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Comparison of canopy extraction methods from UAV thermal images for temperature estimation: a case study from a peach orchard

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Abstract.

Crop water status estimation based on thermal imaging is highly sensitive to the accuracy of canopy extraction, causing inaccuracies in irrigation decisions. Presently, there is not one accepted canopy extraction method nor is there a quantitative sensitivity evaluation of thermal-based crop water status estimations to canopy extraction accuracy. The main objective is to compare the existing canopy extraction methodologies, utilizing a large database of UAV thermal images. In the literature, two main canopy extraction approaches are found: the first approach uses only one thermal infrared (TIR) image (1-source) while the second combines TIR and RGB or multispectral images (2-source). We compared three methods: 1) 2-pixel erosion (2PE) where non-canopy pixels were removed by thresholding followed by morphological erosion (1-source); 2) Edge detection (ED) where edges were identified and then morphologically dilated (1-source); 3) Canopy pixels were identified from an RGB image and used as a binary canopy mask of a thermal image (RGB-BM) (2-source). Ten high-resolution UAV thermal images were acquired in a 4 ha commercial peach orchard in northern Israel during the primary stage of fruit growth (stage III) of 2019. The orchard was divided into 22 management cells (MC). The canopy extraction methods yielded differences in canopy area stability over time, accuracy, reliability, kappa, and temperature estimation. The median canopy area values of the 22 MCs ranged from 374 to 430 m^2 (2PE), 288 to 460 m^2 (ED) and 414 to 474 m^2 (RGB-BM), indicating higher stability, and therefore quality of 2PE as compared to the ED method. The kappa values were 0.54 (ED), 0.66 (2PE) and 0.80 (RGB-BM) indicating that the RGB-BM method was the most accurate. However, a notable difference was found between the two approaches in canopy temperature estimation, as indicated by histogram and visual *analysis. Many between-row grasses were misidentified as peach canopy pixels with the 2-source approach, resulting in a skewed right distribution of temperature and higher average temperatures compared with the 1-source approach. These differences can directly affect crop water status estimations and ensuing irrigation decision-making. Precision agriculture toolbox could benefit from the above comparison improving irrigation management capabilities.*

Keywords.
remote sensing, spatial analysis, confusion matrix, canopy pixels, canopy temperature, crop water status.

Introduction

Crop water status estimation can be significantly affected by the extraction of canopy pixels from a thermal image. Misidentification of soil and mixed pixels as canopy pixels can alter the canopy temperature calculation and thus the crop water status (Zhou et al. 2021). Canopy extraction approaches incorporating thermal imagery include methods that use a single thermal infrared (TIR) image (1-source) and others that use a TIR image and an additional remotely sensed image, usually RGB (2-source). One-source methods include canopy extraction by purely threshold-based statistical analysis and coupled statistical and spatial analyses. Statistical analysis of a temperature histogram to identify canopy pixels within a thermal image was performed in orchards (Rud et al. 2015; Egea et al. 2017) where canopy can be distinguished from soil. Temperature histograms are characterized by a bimodal distribution, where the canopy and soil pixels are represented by the cooler and warmer peaks, respectively. Mixed pixels, combinations of canopy, soil, weeds, and shade in a single pixel and generally compose the “saddle” area between the two peaks. Depending on the crop architecture, the distance between plants and the degree of complexity, there can be significant overlap between mixed pixels, pure-canopy and pure-soil, creating a challenge in identifying pure-canopy pixels. Also, water-stressed trees may have higher canopy temperatures and could be misidentified as mixed or soil pixels (Agam et al. 2013). Additional 1-source methods include delineation of regions-of-interest of a single canopy (Zhou et al. 2021) as well as pure edge detection analysis (Bian et al. 2019).

An additional group of 1-source methods incorporates statistical and spatial analyses of a single thermal image. Spatial watershed segmentation has been coupled with binary thresholding to extract pure canopy pixels in palm trees (Cohen et al. 2012) and in vineyards (Baluja et al. 2012). Camino et al. (2018) incorporated watershed segmentation and quartile histogram analysis in an almond orchard. In peach orchards, one technique involved thresholding to remove non-canopy pixels and then morphological erosion to remove mixed-pixels and to extract the pure-canopy (Katz et al. 2022). A second method used edge-detection algorithms followed by morphological dilation to remove mixed pixels (Park et al. 2017). The incorporation of two types of analyses on one thermal image claims to improve the quality of canopy extraction.

