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Multisite evaluation of microtensiometer and osmotic cell stem water potential sensors in almond orchards

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ABSTRACT

In the face of climate change, optimization of almond irrigation management is critical for ensuring the long-term sustainability of nut production and water resources. To achieve optimal irrigation management, continuous monitoring of the plant water status is critical in scheduling irrigation. It is a widely accepted practice to use stem water potential (SWP) as a measure of plant water status in woody perennials like almonds. However, the pressure chamber (PC) commonly used to make these measurements is labor-intensive and does not provide continuous data without significant additional labor. In this study, we evaluated two recently developed stem water potential sensors (Microtensiometer [MT], and Osmotic Cell [OC]), both of which can measure the SWP nearly continuously when embedded in stem sapwood tissue (typically in the trunk or branch of a tree). SWP sensors were evaluated in nine commercial almond orchards in the Central Valley of California. The SWP values obtained from both sensors were compared to the values measured using a PC using statistical software called FITEVAL. Overall, sensor performance varied from good to acceptable and from acceptable to unacceptable for MT and OC sensors respectively. The MT sensors demonstrated higher accuracy with a Nash-Sutcliff Coefficient of Efficiency (NSE) of 0.84 (95 % CI: 0.78–0.88) and a Root Mean Square Error (RMSE) of −0.24 MPa (95 % CI: −0.21 to −0.28 MPa), while the OC sensor had an NSE of 0.68 (95 % CI: 0.61–0.74) and an RMSE of −0.32 MPa (95 % CI: −0.29 to −0.35 MPa). MT sensors exhibited the added advantage of providing sub-hourly data and displaying tree recovery from water stress following irrigation, positioning them as potentially superior for precision almond orchard water management. If widely adopted, SWP sensors have the potential to optimize water use in almond production.

1. Introduction

Considering its Mediterranean climate, the prevalence of fertile soils in the Central Valley, and its extensive water supply infrastructure, California accounts for 80 % of global almond production (Alonso et al., 2012). Almonds generated the second largest economic revenue after grapes in California in 2021 ("CDFA - Statistics," 2024). Almond production consumes nearly 10 % of California's annual available agricultural water supply (Holthaus, 2014). Almond growers typically use groundwater for irrigation when surface water supplies are curtailed during droughts. However, in 2014 as a response to the negative consequences of groundwater overdraft, the State of California enacted the landmark Sustainable Groundwater Management Act (SGMA), which has restricted groundwater pumping for irrigation in some areas. Almond growers are now faced with a future in which they must produce almonds with limited and uncertain water supplies. Consequently, enhancing the water use efficiency of almond production is now imperative.

Climate change, regulation of water resources, and competition for water from other beneficial uses have placed increased pressure on the

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agricultural sector to use water more efficiently to secure future water supplies (Hayhoe et al., 2004; Parker et al., 2021; Peddinti and Kisekka, 2022). The most common methods used to guide irrigation scheduling in almonds are based on either soil water content or weather-based approaches, such as evapotranspiration and crop coefficients (Cahn and Johnson, 2017; He et al., 2017; Kisekka, 2023; Peddinti and Kisekka, 2022). However, there is uncertainty when making irrigation decisions without directly measuring plant water status as an integrated indicator of soil, climate, temporal, and spatial variability within the orchards. Automatic, direct measurements of the plant-water status of trees represent an important step toward precision irrigation. For a long time, the pressure chamber (PC) has been the only accurate tool to reliably measure stem water potential (SWP), but the high labor needs required decreases the frequency of its use. A survey by the Almond Board of California revealed that only 31 % of growers use the PC to guide irrigation decisions. In contrast, 89 % use the hand-feel method to assess soil moisture, and 75 % rely on evapotranspiration-based irrigation scheduling (Kisekka, 2023).

Critical SWP values vary according to the phenological stages of almond trees, including dormancy, bloom, fruit set, hull split, and harvest periods (Micke, 1996). These stages require careful monitoring to optimize water management and ensure tree health and productivity. During dormancy, SWP values typically range from −0.8 to −1.2 MPa, reflecting the minimal water needs of the tree. During the bloom stage, critical SWP values should be maintained between −0.8 to −1.0 MPa to ensure adequate water supply for bud development and flowering. For the fruit set stage, SWP values should range from −1.0 to −1.2 MPa to support fruit development without inducing water stress. The hull split stage is particularly critical, where SWP values need to be managed between −1.2 to −1.4 MPa to prevent hull rot and other abiotic stress-related issues. During the harvest stage, maintaining SWP values between −1.0 to −1.2 MPa is important for tree recovery and preparation for the next growing season (Micke, 1996). Thresholds for moderate to severe water stress in almonds are generally considered as follows: SWP values between −1.4 to −1.8 MPa indicate moderate stress, potentially leading to reduced growth and yield if prolonged, while SWP values exceeding −1.8 MPa signify severe stress, which can cause significant damage to the tree's health and productivity (Micke, 1996).

SWP measurements made using PC provide valuable information for guiding irrigation decisions; however, the process of acquiring the data is laborious and requires specialized personnel i.e., going to the orchard at solar noon, bagging sample leaves in the lower tree canopy to create non-sunlit and non-transpiring leaves, and then manually excising the sample leaves from the trees and taking PC readings (Fulton et al., 2014). The selected leaf is typically covered in a reflective plastic envelope for at least 10 min to allow the water potential of the sample leaf to equilibrate with the water potential (tension) in the active woody tissue (xylem) before PC readings are made. The recommended method that is currently used to account for the direct effects of weather conditions (air Vapor Pressure Deficit, VPD) on SWP at the time of measurement is the so-called 'baseline' SWP (i.e., non-soil–water limited SWP) (McCutchan and Shackel, 1992). VPD is typically determined using the ambient air temperature and relative humidity (Fulton et al., 2014, 2001). Measuring SWP in almonds with a PC typically only provides intermittent mid-afternoon values of SWP, and the desire to automate this process for higher frequency measurement of SWP has led to the commercial development of the Microtensiometer (MT) (Pagay, 2021) and Osmotic Cell (OC) (Blanco and Kalcsits, 2021; Meron, 2019) SWP sensors.

2. Microtensiometer stem water potential sensor working principle

The MT sensor is a sophisticated sensor designed to measure the water potential in plant tissues with high precision and continuous monitoring capability. This sensor operates based on the principles of microfluidics and tensiometry (Pagay, 2022; Stroock et al., 2014), specifically designed to handle the challenges of measuring negative pressures in plant xylem, where the water is often under significant tension. Fig. 1 depicts the key components of the MT sensor . It presents the microfabricated silicon chip, the water reservoir, the porous membrane, and the pressure transducer.

The microfabricated silicon chip houses a micro-scale water reservoir in contact with a porous membrane. This membrane is crucial for maintaining selective permeability, allowing only water vapor to pass through while preventing the movement of liquid water. The water potential within the reservoir equilibrates with the water potential in the surrounding plant tissue through the porous membrane. Changes in water potential cause corresponding changes in the pressure within the water reservoir, which are detected by a highly sensitive pressure transducer integrated into the silicon chip.

The initial setup involves inserting the MT sensor into an incision made in the xylem. This incision ensures that the porous membrane is in direct contact with the plant's vascular system, allowing for accurate measurement of the stem water potential. The micro-scale reservoir in the MT sensor is filled with a calibrated solution, typically water, which maintains a known water potential baseline. The MT sensor's design allows it to measure a wide range of water potentials, including very negative values that are common in plant xylem under transpiration stress.

During the operation, as the plant tissue's water potential fluctuates due to environmental conditions such as soil moisture levels and atmospheric demand, water vapor moves into or out of the reservoir. This movement causes changes in the reservoir's pressure, which are detected by the pressure transducer. The transducer converts these pressure changes into electrical signals, which are then processed by an on-board Micro Electro-Mechanical System (MEMS). The processed data is wirelessly transmitted to a central data logger for real-time monitoring and analysis. The continuous data transmission capability of the MT sensor allows for uninterrupted monitoring of water potential, providing critical insights into a plant's response to its environment and management.

3. Osmometer cell stem water potential sensor working principle

The OC sensor is designed to measure the water potential in plant tissues by utilizing the principle of osmometry (Meron, 2019, 2018; Meron et al., 2015). The sensor comprises a compartment with a rigid body that contains an osmoticum (Fig. 2), a substance capable of absorbing water. This compartment includes at least one opening, covered by a selective barrier, typically a semi-permeable membrane. This membrane allows the selective transfer of water between the plant tissue and the osmoticum while preventing the passage of solutes and other non-water molecules. The OC sensor is equipped with a pressure sensor that detects changes in pressure within the compartment (Fig. 2). These pressure changes are directly correlated to the water potential of the plant tissue. The device is inserted into the plant xylem, creating a direct hydraulic continuum with the plant's vascular system.

The initial setup involves carefully inserting the OC sensor into an incision made in the plant trunk or stem. The dimensions of the incision ensure a snug fit, allowing the external walls of the sensor to maintain direct contact with the plant tissue. The osmoticum compartment, containing a solution such as PolyEthyleneGlycol (PEG) or a hydrogel (Meron, 2019), is initially set to have a lower water potential than the expected minimum water potential in the plant tissue. This setup ensures that the sensor can accurately detect changes in water potential by allowing water to flow across the semi-permeable membrane due to the potential gradient between the plant tissue and the osmoticum.

