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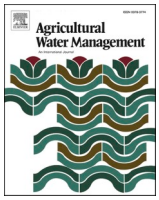
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Evaluation of the LI-710 evapotranspiration sensor in comparison to full eddy covariance for monitoring energy fluxes in perennial and annual crops

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ABSTRACT

Reliable and low-cost sensors for measuring evapotranspiration (ET) and associated energy fluxes are crucial for hydrologic monitoring and water management; however, conventional methods such as eddy covariance (EC) can be prohibitively expensive and complex. This study evaluates the performance of the LI-710 sensor across perennial (citrus, almond, pistachio) and annual crops (processing tomatoes) by comparing daily ET, sensible heat flux (H), and latent heat flux (LE) measurements with those from full EC systems under California's Central Valley climatic conditions. Measurements from the LI-710 were corrected for unclosed energy balance using an energy-balance-residual (EBR) method that incorporates independent net radiation and soil heat flux data. Uncorrected LI-710 fluxes exhibited a consistent underestimation, as reflected in low or negative Nash–Sutcliffe efficiency (NSE) values. For ET, processing tomato NSE increased from 0.35 to 0.94 with EBR correction, citrus from 0.32 to 0.73, almond from −2.09 to 0.79, and pistachio from 0.72 to 0.95. H improved similarly (processing tomato: 0.86–0.97; citrus: 0.13–0.67; almond: −0.35 to 0.75; pistachio: 0.20–0.85), while LE accuracy rose from 0.44 to 0.95 in processing tomatoes, −0.10 to 0.77 in citrus, −1.51 to 0.76 in almonds, and 0.71–0.93 in pistachios. Corresponding reductions in root mean square error (RMSE) confirmed that EBR-corrected LI-710 measurements closely aligned with EC observations, effectively capturing seasonal peaks and phenological transitions. These results highlight the LI-710 sensor's potential as a lower-cost, user-friendly alternative to full EC systems for routine flux monitoring, provided that energy-balance adjustments are implemented. Such an approach can support precision irrigation and sustainable water management, particularly in regions facing increasing pressures on freshwater resources.

1. Introduction

Evapotranspiration (ET) is a key component of the hydrologic cycle, combining water loss through soil and plant surface evaporation with plant transpiration (Katul et al., 2012). It plays a vital role in water resource management (Peddinti et al., 2020), agricultural productivity (Keller, 2005), ecosystem stability (Liu et al., 2017), and climate regulation (Fisher et al., 2017). Accurate ET measurement is essential for optimizing water use, improving irrigation scheduling, managing drought, water accounting, and promoting sustainable agriculture, particularly in regions with limited or variable water supplies (Pereira et al., 2015). In agriculture, ET determines crop water requirements and guides irrigation decisions to optimize yield and minimize water waste, a balance particularly important in regions facing water scarcity (Goldhamer and Fereres, 2017; Maraveas et al., 2024). ET is also used in setting and monitoring water allocations. However, accurately quantifying ET is challenging, especially in orchards, where complex canopy structures, variations in microclimate, and seasonal changes in water demand make flux estimation difficult (Dzikiti et al., 2018; Fisher et al., 2017; Gutiérrez-Gordillo et al., 2020; Kisekka, 2023; Peddinti et al., 2024). Over the years, researchers have developed various methods to measure or model ET, each with trade-offs in accuracy, cost, scalability, and practicality. However, no single approach fully resolves these challenges across diverse agricultural and natural ecosystems.

Lysimeters, widely recognized as the standard method, provide a direct measurement of ET by assessing changes in soil water content within a defined soil volume (Evett et al., 2012). They are considered accurate and reliable; however, lysimeters are expensive,

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labor-intensive, and restricted to relatively small scales, making them impractical for routine monitoring or large-scale agricultural applications (Evett et al., 2012; Riedl et al., 2022). The eddy covariance (EC) method is another widely accepted approach, known for directly measuring turbulent energy fluxes of sensible heat flux (H) and latent heat flux (LE) through high-frequency measurements of vertical wind velocity coupled with scalar variables like water vapor and temperature (Aubinet et al., 2012; Baldocchi, 2003; Burba, 2013). EC systems, generally composed of sonic anemometers and infrared gas analyzers (IRGAs), provide detailed insights into diurnal and seasonal ET variations and have been extensively validated across various ecosystems, including agricultural lands, forests, and grasslands (Baldocchi, 2003; Mauder et al., 2013; Wang and Dickinson, 2012; Yang et al., 2023). Nevertheless, EC systems are expensive, technically complex, and demand significant maintenance, advanced data processing capabilities, and expert operational skills (Dong et al., 2021; Ferrara et al., 2021).