In general, 2-source methods are based on statistical analysis of a visible (RGB) or multispectral image to extract the canopy pixels which is then used as a binary mask that is superimposed on a thermal image. This technique has been implemented in crops including potato (Rud et al. 2014), mint (Osroosh et al. 2018), and grape (Zhou et al. 2022). Poor overlap of RGB and thermal images can cause misidentification of canopy pixels.

Presently, there is not one accepted canopy extraction method, although several techniques are described in the literature. Additionally, a sensitivity analysis of canopy extraction accuracy on temperature and crop water status estimation is missing. This study tested the hypothesis that the canopy extraction method based on thermal imaging significantly affects the extraction quality, namely canopy area stability and accuracy. The objective was to test this hypothesis by comparing the canopy extraction quality of three different methods: 1) 2- Pixel Erosion (2PE) (1-source approach); 2) Edge Detection (ED) (1-source approach); 3) Binary canopy mask extracted from the RGB image (RGB-BM) (2-source approach) to extract canopy pixels from a thermal image.

Methods

Research area

The study was conducted during season 2019 in a 4 ha commercial late-harvest peach orchard (*Prunus persica cv. 1881*) located near Mishmar Hayarden, Israel (33.01°N; 35.60°E). The orchard was planted in 2007 with spacing of 2.6 m and 5 m between trees and rows, respectively and was divided into 22 management cells (MC) of 35 m X 35 m to enable a precision drip irrigation regime that was implemented and described in Katz et al. (2022).

Imaging acquisition

Ten thermal images were acquired during growth stage III, the primary stage of fruit growth and period of peak irrigation, between 21 July and 26 Aug 2019. A FLIR SC655 camera (FLIR® Systems, Inc., Bilerica, MA, USA) with 640 X 480 resolution was mounted on a 6-engine drone (Datamap Group, Bnei Brak, Israel). The flight height for all campaigns was 100m and the subsequent ground spatial resolution was approximately 7 cm. All campaigns were conducted midday between 12:30 and 15:15. The mosaic was created using the ThermaCam software (FLIR® Systems, Inc., Bilerica, MA, USA) and Pix4D mapper software (Pix4D, Prilly, Switzerland). All of the thermal images were then resampled to the average pixel size of the ten images, 7.3737 cm.

Two RGB images were acquired on 21 July and 12 Aug 2019 immediately prior to the respective thermal image campaign using the Phantom 4 Pro V2 (DJI Technology Co., Ltd., Shenzhen, China). The ground spatial resolution was approximately 3 cm.

Canopy extraction methods

The following canopy extraction methods were implemented in this study using ArcGIS Pro software (ESRI, Redlands, CA, USA).

2-Pixel Erosion (2PE) – 1-source approach

1) Extraction of the lowest two thirds of the temperature pixels from the whole orchard histogram to remove mixed and soil pixels (Katz et al. 2022) (statistical); 2) Morphological erosion of two pixels (Dag et al. 2015) (spatial). The temperature values per pixel were retrieved by multiplying the final layer of canopy pixels by the original thermal image.

Edge detection (ED) – 1-source approach

1) Image sharpening with high pass filter (spatial); 2) Thresholding to determine edges (statistical); 3) Morphological expansion of three pixels (spatial); 4) Thresholding to extract canopy pixels only (statistical) (Park et al. 2017). The temperature pixels were retrieved by multiplying the final layer of canopy pixels by the original thermal image.

RGB binary masking (RGB-BM) – 2-source approach

1) With the RGB image, the excess green index (ExG) (2G-R-B) was calculated per pixel and then resampled to 7cm for synchronization with the thermal images. The ExG index is considered to sufficiently differentiate between plants and soil pixels (Hamuda et al. 2016); 2) Otsu thresholding (Otsu, 1975) of the ExG layer to remove mixed and soil pixels (statistical); 3) Masking

of the thermal image with the ExG layer (spatial) (Osroosh et al. 2018).

Evaluation of canopy extraction quality

The quality of canopy extraction was determined by measuring the canopy area per MC of different images and dates as well as assessing the accuracy of each method (ArcGIS Pro software, ESRI, Redlands, CA, USA).