During periods of high-water potential in the plant, such as after irrigation or at night, water moves from the plant tissue into the osmoticum compartment, increasing the internal pressure. Conversely, during periods of low water potential, such as during the day when the

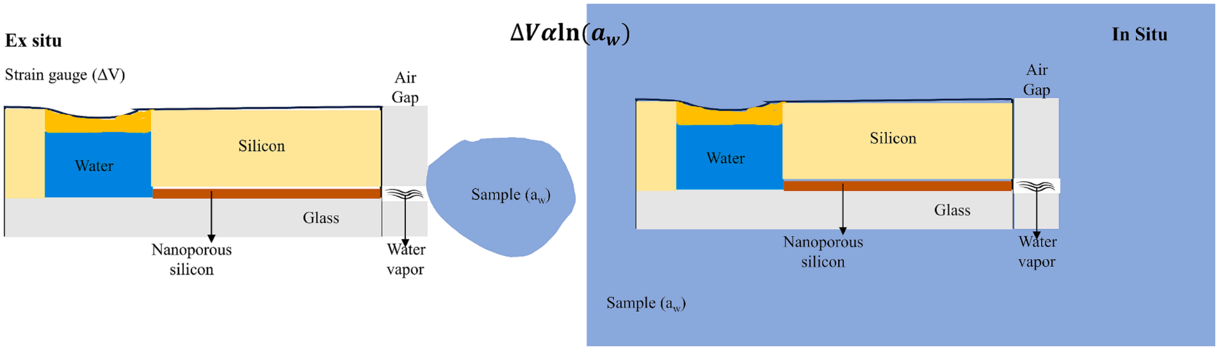

Fig. 1. A schematic of a microtensiometer (MT) stem water potential sensor with functional parts.

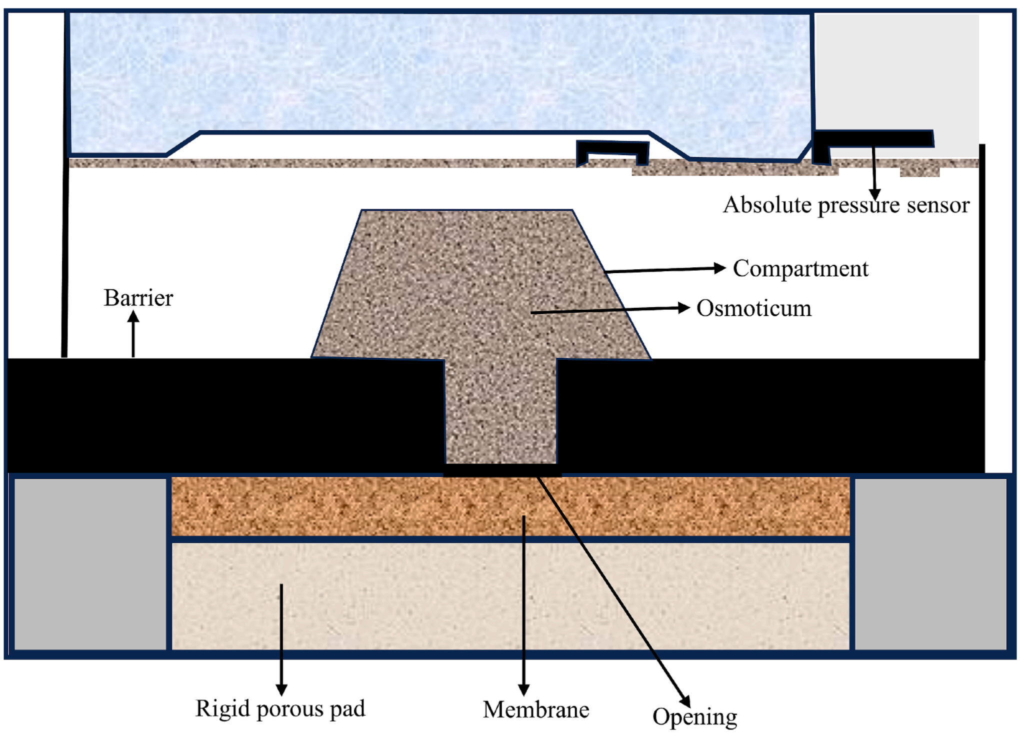

Fig. 2. A schematic of an Osmotic Cell (OC) stem water potential sensor with functional parts.

plant is transpiring, water flows out of the osmoticum compartment, decreasing the internal pressure. The pressure sensor within the OC sensor continuously monitors these pressure changes in the osmoticum compartment. These changes in pressure are related to stem water potential.

Almond growers have expressed the need to validate MT and OC sensor's accuracy vis-à-vis the PC. There are also research questions related to the diurnal variations in SWP in relation to the environment and management. An investigation conducted by (Blanco and Kalcsits, 2021) in pear orchards confirmed the efficacy of the MT sensor by corroborating SWP measurements against the PC. Their findings unveiled a robust linear relationship between SWP-MT and SWP-PC, exhibiting an R^2 value exceeding 0.8. Also, several studies have demonstrated the efficacy of stem water potential in enhancing irrigation management practices (Abrisqueta et al., 2015; Martí et al., 2013; Mucchiani and Karydis, 2024; Ohana-Levi et al., 2022; Valdés-Vela et al., 2015). These advancements provide a robust framework for optimizing water usage and improving crop yield through precise and predictive irrigation strategies.

However, the assessment of the performance of MT and OC SWP sensors in almonds is currently lacking in the literature. Thus, this study endeavors to fill this research gap by evaluating the performance of MT and OC sensors compared to the PC, which serves as the benchmark, in various commercial almond orchards in California's Central Valley. Additionally, this study evaluated the repeatability of MT sensors on the different almond trees to accurately capture diurnal SWP dynamics. We hypothesize that MT and OC sensors can accurately measure SWP in almond trees, providing data comparable to the PC method. Furthermore, we hypothesize that MT sensors will effectively capture diurnal SWP fluctuations and respond to irrigation events, thereby providing useful feedback for precision irrigation management in almond orchards.

4. Materials and methods

4.1. Site description

Field evaluations were conducted throughout the 2020 and 2022 growing seasons in nine almond orchards in California's Central Valley as shown in Fig. 3. These orchards were named CAPEX, Gruenwald, CSUC, Nickels, Westwind, Jasleen, Sharma, UC Kearney, and Clark Ranch (Fig. 3). At each site, several specific almond trees were

Fig. 3. Study sites in the Central Valley of California, where Microtensiometer and Osmotic cell stem water potential sensors were installed in almond trees.

monitored (Table 1). Stem water potential (SWP) data were measured at weekly or biweekly intervals using the PC from the same trees, where either the MT or OC sensors were embedded into the tree trunk. Table 1 shows the number of monitored trees at each site and the respective soil type in the study area. These orchards represented commercial conditions throughout the almond production regions of California.

Table 1
Monitoring trees to assess stem water potential (SWP) using microtensiometer (MT), Osmotic Cell (OC) sensors, and Pressure Chamber (PC) at each site evaluated in this study, as well as the types of sensors installed, the crop season considered for analysis, and the respective soil types at each site.

Site name	Monitoring trees	Irrigation method	Sensor embedded	Season of analysis	Soil type
CSUC	6	Drip	MT	2022	Clay loam
CAPEX	13	Drip/ sprinkler	OC	2020	Sandy clay loam
Gruenwald	6	Drip	OC	2022	Sandy clay loam
Nickels	5	Drip/ sprinkler	OC	2020	Clay Loam
Westwind	4	Drip/ sprinkler	OC	2022	Clay Loam
Jasleen	3	Drip/ sprinkler	MT	2022	Clay Loam
Sharma	6	Drip	OC	2020	Clay Loam
Clark Ranch	9	Drip	OC	2022	Sandy clay loam
UC Kearney	2	Drip	MT	2022	Sandy clay loam

4.2. Stem water potential measurements

The MT (FloraPulse Inc., Davis, California, United States of America) and the OC (Saturas Ltd., Migdal HaEemeq, Israel) are the two commercially available SWP sensors that were evaluated in this study. These SWP sensors were embedded into the trunks of almond trees to obtain continuous measurements of SWP. The number of trees at each of the various study locations in the Central Valley where these sensors were installed is presented in Table 1. The OC sensors were installed by embedding them into the trunk of the almond tree. To prevent direct sunlight, which can impact readings, the sensor installations were shaded. The sensors were connected to a data logger that records SWP measurements at regular intervals, providing a single data point every day in the case of OC sensors (https://saturas-ag.com/). The MT sensors were installed by drilling a small hole into the tree trunk and inserting the sensor, ensuring effective contact with the xylem tissue. The installation area was then sealed with a waterproof sealant to protect the sensor. The MT sensors used in this study can provide the SWP data at regular intervals of 20 min. In addition, MT sensors contain two independent sensors for each data logger mounted on each tree. These two sensors serve as measurement error checks for each other and hence increase confidence in the sensor measurements when they closely match.