To address the limitations of conventional ET estimation methods, various direct and semi-direct alternatives have been developed. The Bowen ratio-energy balance (BREB) method estimates ET by solving the surface energy balance equation using vertical gradients of temperature and humidity (Bowen, 1926). While simpler and more affordable than EC, BREB requires steady-state atmospheric conditions and homogeneous terrain, making it less reliable in orchards with irregular canopy structures (Perez et al., 1999; Wolf et al., 2008). Surface renewal (SR) theory, introduced by Paw et al. (1995), estimates H and LE using high-frequency temperature data from fine-wire thermocouples. Although SR achieves 80–90 % agreement with EC at a fraction of the cost, it requires frequent crop-specific calibration, limiting its standalone applicability (Castellví, 2012; Shapland et al., 2014). Scintillometry provides large-area turbulence measurements (0.1–10 km) by analyzing light intensity fluctuations due to atmospheric refraction (Meijninger et al., 2006, 2002). This method is effective for regional ET monitoring but faces challenges in fragmented landscapes with mixed canopy heights and has costs comparable to EC (Kleissl et al., 2008; Liu et al., 2016; Moorhead et al., 2017). Indirect methods, such as remote sensing and empirical models, offer scalable alternatives but introduce their own uncertainties. The FAO-56 Penman-Monteith equation, the global standard for irrigation scheduling, computes ET from meteorological data and crop coefficients (Kc) (Pereira et al., 2015). While cost-effective, its reliance on static Kc values introduces errors in orchards, where Kc varies dynamically with canopy cover, phenology, and root depth (Dzikiti et al., 2010; Marino et al., 2021). Remote sensing approaches, including the Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998a, 1998b), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) (Allen et al., 2007), the Surface Energy Balance System (SEBS) (Su, 2002) model and Two Source Energy Balance (TSEB) (Norman et al., 1995) derive ET from satellite-measured land surface temperature (LST) and vegetation indices. These methods scale to regional levels but suffer from coarse spatial (30–1000 m) and temporal (5–16 days) resolution, missing short-term variability critical for irrigation decisions (Melton et al., 2022). Although recent advances in satellite remote sensing, such as the Hydrosat's VanZyl-1 satellite (launched in 2024), which promises to provide high-resolution, daily thermal data, may reduce latency, these data are not freely available.

The persistent limitations of existing methods have driven innovation in simplified, cost-effective sensor technologies. For example, Callejas-Rodelas et al. (2024) evaluated a low-cost EC setup that retained the sonic anemometer but replaced the IRGA with a relative humidity (RH) sensor (HIH-4000, Honeywell International Inc., Charlotte, NC, USA). Shapland et al. (2012) introduced an alternative, low-cost method based on the surface renewal concept, estimating ET as the residual of the energy balance. This method led to the development of the commercial Tule ET sensor (https://tule.ag/sensors/). Markwitz and Siebicke (2019) investigated a compact, low-cost EC setup using a BME280 sensor alongside a sonic anemometer for ET flux measurements across agroforestry and monoculture systems. Macagga et al., (2024) presented a low-cost, chamber-based device built with a non-dispersive infrared (NDIR) CO_2 sensor and an RH sensor, validated through laboratory and field testing in sub-Saharan Africa. These efforts underscore the increasing relevance of low-cost ET sensors in advancing scalable and inclusive environmental monitoring. Despite these innovations, comprehensive evaluation of such low-cost sensors under diverse environmental conditions remains limited, which may hinder broader adoption.