Canopy area stability

Vegetative growth of peach trees is minimal to non-existent during this growth stage (Steduto et al. 2012). Therefore, the canopy area stability can be used as a measure of extraction quality. Canopy area stability was evaluated for the 2PE, ED and RGB-BM methods by calculating the canopy area (m^2) per MC ($n = 22$). The median values were compared between two dates, 21 July and 12 Aug, and the student t-test was used to compare the mean canopy area of these dates per method. Additionally, the coefficient of variation (CV) was calculated with the canopy area median values for the entire ten-day period of data acquisition for the 2PE and ED methods.

Accuracy assessment

Accuracy assessment was based on a single date, 12 Aug 2019, when all three methods were performed. For each method, all orchard pixels were reclassified into two categories using the final extraction layer: pure canopy and soil. One hundred sample points were divided equally between these categories. Synchronization between the final extraction layer (thermal or other) and RGB ground truth image was verified. Ground truth validation was visually determined with the original RGB image from the 12 Aug. The accuracy (producer's accuracy) and reliability (user's accuracy) of the canopy classification, the overall accuracy and kappa values were calculated. These parameters provide another measure of canopy extraction quality.

Temperature estimation

The temperature of all extracted canopy pixels was retrieved and estimated. A histogram was built per MC and the respective canopy temperature was calculated by averaging the coolest 33% of canopy pixels (Meron et al. 2010).

Results

Differences in canopy area stability patterns over time were recorded between the tested extraction methods (**Fig. 1**). A difference in canopy area was recorded between the two RGB-BM images on 21 July and 12 Aug: the median values were 414 and 474 m^2, respectively. This is a difference of 60 m^2 while minor differences were observed between these dates with the 2PE and ED methods: 6 and 4 m^2, respectively. As a result, a significant difference in canopy area mean (increase) was calculated between these two RGB-BM images ($p < 0.001$), while no difference was calculated for the 2PE and ED methods ($p > 0.05$).

The 2PE method appeared to be the most stable, with median values per date ranging from 374 to 430 m^2 (a difference of 56 m^2). The median values of the ED method ranged from 288 to 460 m^2 (a difference of 172 m^2, 3-fold of the 2PE method), indicating less stability over time. The difference in stability between the 2PE and ED methods is also demonstrated in the coefficient of variation (CV) values of 0.05 and 0.13, respectively.