For comparison and ground truthing, the PC (Plant Moisture Stress (PMS) Instrument Company, Albany, OR, USA) was utilized to determine the SWP values for each of the selected almond trees (Table 1). Measurements were taken on two or three covered (non-transpiring) leaves from each tree in the lower canopy. The measurements were taken on a weekly to biweekly basis at all of the tree locations between 12:00 and 15:00 h (Fulton et al., 2014). Prior to the actual excision, the leaves were encased in a foil covered and plastic lined bag to prevent any post-excision water loss (Fulton et al., 2001). The leaves were bagged to equilibrate the water potential of the leaves with the water potential of the xylem sap in the stem. The SWP values obtained from each tree using the PC were compared with the SWP values obtained from the MT and

OC sensors. To address the timing difference between the instantaneous PC readings over the 3 h and the continuous measurements from the MT sensors, a time-averaging approach was employed. Specifically, we calculated the average SWP values recorded by the MT sensors between 13:00 and 15:00 h. This allowed for a meaningful comparison with the individual SWP values obtained from each tree using the PC. In the case of the OC sensor, which provides a single value of SWP, we used the single daily value to represent the 3 h under consideration. This approach was chosen to align with the available data and allow for a meaningful comparison with the instantaneous PC readings, considering that daily averages can reflect overall plant water status effectively.

4.3. Agrometeorological data

The climate data for the study period from 2020 and 2022, including average daily temperatures, relative humidity, vapor pressure deficit, and total precipitation data, were collected from the nearest CIMIS (California Irrigation Management Information System) stations corresponding to each site. For Jasleen (CIMIS No. 6), Sharma (CIMIS No. 212), Westwind (CIMIS No. 226), CAPEX (CIMIS No. 222), Nickels (CIMIS No. 250), Gruenwald (CIMIS No. 222), Clark Ranch (CIMIS No. 2), CSUC (CIMIS No. 12), and UC Kearney (CIMIS No. 39). The CIMIS weather station network is managed by the Department of Water Resources (DWR). The air temperature and humidity sensors were installed at a height of 1.5 m, and the rain gauge at 2 m. Vapor pressure was calculated from the measured relative humidity and air temperature data, providing an accurate indicator of atmospheric humidity. DWR has standardized procedures for network operations and maintenance to ensure accuracy. CIMIS employs stringent quality control processes to flag potential data discrepancies, such as sensor failures, weather anomalies, and communication disruptions, ensuring reliable climatological information.

4.4. Statistical analysis

The software application called FITEVAL (Ritter and Muñoz-Carpena, 2013) (https://abe.ufl.edu/faculty/carpena/software/FITEVAL.shtml) was used to perform the goodness-of-fit statistical evaluations of SWP values from the PC and two sensors (MT, and OC). In FITEVAL, the evaluation results are shown graphically and numerically. The graphs show the root mean squared error (RMSE), the Kling-Gupta efficiency (KGE), and a p-value based on the Nash and Sutcliffe efficiency coefficient (NSE). The null hypothesis (H_0) represents that the median NSE is less than the set threshold NSE below which goodness-of-fit for sensor performance is unacceptable ($NSE < NSE_{threshold}$). The null hypothesis (H_0) is rejected, and the alternative (H_1) is accepted when ($NSE \geq NSE_{threshold}$), the sensor performance is considered significantly acceptable when the *p-value* is less than α.

FITEVAL also provides an approximated probability distribution of NSE based on block bootstrapping and detects outliers and sensor bias (Politis and Romano, 1994). RMSE was used as a measure of the average size of the error between predicted (assumed the MT and OC sensor readings) and observed values (assumed the PC reading), with smaller values indicating better sensor performance. KGE is a comprehensive metric that considers bias, correlation, and variability, giving a fair evaluation of sensor accuracy where 1 is perfect. On the basis of the NSE distribution, the FITEVAL divides the performance of the sensor into the following four categories: very good (NSE = 0.90 to 1), good (NSE = 0.80 to 0.89), acceptable (NSE = 0.65 to 0.79), and unsatisfactory (NSE < 0.65).

5. Results

5.1. Agrometeorological data analysis

The weather data (Fig. 4) from the nine study locations in the Central Valley of California were analyzed for the period spanning the 2020 to 2022 almond season. The geographical distribution of the study sites is shown in Fig. 3, highlighting the differences in climatic conditions across the Central Valley. The agrometeorological data included air temperature, relative humidity, vapor pressure, and precipitation. Key almond growth stages such as Dormancy, Bloom, Fruit Set, Hull Split, and Harvest are indicated with vertical dashed lines in Fig. 4 to provide context regarding weather conditions during these critical periods.

Across all locations, the temperature and vapor pressure followed a clear seasonal pattern, with peaks during the summer months. This seasonal temperature variation is critical for almond phenology. During the dormancy stage, which typically occurs in the winter months, cooler temperatures and higher humidity levels were prevalent. Almond trees require enough cold temperatures or Chill hours (200–300 h of temperatures below 7.2 degrees Celsius) in the winter to break dormancy. Exposure to sufficient winter cold is necessary for the normal growth of flowers and shoot buds.

As the almond trees transitioned into the bloom stage, generally occurring in late winter to early spring, the data showed a gradual increase in temperatures and a decrease in relative humidity. Adequate chill hours accumulated during the dormancy period are crucial for synchronized and successful blooming. The onset of bloom coincided with rising temperatures and moderate humidity levels, which are favorable for pollination. However, precipitation during this period could adversely affect bloom and pollination processes by washing away pollen and limiting bee activity.

The weather conditions during fruit set showed a continued rise in temperature and decreasing humidity, coupled with lower vapor pressure. These conditions are generally beneficial for fruit set provided sufficient water is available from winter precipitation or irrigation to crop water needs.

As the trees advanced to the hull split growth stage, which typically takes place in mid to late summer, temperatures were at their peak, and humidity levels were at their lowest. High temperatures and low humidity during this stage are advantageous as they facilitate the drying and splitting of the hulls, which is necessary for harvesting. However, extreme heat and insufficient water availability could stress the trees, potentially affecting nut quality and yield.

The harvest stage usually occurs in late summer to early fall, where the data indicate sustained high temperatures and low humidity. These conditions are ideal for drying the nuts on the trees and the ground, making mechanical harvesting more efficient. Minimal precipitation during this period is beneficial as it prevents mold and fungal growth on the harvested nuts.

Overall, the analysis of weather data across these diverse locations highlights the critical influence of climatic conditions on almond crop phenology. Each phenological stage has specific weather requirements that must be met to optimize almond production. Understanding these conditions helps in developing effective agricultural practices tailored to the climatic characteristics of each region, ensuring the successful cultivation of almonds in the Central Valley. The geographical diversity of the study sites provided a comprehensive understanding of how varying weather patterns and management impact almond growth and development in the Central Valley.

5.2. Comparisons of mid-day stem water potential from OC sensors with the pressure chamber

Fig. 5 presents a comprehensive assessment of the goodness-of-fit and regression outcomes between mid-day SWP measured by OC sensors and PC devices across six sites (CAPEX, Gruenwald, Nickels, Sharma, Clark Ranch, and Westwind) over 43 tree locations. This figure includes detailed graphical representations depicting the regression analysis (Fig. 5a), the cumulative probability of the Nash-Sutcliffe Efficiency (NSE) (Fig. 5b), a FITEVAL goodness-of-fit model report (Fig. 5c), and a correlation plot (Fig. 5d) illustrating the correlation between SWP