The recently developed LI-710 ET sensor (LI-COR Inc., Lincoln, Nebraska, USA) low cost ET sensor utilizes a vertical path-integrated design to estimate latent heat and sensible heat fluxes based on humidity and vertical wind speed measurements, eliminating the need for complex three-dimensional anemometry (Burba et al., 2024). It processes these measurements internally to provide fully corrected fluxes at regular intervals (typically 30 minutes), significantly simplifying field deployment, reducing maintenance requirements, and increasing accessibility for a broader range of users, including precision irrigation management. The LI-710 retains the key advantage of the EC techniques by directly measuring the turbulent exchange of moisture between the surface and the atmosphere while reducing operational complexity and cost. Its streamlined design integrates essential measurement components, minimizing instrument drift and maintenance challenges associated with traditional EC systems. As a result, the LI-710 has the potential to bridge the gap between the high accuracy of conventional methods and the practical applicability needed for routine agricultural and environmental monitoring (Burba et al., 2024).

However, despite these promising features, the performance and reliability of the LI-710 sensor across diverse cropping systems remain inadequately documented. Most validation studies have focused on relatively homogeneous cropping environments such as alfalfa and Soybean (Burba et al., 2024). Comprehensive evaluations in complex cropping systems, particularly perennial orchards characterized by heterogeneous canopy structures and unique microclimates, remain notably limited (Gohil and He, 2023; Kisekka, 2023). Orchard systems, including citrus, almonds, and pistachios, present specific challenges for ET measurement due to complex canopy architecture, significant variations in leaf area index, and pronounced phenological changes throughout the growing season. These factors directly influence microclimate dynamics, creating spatial and temporal variability in ET that requires accurate measurement for precise irrigation scheduling and sustainable water resource management (García-Tejero et al., 2011; Gutiérrez-Gordillo et al., 2020; Maraveas et al., 2024).

Addressing this research gap, the present study undertakes a comprehensive evaluation of the new LI-710 ET sensor by directly comparing its measurements with traditional EC systems across multiple cropping environments, including perennial orchard crops (citrus, almonds, and pistachios) and an annual cropping system (processing tomatoes). Specifically, the research objectives are to:

1. Evaluate the accuracy and reliability of the LI-710 ET sensor relative to conventional EC systems across diverse cropping systems and environmental conditions.
2. Assess the impacts of canopy complexity, phenological variability, and environmental conditions on the measurement accuracy and reliability of the LI-710.
3. Determine the practical feasibility of adopting the LI-710 sensor as a cost-effective alternative for routine ET monitoring and precision irrigation management.

To achieve these objectives, this study employed the co-located deployment of both the LI-710 and EC systems across various orchard and field crop environments, applying necessary energy balance residual (EBR) corrections to enhance data accuracy. The outcomes of this research are expected to facilitate the broader adoption of accurate and economically viable ET measurement tools, thereby optimizing

precision irrigation practices, enhancing crop yields, and contributing to sustainable water resource management, particularly in water-stressed regions. Ultimately, this study makes a significant contribution to existing literature by providing empirical evidence on the performance of the LI-710 sensor in various agricultural settings.

2. Materials and methods

2.1. Study sites description

The study was conducted across three diverse orchard sites and one field crop site in California's Central Valley: Esparto (processing tomatoes), Modesto (almonds), Madera (pistachios), and Fresno (citrus) (Fig. 1). This region has a Mediterranean and semi-arid climate marked by hot, dry summers and mild winters (Null and Mogil, 2010), providing ideal conditions for high-value crops that demand precision water management. These sites enabled a comprehensive comparison of evapotranspiration (ET) measurements under varying canopy structures, water requirements, and growth cycles across the 2024 crop season. Esparto and Modesto experience a hot-summer Mediterranean climate, with summer temperatures around 95 °F (35 °C) and mild winters of 39 – 47 °F (4 – 8 °C). Madera and Fresno have semi-arid climates featuring prolonged, hot summers reaching about 97 °F (36.5 °C), and average annual rainfall near 12 inches (305 mm) (Bailey, 2023). Such conditions create high evaporative demand during peak growing seasons, highlighting the value of real-time actual ET monitoring for efficient irrigation scheduling.