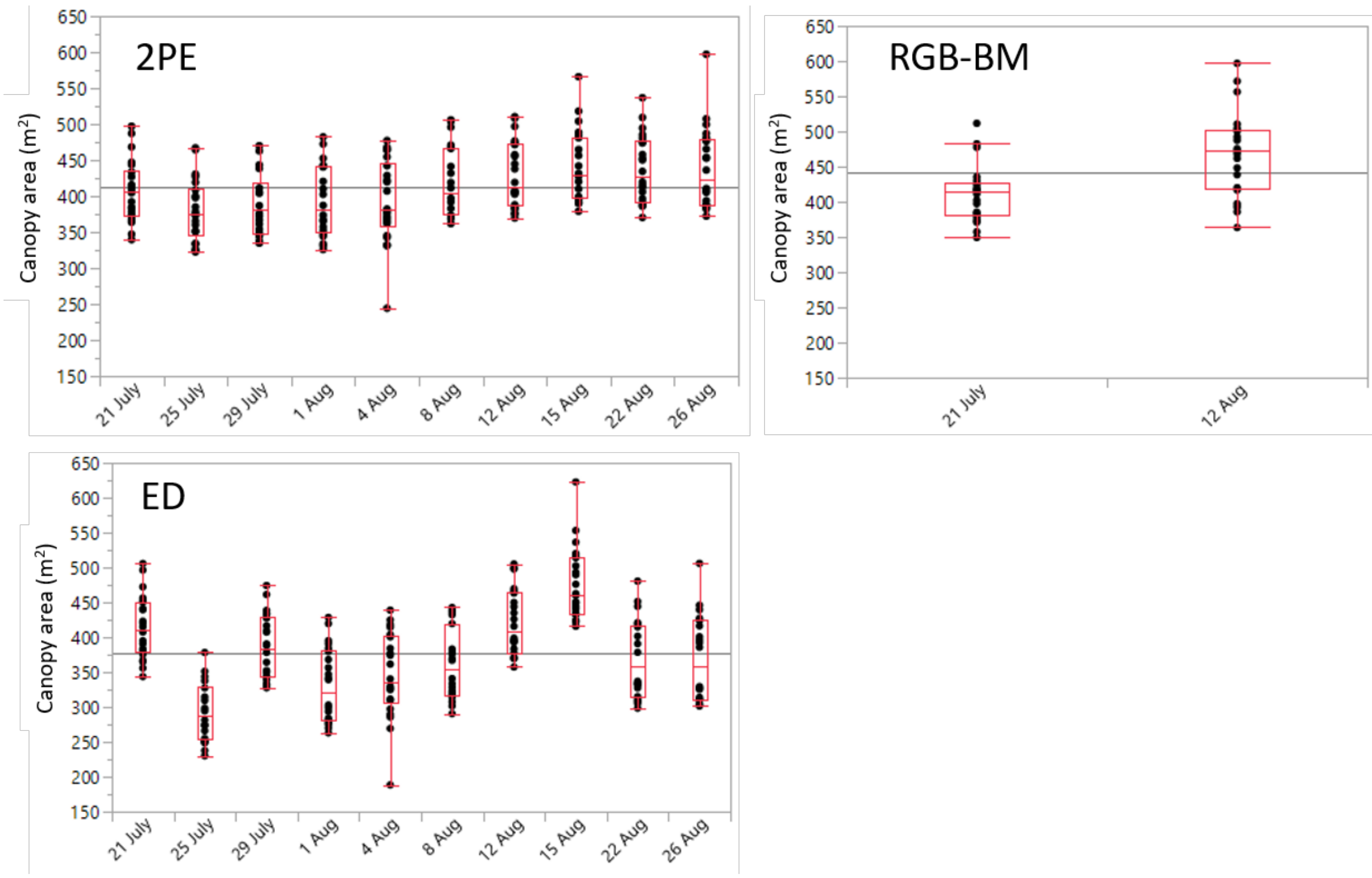


Fig. 1 Canopy area (m^2) per management cell (MC) (black dot) and (red) box plot per day between 21 July and 26 Aug 2019 for 2-Pixel-Erosion (2PE), Edge Detection (ED), and RGB-BM methods of canopy extraction. Horizontal black line is the grand mean.

Accuracy assessment of the 2PE, ED and RGB-BM methods illustrated that the RGB-BM method was the most accurate (**Table 1**). This is demonstrated through high values for all of the calculated parameters: accuracy (100%) and reliability (80%) for pure-canopy classification, overall accuracy (90%) and kappa (80%). The 2PE method was also substantially accurate for pure-canopy classification (87%), overall accuracy (83%) and kappa (66%). All of the ED accuracy parameters were the lowest of the three methods.

Ground truth

Classification

2PE

Class	Non-canopy	Pure - canopy	Total	U_Accuracy	Kappa
Non-canopy	44	6	50	0.88	
Pure - canopy	11	39	50	0.78	
Total	55	45	100		
P_Accuracy	0.8	0.87		0.83	
Kappa					0.66