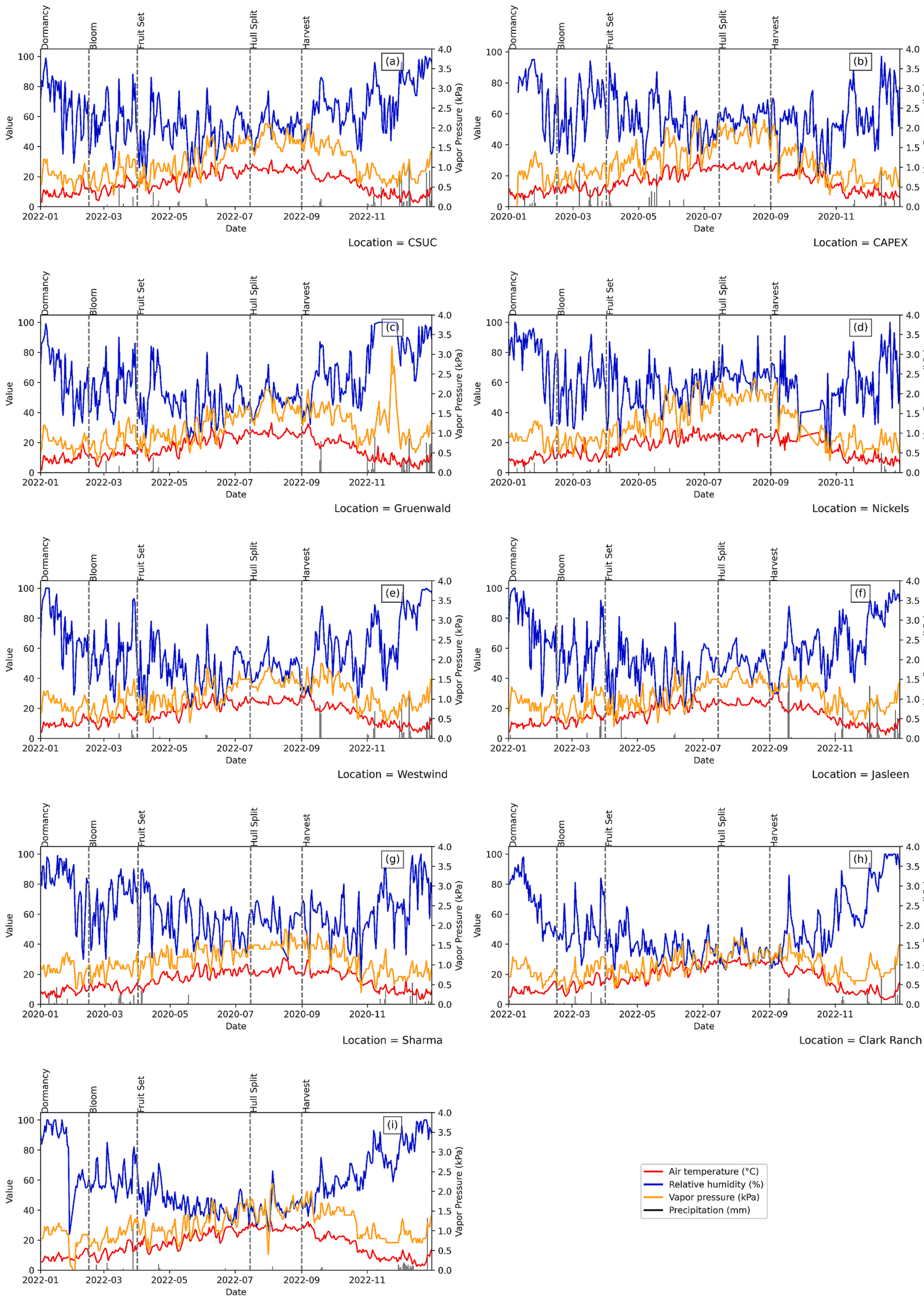

Fig. 4. Agrometeorological conditions for the nine experimental sites: (a) CSUC, (b) CAPEX, (c) Gruenwald, (d) Nickels, (e) Westwind, (f) Jasleen, (g) Sharma, (h) Clark Ranch, and (i) UC Kearney, where Osmotic cell and Microtensiometer sensors were installed throughout California. The weather data includes daily average air temperature, relative humidity, vapor pressure deficit, and total precipitation.

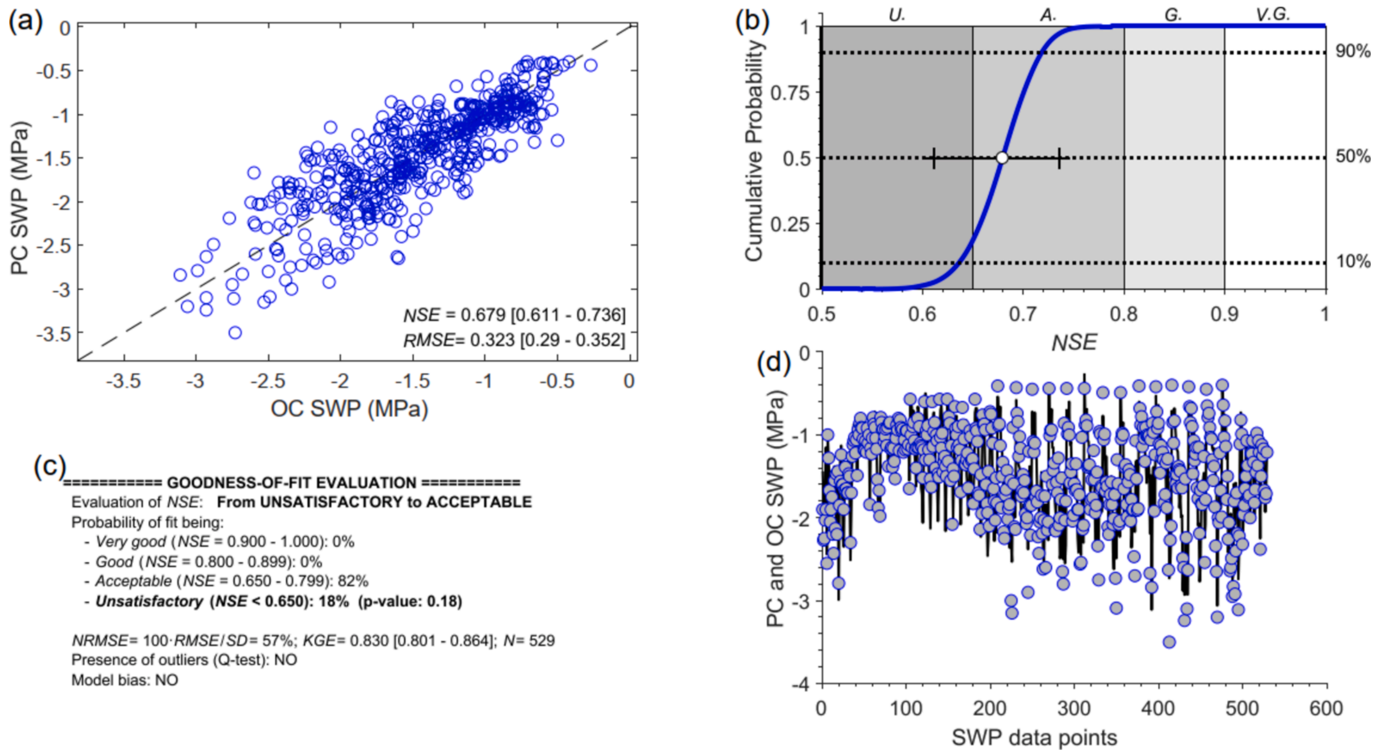

Fig. 5. Assessment of goodness-of-fit and regression outcomes between mid-day stem water potential measured by Osmotic cell (OC) sensors and Pressure Chamber (PC) devices across 6 sites (CAPEX, Gruenwald, Nickels, Sharma, Clark Ranch, and Westwind) over 43 tree locations. The detailed graphical representations depicting (a) the regression analysis between OC and PC measured SWP data, (b) the cumulative probability of NSE, with the median value indicating the reported NSE, (c) a FITEVAL model report encompassing hypothesis testing outcomes, identification of outliers, and sensitivity analysis concerning model bias, and (d) a scatter plot illustrating the correlation between SWP values from OC sensors and PC measurements at the specified tree locations.

values from OC sensors and PC measurements.

Fig. 5a illustrates the regression analysis between SWP data measured by PC devices and OC sensors. The scatter plot reveals a strong linear relationship between the two sets of measurements, with a NSE value of 0.68 (95 % confidence interval: 0.61–0.74) and a Root Mean Square Error (RMSE) of −0.32 MPa (confidence interval: −0.29 to −0.35 MPa). The close alignment of data points along the 1:1 line indicates a good agreement between the two measurement methods, suggesting that OC sensors provide continuous estimates of SWP that align well with the periodic field measurements taken using PC devices. This relationship is crucial for validating the use of OC sensors in practical field applications where frequent and accurate SWP measurements are essential for effective irrigation management. The cumulative probability distribution of the NSE values, illustrated in Fig. 5b, reveals that the mean NSE fell within the "Acceptable" range ($0.65 \leq NSE < 0.8$) but there were some unacceptable sensor measurements. This distribution underscores the ability of OC sensors to capture the variability of SWP across different environmental conditions and tree locations. The FITEVAL report, shown in Fig. 5c, provides a detailed evaluation of the model's goodness-of-fit. The report indicates that 82 % of the NSE values fall within the "Acceptable" range, while 18 % are classified as "Unsatisfactory". No NSE values fall within the "Good" or "Very Good" categories. The RMSE standardized to the mean observed values (NRMSE) was 57 %, and the Kling-Gupta Efficiency (KGE) was 0.83 (confidence interval: 0.80 to 0.86). Additionally, the report confirmed the absence of outliers (as indicated by the Q-test) and no significant model bias, further validating the robustness of the regression model. These statistics indicate that OC sensors are generally reliable. In addition, Fig. 5d provides a correlation plot showing the alignment between SWP values measured by OC sensors (represented by the continuous line) and PC devices (represented as corresponding data points). The data points exhibit a strong correlation with the line graph indicating that OC sensors effectively track the trends observed in the PC measurements. However, there are instances of both underprediction and overprediction by the OC sensors. These deviations are generally within the RMSE range of −0.32 MPa, suggesting that while OC sensors are reliable, they occasionally underpredict or overpredict SWP values compared to PC measurements. Overall, the analysis demonstrates that OC sensors provide an acceptable level of accuracy in measuring mid-day SWP when compared to PC devices. The strong linear relationship, satisfactory NSE values, and lack of significant model bias indicate that OC sensors are a viable alternative for continuous SWP measurement across different almond orchard sites. This finding is significant for optimizing irrigation management and ensuring efficient water use in almond production, as reliable SWP measurements are critical for maintaining tree health and maximizing yield.