Processing tomatoes were planted on raised beds 5 feet (1.5 m) apart and irrigated using a subsurface drip irrigation (SDI) system, with drip lines buried at 20 cm depth and emitters spaced at 30 cm with a flow rate of 0.6 L h^{-1} (Raij-Hoffman et al., 2024). The soil at the Esparto site is a Capay silty clay, which offers high water-holding capacity, good drainage, and low spatial heterogeneity, verified using electrical resistivity tomography (ERT) and soil moisture sensors (Raij-Hoffman et al., 2024). At the Modesto site, almonds were planted at a spacing of 22 feet (6.7 m) between rows and 18 feet (5.5 m) between trees. Trees average about 3 m in height and are irrigated using surface drip, with four drippers per tree spaced 1.0 m apart, each delivering a flow rate of 1.14 L h^{-1} . Soils are predominantly fertile sandy loams with moderate water-holding capacity and excellent drainage, consistent with common almond cultivation practices in the area (Doll, 2017; Saxton and Rawls, 2006).

At the Madera site, pistachio trees are periodically pruned to promote healthy growth and maximize fruit production. The trees were planted at a spacing of 20 feet (6.1 m) between rows and 16 feet (4.8 m) between trees. Tree height averages 7 m. The irrigation system is a surface drip setup with four drippers per tree, spaced 0.9 m apart, each delivering a flow rate of 3.79 L h^{-1} . The soil type at the Madera site is a clay loam, which is suitable for deep-rooted pistachio production (Saxton and Rawls, 2006). At the citrus site near Fresno, the trees are pruned to optimize canopy structure and light interception, with a hexagonal pattern and a spacing of 18 feet (5.5 m) between trees; the average tree height is 4.5 m. The irrigation system in the citrus orchard consisted of micro-sprayers, with one emitter per tree delivering a flow rate of 40.5 L h^{-1} . The soils at the citrus site are well-drained sandy loams common in citrus growing regions in California (Geisseler and Horwath, 2016; Harter et al., 2004). In general, Capay silty clay (Esparto) exhibits a higher water-holding capacity, with a volumetric water content range of 35–40 % at field capacity. In contrast, sandy loams (Modesto, Fresno) hold around 15–25 %, while clay loams (Madera) typically range from 30–35 %.

To accurately capture ET measurements, eddy covariance (EC) flux towers equipped with LI-710 ET sensors were installed within each orchard, ensuring comparable environmental conditions across measurement systems. Data collection periods spanned the entire 2024 crop season, specifically: Esparto from April 30, 2024, to August 29, 2024;