ED

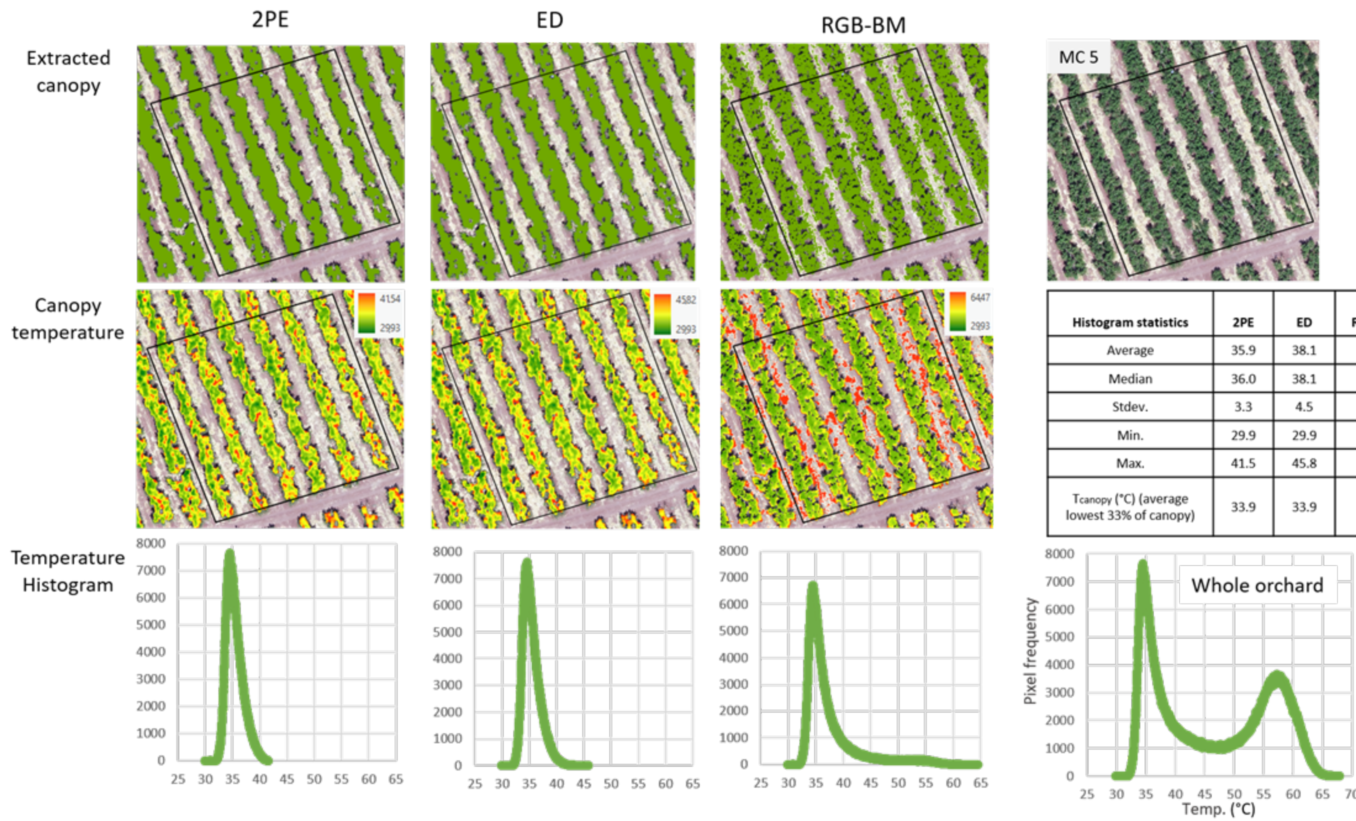
Class	Non-canopy	Pure - canopy	Total	U_Accuracy	Kappa
Non-canopy	43	7	50	0.86	
Pure - canopy	16	34	50	0.68	
Total	59	41	100		
P_Accuracy	0.73	0.83		0.77	
Kappa					0.54

RGB-BM

Class	Non-canopy	Pure - canopy	Total	U_Accuracy	Kappa
Non-canopy	50	0	50	1	
Pure - canopy	10	40	50	0.8	
Total	60	40	100		
P_Accuracy	0.83	1		0.9	
Kappa					0.8

Table 1 Confusion matrix for accuracy assessment of 2-Pixel-Erosion (2PE), Edge Detection (ED), and RGB-BM methods of canopy extraction from 12 Aug images.

Differences between canopy extraction methods are exemplified by a qualitative (visual) and quantitative comparison of extracted canopy pixels and temperature values of MC 5 on 12 Aug images (**Fig. 2**). Similar results were obtained for the additional MCs. The spatial distribution of extracted canopy pixels was similar for the 2PE and ED methods and both were relatively course. The RGB-BM method, however, was able to detect slight differences between canopy and non-canopy pixels within the tree canopy. Additionally, the RGB-BM method noticeably misclassified many between-row pixels as canopy. The strips of soil between tree rows were free of tree canopy but often full of weeds and grass. The ExG index seemingly had difficulty differentiating between the different types of plant material. This was also apparent in the temperature map, where the RGB-BM between-row pixels were substantially warmer than the tree rows. The respective temperature histogram supported this finding, indicating that the warm "tail" pixels included mixed and soil pixels. The temperature range of extracted canopy pixels using the 2PE (30 - 42°C) and ED (30 - 46°C) methods are similar (ED range slightly wider) but substantially narrower than the RGB-BM method (30 – 64°C). Calculated temperature canopy values were 33.9 (2PE), 33.9 (ED) and 34.1 (RGB-BM).



Histogram statistics	2PE	ED	RGB-BM	Whole orchard
Average	35.9	38.1	46.5	49.1
Median	36.0	38.1	46.5	49.1
Stdev.	3.3	4.5	9.3	10.8
Min.	29.9	29.9	29.9	29.9
Max.	41.5	45.8	64.5	67.9
T_{canopy} (°C) (average lowest 33% of canopy)	33.9	33.9	34.1	

Fig. 2 Extracted canopy, canopy temperature, and temperature histogram for management cell (MC) 5 (black outline) on 12 Aug 2019 using of 2-Pixel-Erosion (2PE), Edge Detection (ED), and RGB-BM methods of canopy extraction. Table insert of histogram statistics.