The performance of OC sensors in comparison to PC SWP measurements at individual sites is provided in the supplementary material. At CAPEX Farms (Fig. S1), acceptable alignment between OC and PC SWP values was observed, with NSE values averaging 0.69 and RMSE averaging −0.36 MPa, indicating good correlation and minimal error. At Gruenwald Farms (Fig. S2), the analysis revealed good agreement, with an average NSE of 0.85 and RMSE of −0.08 MPa, showcasing strong statistical similarity between OC and PC measurements. Similarly, at Nickels Farm (Fig. S3), the OC sensors demonstrated good potential with an average NSE of 0.87 and RMSE of −0.10 MPa, confirming high correlation and minimal error. Sharma Farms (Fig. S4) also showed promising results with an average NSE of 0.84 and RMSE of −0.15 MPa, indicating excellent alignment between OC and PC values. In contrast, both Clark Ranch and Westwind Farms (Fig. S5 and Fig. S6) exhibited poor correlations with significant scatter in regression analyses and low NSE values, indicating low statistical significance and high error rates in OC sensor readings compared to PC measurements. These findings suggest that while OC sensors perform well at certain sites, they exhibit limitations at others, emphasizing the need for site-specific validation.

5.3. Comparisons of daily mid-day stem water potential from MT sensors with the pressure chamber

Fig. 6 presents a comprehensive assessment of the relationship between mid-day SWP measured using MT and PC devices across three sites (CSUS, Jasleen, and UC Kearney) over 11 tree locations. The figure includes detailed graphical representations depicting the regression analysis (Fig. 6a), the cumulative probability of the NSE (Fig. 6b), a FITEVAL model report (Fig. 6c), and a correlation plot (Fig. 6d) illustrating the temporal alignment of the two measurement methods.

The scatter plot (Fig. 6a) highlights a strong linear correlation between the two sets of measurements, with an NSE value of 0.84, with a 95 % confidence interval ranging from 0.78 to 0.88. The RMSE is −0.24 MPa, with a confidence interval of −0.22 to −0.28 MPa. The alignment of data points along the 1:1 line indicates excellent agreement between the two measurement methods, suggesting that MT devices provide reliable estimates of SWP compared to PC devices in almonds. This strong correlation is crucial as it validates the use of MT devices for frequent and accurate SWP measurements in field applications, ensuring effective irrigation management. The cumulative probability distribution (Fig. 6b) reveals that 92.9 % of the NSE values are classified as "Good," while 6.7 % fall into the "Acceptable" category. Only 0.4 % of values reach the "Very Good" performance level, and none fall into the "Unsatisfactory" range. This indicates that the majority of the NSE values are within the "Good" category, reinforcing the reliability and accuracy of the MT devices across different measurement scenarios. The high percentage of "Good" NSE values underscores the robustness of the MT sensors in providing consistent and reliable SWP measurements. The FITEVAL model report (Fig. 6c) indicated that the NRMSE was 40 %, and the KGE was 0.92, with a confidence interval of 0.90 to 0.94. Additionally, the report confirms the absence of outliers, as indicated by the Q-test, and no significant model bias. These statistics further support the overall reliability of the MT devices for SWP measurement. The high KGE value signifies that the MT measurements closely align with the PC measurements, demonstrating both accuracy and consistency in the data collected from the MT sensors. The PC data points exhibited a strong correlation with the MT (Fig. 6d), indicating that MT devices effectively track the trends observed in the PC measurements. However, there are instances of both underprediction and overprediction by the MT devices. These deviations are generally within the RMSE range of −0.24 MPa, suggesting that while MT devices are reliable, they occasionally underpredict or overpredict SWP values compared to PC measurements. This correlation plot visually confirms that MT devices can be used reliably for continuous SWP monitoring, aligning closely with the less frequent PC measurements and effectively capturing the temporal dynamics of SWP. Overall, the analysis demonstrates that MT SWP sensors have a high level of accuracy in measuring mid-day stem water potential when compared to PC devices. The strong linear relationship, high NSE values, and lack of significant model bias indicate that MT devices are a viable alternative to PC in almonds.

The performance of MT sensors in comparison to PC SWP measurements at individual sites was provided in the supplementary material. At Jasleen Farms (Fig. S7), the analysis for the 2022 season showed an average NSE of 0.82 and RMSE of −0.22 MPa, indicating good agreement with moderate error between MT and PC measurements. At the UC Kearney (Fig. S8), the analysis demonstrated strong alignment between MT and PC values with an average NSE of 0.84 and RMSE of −0.22 MPa, highlighting low to moderate error and high statistical similarity. The performance evaluation at the CSUC Farm (Fig. S9) revealed a strong agreement between MT and PC measurements, with an average NSE of 0.81 and RMSE of −0.26 MPa. These findings suggest that MT sensors perform well across these individual sites, demonstrating good

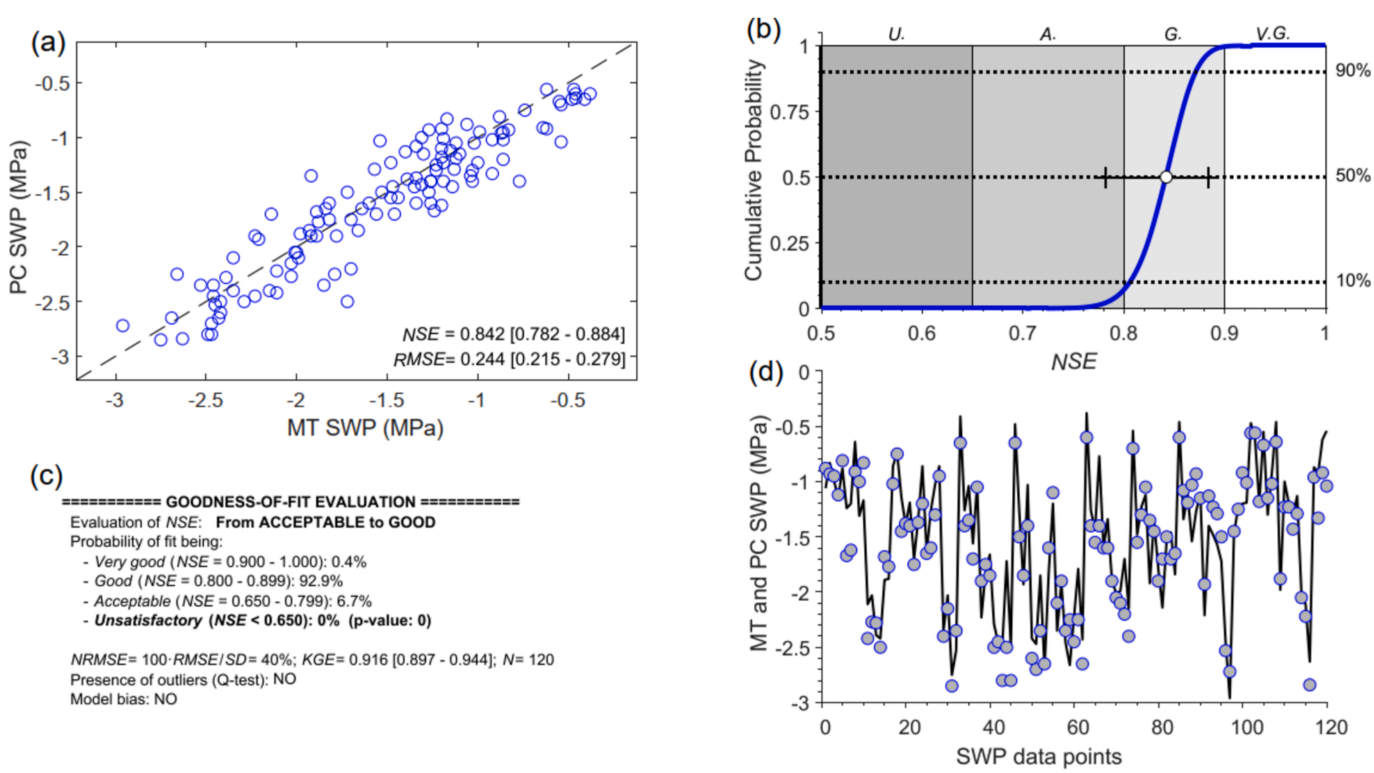

Fig. 6. Assessment of goodness-of-fit and regression outcomes between mid-day stem water potential measured by Microtensiometer (MT) sensors and Pressure Chamber (PC) devices across 3 sites (CSUS, Jasleen, and UC Kearney) over 11 tree locations. The detailed graphical representations depicting (a) the regression analysis between MT and PC measured SWP data, (b) the cumulative probability of NSE, with the median value indicating the reported NSE, (c) a FITEVAL model report encompassing hypothesis testing outcomes, identification of outliers, and sensitivity analysis concerning model bias, and (d) a scatter plot illustrating the correlation between SWP values from MT sensors and PC measurements at the specified tree locations.

correlations and minimal errors.