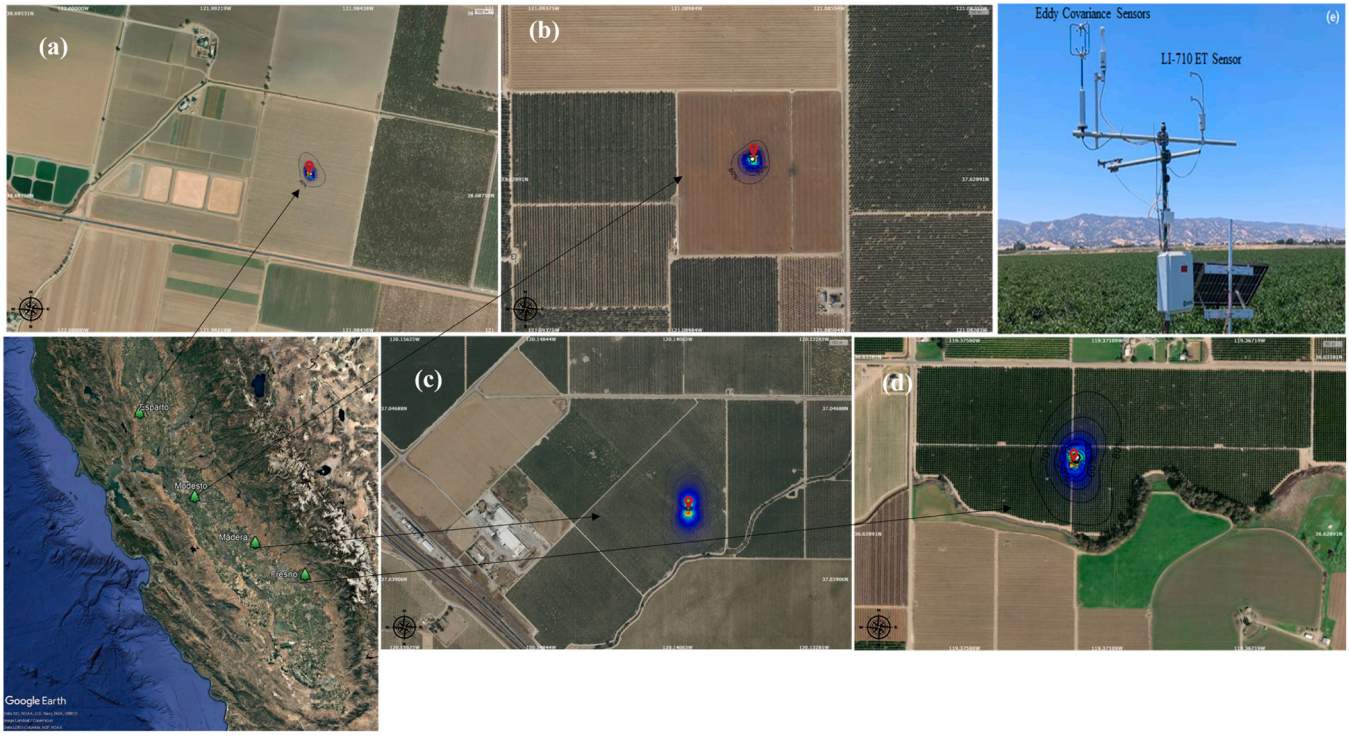


Fig. 1. Study area map and site-specific locations for eddy covariance flux towers with LI-710 evapotranspiration (ET) sensors across orchards in California, USA. The bottom left panel shows the Central Valley of California area, including four main sites: Esparto, Modesto, Madera, and Fresno. Panels (a), (b), (c), and (d) provide zoomed-in views of each site, indicating the exact placement of the eddy covariance flux towers with LI-710 ET sensors. The blue intensity gradients represent the footprint area of each flux tower, with contour lines showing varying levels of measurement sensitivity relative to distance from the tower. Panel (e) is an example of an eddy covariance and LI-710 ET sensor installation in a processing tomato field near Esparto, California.

Modesto from February 16, 2024, to October 10, 2024; Madera from October 12, 2023, to October 3, 2024; and Fresno from March 16, 2024, to October 9, 2024.

2.2. Eddy covariance system

The EC system used in this study was designed to capture high-frequency measurements of sensible and latent heat fluxes, as well as CO_2 fluxes, providing a comprehensive assessment of energy balance components at each site. The EC setup at each site consisted of a 3D sonic anemometer (Gill R3–50, Li-Cor Inc., NE, USA) to measure the three orthogonal wind velocity components and an open-path gas analyzer (LI-7500, Li-Cor Inc., NE, USA) to measure CO_2 and H_2O fluxes. Data was recorded at a frequency of 10 Hz, allowing for detailed measurements of wind, CO_2, and H_2O dynamics that are essential for accurate flux calculations. The height of the EC sensors was customized to match the canopy structure of each crop, ensuring optimal data capture. Specifically, the sensors were positioned at 2.5 m for tomatoes (canopy height: 0.2–1.5 m), 5 m for almonds (canopy height: approximately 3 m), 10 m for pistachios (canopy height: approximately 7 m), and 7 m for citrus (canopy height: approximately 4.5 m). This setup was selected to minimize interference from canopy turbulence and to position the sensors within the constant flux layer. According to standard fetch guidelines outlined in (Allen et al., 2011), the recommended minimum fetch for reliable measurements under neutral atmospheric stability conditions is approximately 100 times the measurement height. Therefore, the required minimum fetch distances for reliable EC measurements are approximately 250 m for tomatoes, 500 m for almonds, 1000 m for pistachios, and 700 m for citrus. All sites in our study meet these fetch criteria as they have homogenous cropping conditions extending well beyond these distances. Additionally, the flux footprints (as shown clearly in Fig. 1) indicate that the contributing source areas for all measurements remained entirely within the orchard boundaries, ensuring data representativeness and reliability.