Discussion

Differences between the one and two-source analysis approaches affect the quality of canopy extraction as seen in comparing the 2PE, ED and RGB-BM methods (**Table 2**). Substantial differences are evident between the one and two-source approaches in both accuracy and between-row pixel misidentification, as apparent in temperature estimation. There appears to be a tradeoff between accuracy and temperature estimation. The ground truth layer (RGB) is also the basis of the RGB-BM method and thus improves the canopy extraction accuracy compared to the thermal-based methods. However, the ExG index and Otsu thresholding incorporated into this method misidentify a noticeable amount of between-row pixels as canopy pixels. The misidentified pixels appear to be grasses (identified as white/light green pixels in the original RGB) or mixed pixels that were indeed present between the tree rows. The grasses are a type of microcosm within the peach orchard. They are distanced from the irrigation lines but evidently thrive from excess water in the soil system. For the most part, the grasses grow close to the ground and are surrounded by very warm soil. Therefore, the temperature of the grasses is higher than that of the peach tree canopy. RGB-BM, in contrast to the 2PE and ED methods, was not able to completely differentiate between these types of vegetation.

Table 2. Comparison of canopy extraction approaches (1-source and 2-source) and methods (2-Pixel erosion (2PE), edge detection (ED), and RGB binary masking (RGB-BM).

Analysis approach	Method	Method description	Stability	Accuracy (Kappa)	Between-row pixel misidentification	Detection of subtle differences between pure and non-canopy pixels
1-source (thermal infrared)	2-Pixel erosion (2PE)	Statistical and spatial analysis	stable	Substantial (0.66)	Almost none	No
1-source (thermal infrared)	Edge detection (ED)	Statistical and spatial analysis	Less-stable	Moderate (0.54)	Almost none	No
2-source (thermal infrared and RGB)	RGB binary masking (RGB-BM)	Statistical analysis and binary masking		Substantial (0.80)	- Noticeable (degree varies by area) - Warm pixels characterize the histogram “tail”.	Yes

The differences in canopy extraction quality can affect the calculated T_{canopy} value (**Fig. 2** table insert). The T_{canopy} of MC 5 following the RGB-BM extraction method was 0.2 °C higher than the 2PE and ED methods. This is a relatively small difference and indicates that using the lowest 33% of temperature pixels to calculate T_{canopy} is a fairly robust method that appears to be less influenced by the histogram tail than other methods. T_{canopy}, for example, has been calculated in the literature using the mean (Gonzalez-Dugo et al. 2015) and median (Gonzalez-Dugo et al. 2013) of extracted canopy. Using RGB-BM extraction coupled with the mean or the median values to calculate the T_{canopy} of MC 5 would produce differences of approximately 10.6 °C higher than the 2PE method, emphasizing the differences between canopy extraction methods. These differences stem from the different temperature histograms resulting from the canopy extraction methods: the RGB-BM approach produced a skewed right distribution characterized by a long "tail" of warm pixels and therefore a higher average temperature was calculated compared with the normally distributed SS approach.

Future research can enrich the insights on canopy extraction drawn from this experiment. First, the addition of data from a purely statistical canopy extraction approach would add depth to the comparison. Also, the analysis of the RGB-BM method from additional days throughout the experiment would shed light on the accuracy of each method over time and enable the calculation of canopy stability. Lastly, the T_{canopy} of each MC per image and per extraction method can be calculated, thus improving the understanding of how canopy extraction affects temperature and crop water status estimation over space and time.

Conclusion

This study aimed to determine to what extent the canopy extraction method incorporating thermal imaging affects the extraction quality, including canopy area stability and accuracy. The 2PE and ED (1-source) and RGB-BM methods (2-source) were compared. The extracted canopy area was more stable using the 2PE than the ED method. The RGB-BM technique was found to be more accurate compared to the other methods. However, many between-row pixels, most likely of grasses and mixed pixels, were misidentified as peach canopy pixels, reducing the overall quality of this method. The largest differences in calculated canopy temperature were found between the RGB-BM and 2PE methods when the mean or median metrics were used to characterize the canopy temperature, indicating that the canopy extraction method affects the canopy temperature. An additional analysis of canopy temperature per MC and per method using the current database would deepen the understanding of canopy extraction and its impact on crop water status estimation, and as a result, refine current techniques.

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