5.4. Diurnal SWP monitoring using microtensiometers

At the CSUC farm, for instance, the clear diurnal patterns in SWP can be seen in Fig. 7 for one month beginning on June 24 and ending on July 24, 2022, with four different trees at different locations. Both sensors consistently read approximately the same values of SWP over all the days. The SWP values exhibited a pattern of initial elevation at the start of the day, followed by a decline to a minimum around noon, subsequently rebounding to a peak in the evening, reflecting the tree's sensitivity to environmental conditions. In instances where the tree was already experiencing stress, the early morning values showed a slight decrease, with further pronounced reductions by midday owing to

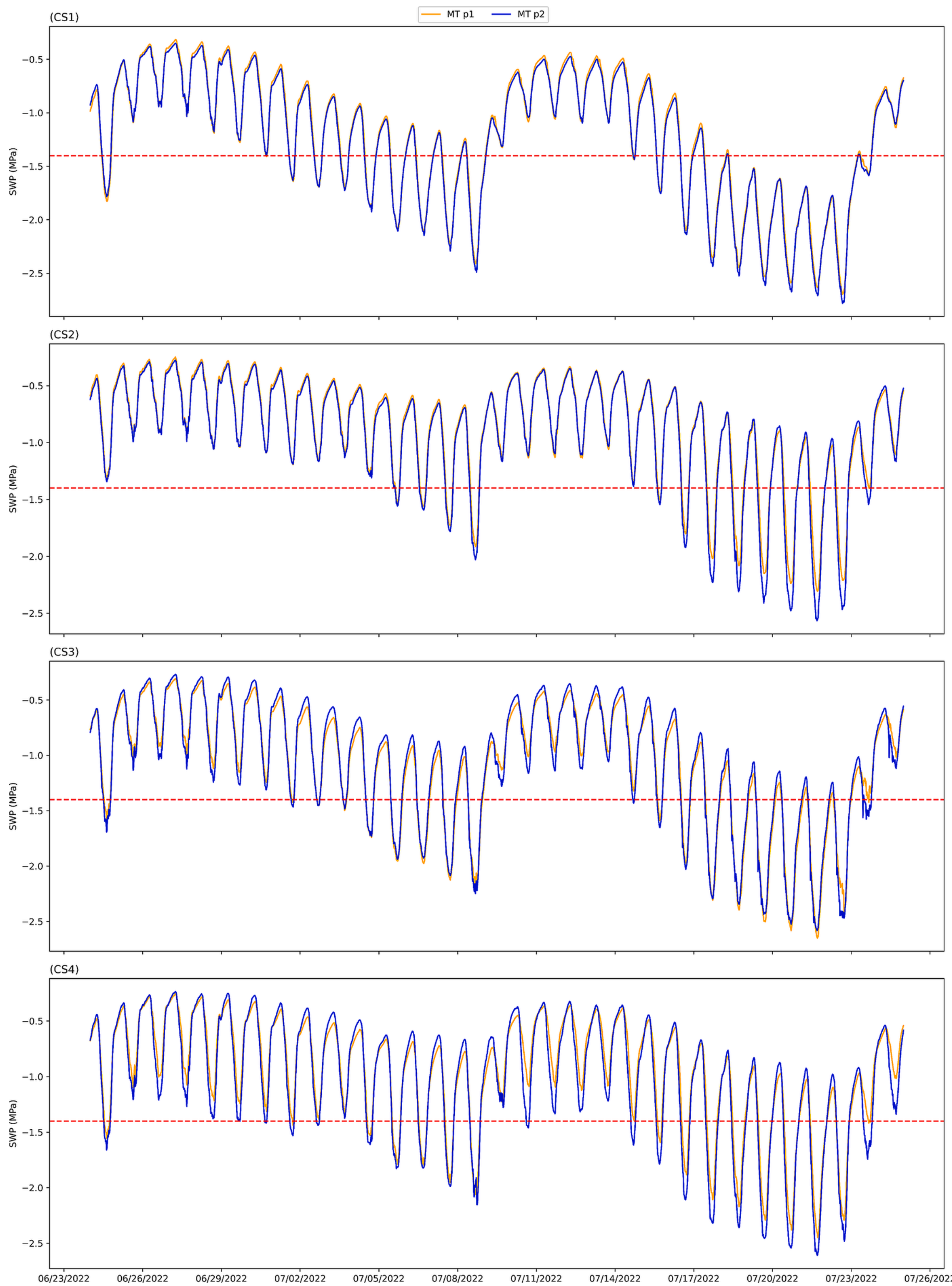

Fig. 7. Variations in stem water potential (SWP) occurred daily as measured by the two Microtensiometer sensors embedded in the same almond tree (CS1 to CS4) at the CSUC site near Chico, California from the 24th of June to the 24th of July 2022. The horizontal line indicates the baseline stem water potential.

increased transpiration. Notably, the MT sensors demonstrated superior capabilities in high temporal resolution monitoring the tree's water status, consistently capturing stress dynamics throughout the day. Conversely, the PC measurements, collected sporadically from the field, provided limited data, insufficient for a comprehensive understanding of the tree's water status and its responses to environmental factors like Vapor Pressure Deficit (VPD) changes.

In addition, Fig. 8 shows the data collected by the two MT sensors at the CSUC farm at 20-minute intervals throughout 24 h on various dates, at each tree location. On the exact day when the data was obtained, the SWP data from the PC was also provided. Most days showed the start of a decline in SWP at around 8 am. After that, the values began to fall, and they reached their lowest point between 14:00 and 16:00 (Fig. 7). The values began to rise again in response to changes in VPD. In addition, the PC-SWP values on July 19 and August 17 corresponded very closely to the readings measured by the MT sensors, in contrast to the other days, for which there is a slight discrepancy between the sensor values and the PC SWP values. These diurnal SWP patterns provide greater insight into knowing how a tree responds at different periods of the day to water availability and weather conditions.

5.5. Irrigation management with MT sensors

In Fig. 9, the daily midday Stem Water Potential (SWP) variations and concurrent irrigation activities are presented for three distinct almond tree locations within the Jasleen farm, near Woodland, CA. This site had pressure transducers installed in the irrigation lines. The analysis reveals a consistent pattern across all locations: when the SWP values reached a value of about −1.4 MPa, indicating crop stress, irrigation was initiated. Subsequently, within one to two days, the trees

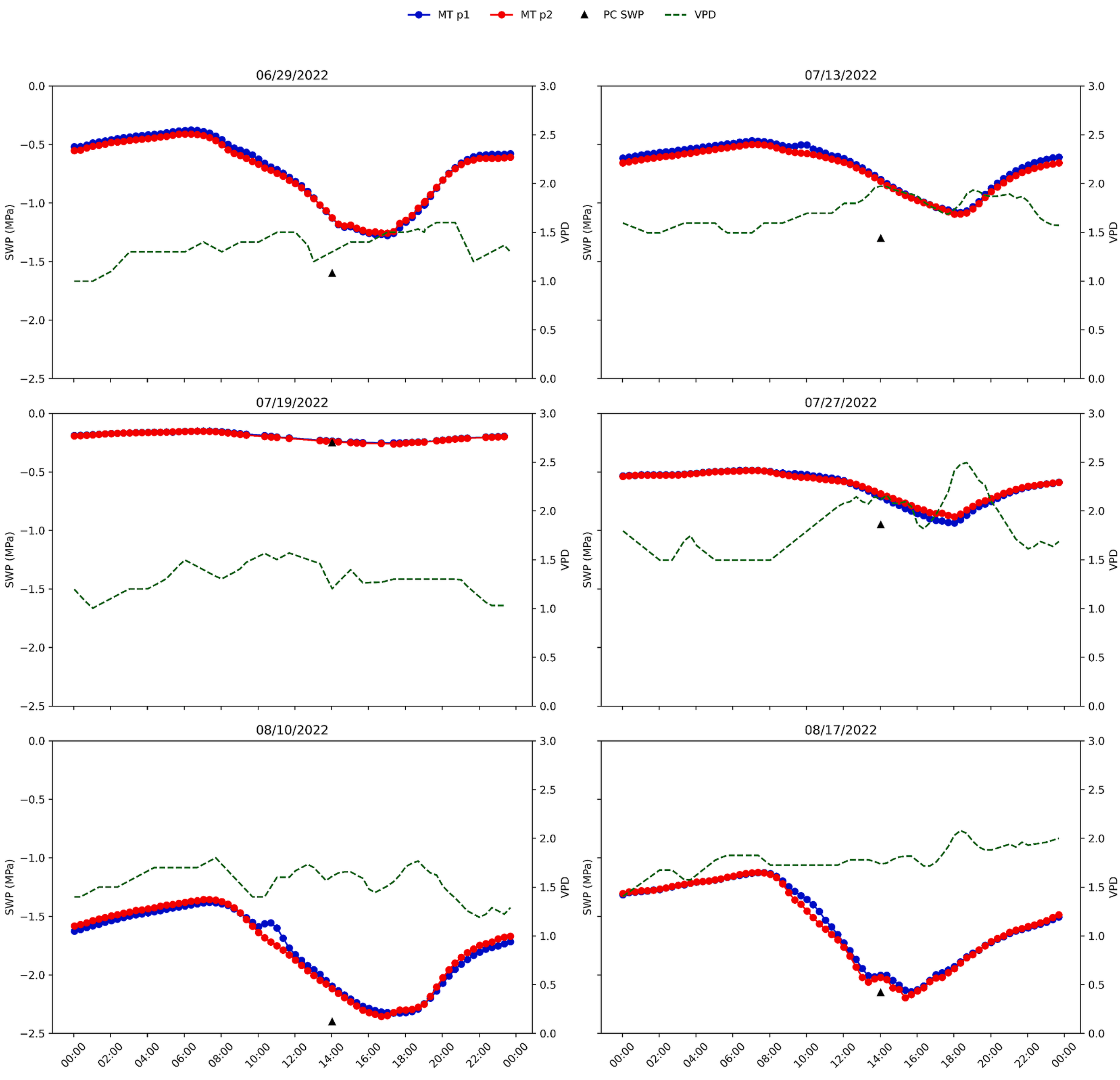

Fig. 8. Diurnal variations in stem water potential (SWP) measured by two microtensiometer (MT) sensors in the same almond tree and corresponding vapor pressure deficit at the CSUC Site in Chico, California on various dates.