To quantify the soil heat flux (G) in the surface energy balance (Hanks, 2012; Klute, 1986), three soil heat flux plates (HFT-3, Radiation Energy Balance Systems, WA, USA) were installed at 8 cm depth at each site. Soil thermocouples (TCAV-L, Campbell Scientific Inc., UT, USA) and soil moisture probes (GS-1, METER Group Inc., WA, USA) were placed at 5 cm depth to measure soil temperature and volumetric water content, respectively. Soil heat storage (ΔS) in the 5–8 cm layer above the plates was calculated as:

$$\Delta S = \frac{dT_s}{dt} \times C_s \times d \tag{1}$$

where $\frac{dT_s}{dt}$ is the rate of change of soil temperature ($^{\circ}C\ s^{-1}$), C_s is the soil heat capacity ($J\ m^{-3}\ ^{o}C^{-1}$), and d is the layer thickness (m). The soil heat capacity was estimated as

$$C_s = (\rho_b \times C_d) + (\theta \times \rho_w \times C_w) \tag{2}$$

where ρ_b is the site-specific bulk density of the soil ($kg\ m^{-3}$) measured via core samplers, C_d is the specific heat of dry soil ($J\ kg^{-1}\ ^{o}C^{-1}$), θ is the soil water content on a volume basis ($m^3\ m^{-3}$), ρ_w is the density of water ($kg\ m^{-3}$), and C_w is the specific heat of water ($J\ kg^{-1}\ ^{o}C^{-1}$). Total soil heat flux was

$$G = G_{plate} + \Delta S \tag{3}$$

where G_{plate} is the flux plate measurement.

Net radiation was measured using a four-component net radiometer (SN-500-SS, Apogee Instruments Inc., UT, USA), which captured shortwave and longwave incoming and outgoing radiation. This standardized EC setup across all four sites, Esparto (processing tomatoes), Modesto (almonds), Madera (pistachios), and Fresno (citrus), allowed for a consistent evaluation of the LI-710 sensor's performance relative to the full EC system under different crop and canopy conditions.

2.3. Eddy covariance data processing and footprint analysis

The data collected from the EC systems installed at the four sites was processed to ensure accuracy and reliability. All data were processed using EddyPro software (Version 7.0.9, Li-Cor Inc., NE, USA), which applies a series of standard corrections and data quality checks essential for accurate flux estimation. The data processing workflow was standardized across all four sites to ensure consistency in evaluating ET and energy balance components.

The first step in data processing involved correcting for coordinate rotation using a two-dimensional rotation technique, aligning the coordinate system with the mean wind direction to minimize tilt errors (Massman and Lee, 2002; Twine et al., 2000). This rotation ensures that the vertical fluxes of heat and moisture are accurately aligned with the true atmospheric flow, a critical aspect in complex canopies where wind direction and turbulence can vary significantly. Spectral corrections, based on the methodology developed by Moncrieff et al. (1997), were applied to account for high- and low-frequency flux losses due to sensor separation, sampling frequency limitations, and path length averaging. These spectral adjustments help to recover signal losses and ensure that the EC data accurately represent the true fluxes within the footprint area. To address fluctuations in heat and water vapor density, the Webb-Pearman-Leuning (WPL) correction (Webb et al., 1980) was applied to the data. This correction accounts for density fluctuations caused by variations in temperature and water vapor, which can introduce biases in CO_2 and H_2O flux measurements. Applying the WPL correction is essential, particularly in semi-arid climates like California's Central Valley, where rapid changes in temperature and humidity are common. TOVI software (Li-Cor Inc., NE, USA) was utilized for footprint analysis, comprehensive data quality assessment, automated gap-filling of missing data, flux partitioning into latent and sensible heat components, and EBR checks, providing a robust framework for managing and analyzing the EC datasets. In addition to data processing, footprint analysis was conducted to verify that each EC tower's measurements accurately represented the target area. Fig. 1 illustrates the footprint for each site, with blue intensity gradients and contour lines showing varying levels of sensitivity relative to the distance from each flux tower. This spatial analysis helped ensure that each measurement captured the desired area around the EC tower, allowing for reliable flux comparisons within the specific crop and orchard layout.

