was assessed by the GIS-based IDW method for spatial interpolation performed using values of every individual tree (Fig. 6a).

When it is impractical to obtain thermal images of the entire orchard in a frequency relevant to monitoring water status (1–2 days), periodic spatial information can be employed to choose representative trees for manual or continuous monitoring. Choice of the representative trees can be made based on criteria most important to the farmer, i.e. the overall distribution strategy, the median based strategy, or the tails based strategy.

The number of sensors needed to represent the histogram is an important question not dealt with in this current study. However, we can generally assume that the larger the number of sensors the better, and that final choice of number will be determined by the sensors' cost relative to the value of expected changes in yield. In this study, each of the three strategies was examined for choosing either five or ten sensor locations. In the overall distribution strategy, the five sample set was based on the values which best summarized the data distribution, i.e. the minimum, maximum, median, 1st quartile and 3rd quartile values. For the ten sample set additional values were selected which represented the overall

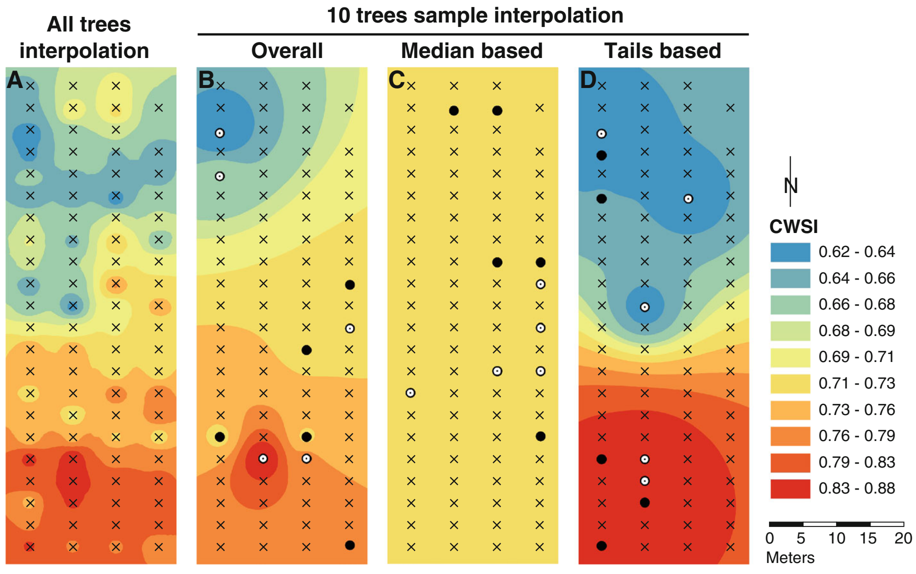


Fig. 6 IDW interpolation maps based on: **a** all 86 trees in the experimental field; **b** the ten-trees sample based on the overall histogram; **c** the ten-trees sample based on the median values; and **d** the ten-trees sample based on the tails of the histogram. The *white open circles* represent the location of the five-sample trees and the *black full circles* represent the location of the additional trees for the ten-trees sample (highlighted within the histograms in Fig. 7). All five-sampled trees are included in the ten-trees sample

distribution. Selected samples are highlighted on the histogram of the 86 sample distribution (Fig. 7a, d for the ten and five sampled trees, respectively). In the median based strategy, the sampled trees were chosen from the median range (Fig. 7b, e), and in the tails based strategy sampling was selected from the tails of the distribution (Fig. 7c, f).