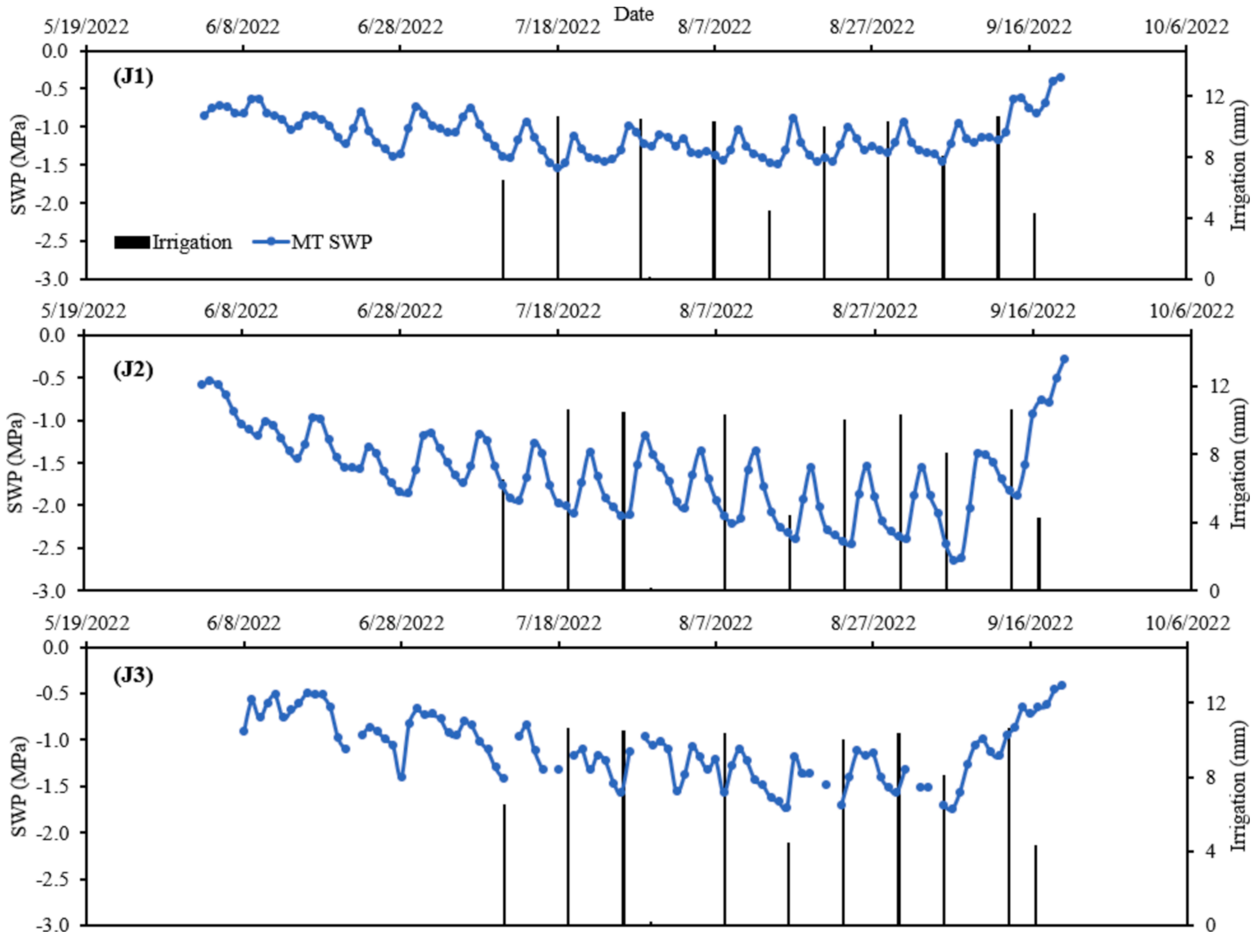

Fig. 9. The daily variations of mid-day stem water potential were measured using Microtensiometer sensors at three distinct almond tree locations within the Jasleen site, alongside the corresponding applied irrigation.

displayed recovery from stress, depicted by the increase in SWP to values above −1.4 MPa, suggesting reduced stress levels for the almond trees. This consistent relationship between SWP values, irrigation application, and subsequent stress recovery underscores the close correlation between SWP dynamics and irrigation scheduling in almonds.

6. Discussion

OC sensors, such as the StemSense™ from Saturas (Meron, 2019, 2018; Meron et al., 2015), and MT sensors from FloraPulse (Stroock et al., 2014), have revolutionized the monitoring of Stem Water Potential (SWP) in some woody perennials. Practical considerations, including cost, lifespan, ease of installation, and cases of sensor failure, are crucial for evaluating their utility. OC sensors are cost-effective and have a relatively low initial cost, making them accessible for large-scale operations. Installation is straightforward as the sensors are embedded into the tree trunk and connected to the vascular tissue. The simplicity of installation and low maintenance requirements make OC sensors user-friendly, allowing farmers to easily integrate them into their irrigation management systems. However, while OC sensors are generally reliable, there have been instances of sensor failure due to improper installation or environmental factors such as extreme temperatures and malfunction related to sensor manufacturing. Additionally, the lifespan of OC sensors can be impacted by harsh field conditions, requiring periodic replacements. MT sensors, on the other hand, are more expensive but offer continuous data updates every 20 min. Their installation requires careful placement to ensure consistent and accurate readings, which can be more challenging compared to OC sensors. The complexity of installation for MT sensors may require professional assistance, increasing the initial setup cost. However, once installed, MT sensors have a longer lifespan due to their robust design. They are less prone to environmental degradation but can still fail under harsh field conditions if not properly maintained. In some instances, the sensors may need to be reinstalled every season. Both sensor types use telemetry, with OC sensors using LoRa communication for data transmission. Although MT sensors provide more detailed data, their higher cost might limit their widespread adoption compared to OC sensors. Cases of failure in MT sensors often stem from physical damage or software malfunction, which require timely interventions to ensure continuous data flow.

The use of these sensors for irrigation scheduling is a significant advancement in agricultural water management (Gu et al., 2020; Roy et al., 2020; Taghvaeian et al., 2020). By providing timely and accurate SWP data, OC and MT sensors can help farmers refine irrigation scheduling decisions. For example, in regions where water resources are scarce, the ability to fine-tune irrigation schedules based on accurate SWP data can lead to substantial water savings and improved crop yield. MT sensors provide continuous sub-hourly stem water potential (SWP) data that capture almond tree recovery from water stress following irrigation. This continuous monitoring is critical for dynamic irrigation scheduling, where water application can be adjusted in real time based on the current water status of the trees. The high temporal resolution provided by MT sensors allows for the detection of rapid changes in plant water status, which can be crucial during critical growth stages such as hull split. Both types of sensors can be integrated into automated irrigation systems, providing real-time feedback to control irrigation events. This integration can enhance irrigation efficiency, reduce water usage, and improve crop yields. Automated systems utilizing data from OC and MT sensors can adjust irrigation schedules without human intervention, responding to the immediate needs of the plants (e.g., https://bluecornercontrols.com/). This approach saves labor and ensures that irrigation is precisely matched to plant requirements, reducing waste and promoting optimal growth conditions. Furthermore, the data collected by these sensors can be analyzed to develop long-term irrigation strategies such as regulated deficit irrigation during hull split or delayed initiation of irrigation in spring.

Despite their advantages, there are cases where sensor results have been less reliable. Several factors could contribute to these inconsistencies, including issues with the PC data used for validation. PC measurements require skilled operators, as the process of taking and reading pressure chamber data is complex and prone to human error. Variability in operator skill and experience can introduce inconsistencies in the data, which in turn affects the validation and accuracy of OC and MT sensors. For instance, different operators might apply varying levels of pressure or misinterpret the visual indicators during PC measurements, leading to discrepancies in SWP readings. Additionally, differences in tree characteristics, such as variety, age, fruit load, and management practices, can influence SWP readings. For example, younger trees or those with a high fruit load may exhibit different water stress patterns compared to mature or less productive trees. Trees with a higher fruit load might require more water, and their SWP readings could be more sensitive to irrigation practices. Environmental factors, such as soil type and weather conditions, also play a significant role. Soil moisture retention capacities and microclimatic conditions can impact tree water status to irrigation, leading to variability in the results. For instance, sandy soils with low water retention may cause more frequent fluctuations in SWP compared to clay soils, which retain water longer. These factors need to be carefully considered when interpreting SWP data and using it for irrigation scheduling.