2.4. LI-710 ET sensor specifications

The LI-710 ET sensor (LI-COR Environmental, Lincoln, NE) computes energy fluxes using the eddy covariance approach that integrates vertical wind speed and high-precision relative humidity measurements ("LI-710 | Operating Instructions," n.d.). It performs onboard flux processing, outputting 30-minute latent heat flux (LE), sensible heat flux (H), and evapotranspiration (ET). The raw high-frequency data are processed internally by the sensor using a built-in algorithm specifically optimized for its compact hardware configuration, and the output is provided directly via the SDI-12 protocol. Unlike traditional EC systems, which require external software (e.g., EddyPro) to process raw 10–20 Hz data, the LI-710 delivers fully processed fluxes in real time. Raw flux data from the LI-710 are not currently made available by the manufacturer.

Its measurement area, or "fetch footprint," is determined by the sensor's height (50–100 times its height) and the wind direction. In random or uniform wind conditions, the measurements represent the surrounding vegetation. Under prevailing winds, they represent the upwind area and vegetation. However, unlike the full EC, the LI-710 does not measure horizontal wind, so it does not explicitly calculate the fetch footprint. The LI-710 ET sensor provides a suite of essential parameters for ET studies, including ET, LE, H, atmospheric pressure, air

temperature, relative humidity (RH), and absolute humidity. In addition to these core measurements, the LI-710 also provides values such as saturation vapor pressure, vapor pressure deficit (VPD), pump voltage, cell pressure, cell relative humidity (RH), and diagnostic indicators that contribute to comprehensive environmental monitoring and quality control. These outputs are automatically generated and formatted for easy integration into data logging systems and workflows.

For this study, the LI-710 was co-located with the EC system. The LI-710 was positioned at the same height as the EC sensors, ensuring that both systems captured the same atmospheric profile. This co-location enabled direct comparisons of ET, LE, and H measurements under various canopy structures and growth conditions, facilitating a robust evaluation of the LI-710's performance relative to the established EC system. Although LI-COR delivers the LI-710 pre-calibrated, maintaining sensor accuracy over time requires regular upkeep, especially the intake filter and air pump. The intake filter, located at the bottom of the sensor's transducer housing, was replaced every two to three months or more frequently in environments with high dust or debris. LI-COR supplies a specialized tool for filter replacement to ensure proper alignment and avoid damage. The air pump, which maintains steady airflow through the sensor, also has a limited lifespan and requires periodic replacement, but the pump was not replaced during the current study. Diagnostic indicators, such as pump voltage and flow rates, continuously monitor the air pump's performance, signaling when maintenance is necessary. Low flow rates or increased drive voltages may suggest that the intake filter or pump is obstructed or nearing the end of its operational life. By adhering to this maintenance schedule, the LI-710 sensor's performance remains optimized throughout the data collection period.

The LI-710 also offers robust diagnostic capabilities, which help maintain high data quality by enabling continuous monitoring of sensor health and operational consistency. A diagnostic code typically reads 0 during normal operation, while other values, as specified in the manual, signal potential issues such as airflow restrictions or component malfunctions, which require immediate inspection. In this study, diagnostic values were routinely checked, with any anomalies promptly addressed to uphold data accuracy. Alongside diagnostics, the sensor outputs a sequence number and sample count, aiding in the verification of data continuity and integrity. Data quality metrics further enhance reliability by indicating the condition of the data in real time based on sensor status and environmental factors. To ensure comparability with the EC dataset, the same gap-filling procedure, Marginal Distribution Sampling (MDS), was applied to the LI-710's 30-minute LE data during post-processing. While the LI-710 does not perform onboard gap-filling, missing values due to power interruptions or sensor diagnostics were filled using the same external MDS method as used for EC data. After gap-filling, the LE values were converted to ET and aggregated to daily totals by summing the 48 half-hourly ET values per day. Additionally, since the LI-710 does not apply EBR corrections internally, the energy balance residual (EBR) correction was applied to both the EC and LI-710 datasets during post-processing, as detailed in Section 2.5. While the LI-710 does not match the full capabilities of a complete EC system, it offers a reliable and efficient method for ET monitoring at a significantly lower cost, typically four to five times less than conventional EC systems.