To evaluate the sampling method spatially and to assess how well spatial variation was represented, the ten-sample sets were interpolated using an IDW method (Fig. 6b–d) and results were compared with the original 86 sample interpolation (Fig. 6a). Five samples were not sufficient for creating a meaningful and reliable interpolation therefore interpolation was not performed. The five locations chosen based on the three methods are overlaid on the ten-location interpolations (Fig. 6b–d). The spatial variability of the interpolation of the ten sample set based on the overall distribution (Fig. 6b) most resembled the spatial variability of the interpolation for all 86-trees (Fig. 6a) (RMSE = 0.036). The tails based interpolation (Fig. 6d) also followed a spatial distribution pattern similar to the one exhibited in the interpolation of the 86 samples, albeit to a lesser extent (RMSE = 0.051). The median based interpolation (Fig. 6c), where representative trees were chosen from the narrow range in CWSI values around the median, resulted in the lowest accuracy (RMSE = 0.062) with all values falling within the same category, thus, in this case, providing no additional spatial information. Note that although RMSE values for all interpolations were small, due to the narrow data range, the RMSE of the overall based interpolation was about half of the RMSE of the median based interpolation. It is not surprising that the overall based interpolation resulted in spatial patterns most closely resembling the actual spatial distribution of an orchard. The other two methods (tails based and median based) are presented here to show the flexibility of the

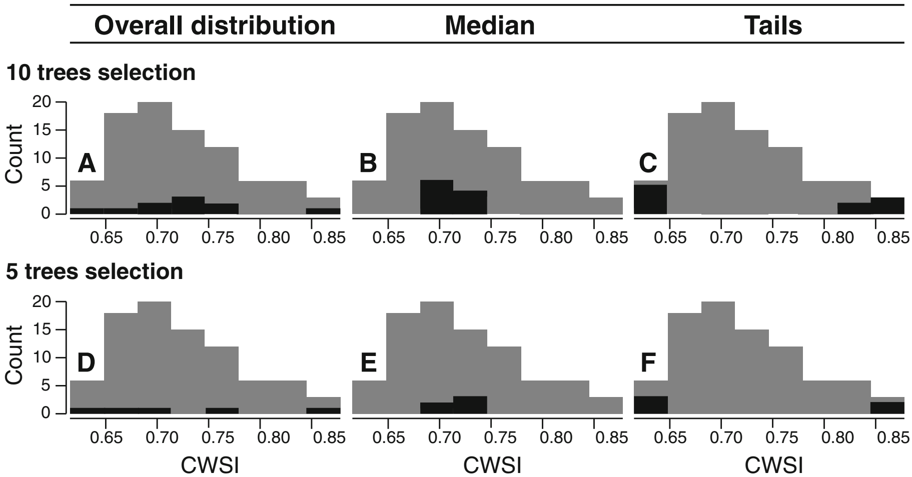


Fig. 7 Selection of ten (**a–c**) and five (**d**, **e**) sample trees (*black bars*) based on the overall distribution (**a**, **d**), the median (**b**, **e**) and the tails (**c**, **f**). Selection is highlighted within the CWSI histogram of the entire field plot (86 trees)

proposed method to provide interpolations that will best reflect a farm manager's interest and needs.

The proposed histogram-based sampling method provides a simple and fast decision-support tool to spatially recognize the location and distribution of trees based on their specific water status. In addition, it provides a method to select which condition of trees to concentrate on and monitor: whether the extreme cases, the most frequent cases or the cases which best represent the overall data distribution in terms of orchard water status. Using this tool, thermal images of the orchard may be taken once to several times throughout the year, from which the representative trees for monitoring are chosen. The number and timing of thermal image acquisition should be studied to test the temporal variability of the spatially distributed histogram (i.e. to test the extent of the representativeness of the selected trees).

Conclusions

We have demonstrated that mild water stress can be identified and quantified by thermal images. We have further shown that data from remote thermal imaging can aid selection of trees for sampling or of placement of continuous water status sensors. The number of monitored trees needed to well represent an orchard will depend on orchard size and variability but will be significantly less than if placed randomly. Sensor placement will vary depending on the manager's objective: to best represent the entire orchard or to advance precision horticulture by spatially representing the orchard's variability. In either case, the technology and methods are expected to promote olive orchard profitability and to conserve water and other resources.

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