In the broader context of tree water status monitoring, other sensors like dendrometers, sap flow sensors, canopy temperature sensors, and ZIM probes also provide valuable data (Carella et al., 2024; Martínez-Gimeno et al., 2017). Each of these sensors has commercial versions claiming to be useful for irrigation scheduling. Dendrometers measure trunk diameter changes (Garnier and Berger, 1986) and indicate water stress indirectly, providing insights into tree growth and health. These sensors can detect subtle changes in trunk diameter that occur due to water uptake and loss, offering an indirect measure of tree water status (Alizadeh et al., 2021). Sap flow sensors monitor water movement within the tree, offering direct measurements of transpiration rates (Garnier and Berger, 1986; Uddin et al., 2014). This data can be used to infer the tree's water uptake and overall water use efficiency. Canopy temperature sensors detect thermal stress in the canopy, which can be related to water availability (Fuchs, 1990; Sullivan et al., 2007). High canopy temperatures often indicate water stress, as the plant reduces transpiration to conserve water. ZIM probes measure leaf turgor pressure (Martínez-Gimeno et al., 2017), giving a direct indication of water status. Turgor pressure is a critical factor in maintaining leaf structure and function, and its measurement provides a direct insight into the water status of the plant. While these sensors provide useful data, they often require more complex installation and calibration processes and can be more expensive than OC and MT sensors. For instance, sap flow sensors require precise insertion into the tree's vascular system, and canopy temperature sensors need to be positioned accurately to avoid interference from external heat sources. However, their data can complement SWP readings, providing a more comprehensive understanding of tree water status. Integrating data from multiple sensor types into a single decision support system can enhance the accuracy and reliability of irrigation scheduling. For example, combining SWP data with sap flow and canopy temperature measurements can provide a holistic view of the plant's water status, improving decision-making processes.

There is a growing body of literature on the importance and use of continuous plant water status sensing in irrigation management. Pagay (2021) emphasized the dynamic aspects of plant water potential revealed by MT sensors, noting their sensitivity and accuracy in capturing rapid changes in water status. Valente et al. (2022) explored an IoT-based system for smart agriculture, demonstrating how integrating various sensor types can enhance irrigation precision and efficiency. Other studies, such as those by (Black et al., 2020; Conesa et al., 2023), further support the utility of MT sensors in continuous water status monitoring. Black et al. (2020) focused on the technological aspects, highlighting the precision of MEMS tensiometers, while (Conesa et al., 2023) emphasized the practical applications in nectarine trees. Additionally, (Divya and Chinnaiyan, 2019) and (Aggarwal and Singh, 2021) discussed the broader implications of AI and IoT in agriculture, suggesting that combining different sensors can optimize resource use and improve crop management. (Dhillon et al., 2017) and (Siddiqi et al., 2021) highlighted the benefits of using sap-flow and stem-psychrometer technologies for precision irrigation, noting their effectiveness in water-saving and plant health monitoring. Similarly, (Dainese et al., 2022) and (Stoochnoff et al., 2018) emphasized the importance of accurate and continuous monitoring tools for managing irrigation in various agricultural settings. González et al. (2022) and (Gonzalez Nieto et al., 2023) demonstrated the efficacy of MT sensors in managing water stress in apple orchards, achieving significant improvements in fruit size and quality. Their studies highlighted the benefits of continuous monitoring in optimizing irrigation schedules and improving crop yield. Similarly, (Blanco and Kalcsits, 2023) validated the use of MT sensors for continuous trunk SWP measurements in pear trees, highlighting different diurnal patterns under limiting water conditions. Their research emphasized the importance of understanding diurnal variations in water potential for effective irrigation management. Our study extends the use of MT and OC sensing of SWP to almond trees, showing significant statistical accuracy across most almond tree locations. (Blanco and Kalcsits, 2023) noted strong linear correlations ($R^2 > 0.8$) between SWP from MT sensors and PC readings but observed increased variability and lower SWP-MT values, particularly below −1.5 MPa during the evening. Conversely, our prolonged investigation unveiled SWP patterns intricately linked to irrigation and crop growth stages throughout the entire season.

Notably, our findings demonstrate significant accuracy across most tree locations, with an average error of −0.22 MPa at the Jasleen site, −0.26 MPa at the CSUC site, and −0.22 MPa at the UC Kearney site. Additionally, strong linear correlations were found at these sites between MT-SWP and PC-SWP, showcasing slightly reduced variability compared to (Blanco and Kalcsits, 2021) findings. Furthermore, our analysis highlighted dynamic SWP fluctuations, indicating low stress early in the season crop due to sufficient root zone soil moisture from winter precipitation or irrigation application and increased stress during harvest. This holistic perspective underscores the reliability of MT sensors in estimating SWP over an extended duration, providing critical insights into the evolving dynamics of plant water status throughout the cropping season.

In the (Meron et al., 2015) study, laboratory-calibrated OC sensors were installed into peach and tangerine trees, revealing comparable SWP values and diurnal patterns when compared to PC measurements, albeit with a slight time lag. However, in our current investigation, we have observed varying degrees of correlation between OC and PC readings across most sites, with RMSE values ranging from −0.08 to −0.35 MPa, indicating a range of minimal to high errors between OC sensor-obtained SWP and PC-SWP, following SWP interpretation guidelines by (Fulton et al., 2001). Yet, certain sites, such as Clark Ranch and Westwind, exhibited considerable discrepancies with higher RMSE and lower NSE values, indicating significant errors between OC and PC SWP measurements. Moreover, some locations experienced sensor malfunctions, warranting further exploration into the causes behind these malfunctions and the factors contributing to elevated errors on certain days.

MT sensors represent a significant leap in capabilities for both growers and the scientific research community. Their adoption stands to drive further advancements in irrigation management tailored to precision orchard water management in various woody perennials, facilitating more informed and efficient water use. Future research should involve the development of simpler interpretation methods and guidelines to integrate these sensors into automated irrigation scheduling systems, which use SWP as feedback. For example, instead of delivering and presenting detailed trendlines, perhaps additional research studies can lead to simpler interpretive guidelines or indices that reflect cumulative measures of stress hours or days and relate them to favorable and unfavorable almond tree growth and nut developmental responses. This integrated approach, combining multiple sensor technologies and data sources, can significantly improve our understanding and management of water resources in agriculture. By enhancing the accuracy and reliability of irrigation scheduling, these advancements contribute to more sustainable agricultural practices and better resource management in the face of growing environmental challenges.

7. Conclusion

In this study, we undertook a comprehensive analysis by comparing almond midday stem water potential (SWP) values obtained from two cutting-edge SWP sensors namely, the Osmotic Cell (OC) and Microtensiometer (MT) with measurements derived from the conventional Pressure Chamber (PC). The study spanned two growing seasons, 2020 and 2022, and encompassed multiple commercial and research almond orchards distributed across the Central Valley of California. Overall, sensor performance varied from good to acceptable and from acceptable to unacceptable for MT and OC sensors respectively. The MT sensor achieved a Nash-Sutcliff Coefficient of Efficiency (NSE) of 0.84 (95 % CI: 0.78–0.88) and a Root Mean Square Error (RMSE) of −0.24 MPa (95 % CI: −0.21 to −0.28 MPa), compared to the OC sensor's NSE of 0.68 (95 % CI: 0.61–0.74) and RMSE of −0.32 MPa (95 % CI: −0.29 to −0.35 MPa). Although the overall performance was good, certain tree locations exhibited larger RMSE values exceeding −0.24 MPa for the MT sensor and −0.32 MPa for the OC sensor, indicating a higher level of uncertainty in those specific instances. This higher uncertainty could presumably be associated with sensor malefaction or improper installation. These findings highlight the MT sensor's effectiveness for continuous and precise SWP monitoring, providing a more reliable tool for orchard precision water management. Noteworthy insights emerged from the diurnal fluctuations in SWP measured by the MT sensors, offering valuable indications of the water status responses to varying environmental conditions. These diurnal patterns present an avenue for the development of innovative and user-friendly interpretive guidelines for irrigation management, surpassing the current guidelines established based on PC-measured SWP. In summary, both OC and MT sensors demonstrated good to acceptable performance across most sites investigated in this study, affirming their suitability for almond irrigation management when correctly installed. While the MT sensors exhibited the added advantage of providing sub-hourly data and displaying tree recovery from water stress following irrigation, positioning them as potentially superior for precision almond orchard water management, it is crucial to acknowledge that both sensors remain in the developmental stage. Further research and field evaluations, encompassing diverse crop types and irrigation systems, are imperative to solidify the robustness of these sensors across various environmental contexts. It is important to note that, despite their commercialization, SWP sensors (e.g., FloraPulse (MT sensors, and ICT stem psychrometers) face practical challenges such as high cost, and short lifespan. Saturas (OC sensors), in particular, have had an inconsistent presence in the market, further limiting their commercial applicability. Wide-scale adoption of SWP sensor technology has the potential to optimize the use of limited water resources in almond production.

CRediT authorship contribution statement

Isaya Kisekka: Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Srinivasa Rao Peddinti:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Peter Savchik:** Writing – review & editing, Data curation. **Liyuan Yang:** Writing – review & editing, Data curation. **Mae Culumber:** Writing – review & editing, Methodology, Investigation. **Khalid Bali:** Writing – review & editing, Investigation. **Luke Milliron:** Writing – review & editing, Investigation. **Erica Edwards:** Writing – review & editing, Investigation. **Mallika Nocco:** Writing – review & editing, Investigation. **Clarissa A. Reyes:** Writing – review & editing, Investigation. **Robert J. Mahoney:** Writing – review & editing, Methodology. **Kenneth Shackel:** Writing – review & editing, Investigation. **Allan Fulton:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2024.109547.

Data availability

Data will be made available on request.

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