2.5. Energy balance residual correction for H and LE

The lack of closure in the surface energy balance is a well-known challenge in hydrometeorological research when using the EC method to measure H and LE fluxes (Mauder et al., 2018; Stoy et al., 2013). This discrepancy arises when the sum of H and LE does not match the available energy, defined as net radiation (Rn) minus soil heat flux (G). A common hypothesis attributes this imbalance to the inability of traditional EC systems to capture large-scale atmospheric transport phenomena, which leads to systematic underestimation of H and LE. Other studies have attributed the lack of EBR corrections to canopy energy storage. To address this, several correction methods have been proposed to adjust EC-derived flux measurements and achieve a better EBR.

One of the most widely accepted correction methods proposed by Mauder et al., (2013) uses the energy balance residuals to correct H and LE while preserving the Bowen ratio (H/LE), thereby providing a more realistic partition of turbulent heat fluxes. This approach calculates a correction factor, C, by evaluating the ratio of the total available energy to the sum of the measured H and LE fluxes. In this study, the same procedure was applied to both EC and LI-710 data, ensuring consistency in EBR corrections across the measurement sites.

The correction factor C is calculated daily to reflect the EBR ratio. Specifically, C is defined as:

$$C = \frac{\sum_{i=1}^{k} H_i + LE_i}{\sum_{i=1}^{k} R_{n,i} + G_i} \tag{4}$$

where H is sensible heat flux (W m^{-2}), LE is latent heat flux (W m^{-2}), R_n is the net radiation (W m^{-2}), G is the soil heat flux (W m^{-2}), and k is the number of valid observations of H and LE in each day when $R_n > 20$ W m^{-2}. This threshold focuses the correction on periods with sufficient radiative energy, excluding nighttime measurements where turbulent fluxes are minimal.

Once C is determined, it is applied equally to both H and LE, yielding corrected fluxes that proportionally scale the original measurements:

$$H_{corr} = \frac{H_{meas}}{C} \tag{5}$$

$$LE_{corr} = \frac{LE_{meas}}{C} \tag{6}$$

where H_{corr} and LE_{corr} are the corrected sensible and latent heat fluxes, respectively.

This approach adjusts both fluxes proportionally to achieve a balance between the total available energy and the combined heat fluxes, thereby ensuring that each 30-minute interval aligns with the expected EBR. The EBR correction procedure was consistently applied to 30-minute LE and H data from both the EC system and the LI-710 sensor across all four sites, using only daytime periods ($Rn > 20$ W m^{-2}). ET was subsequently derived from the corrected LE values for both systems while preserving the Bowen ratio. Implementing this correction method across different crops provided a consistent basis for comparing the performance of the LI-710 ET sensor and EC systems in capturing H and LE fluxes. This approach is particularly useful for examining the LI-710's potential as an alternative to the full EC system, as it allows for standardized adjustments across diverse canopy structures and microclimates.

2.6. Evaluation of LI-710 sensor performance using FITEVAL framework

FITEVAL (Ritter and Muñoz-Carpena, 2013) was used as a standardized framework to evaluate the goodness-of-fit between the flux measurements (ET, LE, and H) from the LI-710 sensor and the EC system. The analysis was conducted to assess the performance of the LI-710 sensor in comparison to EC measurements for EBR-corrected and uncorrected conditions.

The evaluation process involved calculating key statistical indicators, including the Root Mean Squared Error (RMSE), the Nash-Sutcliffe Efficiency (NSE), and the Kling-Gupta Efficiency (KGE). RMSE quantified the model prediction error in the same units as the fluxes, while NSE and KGE provided dimensionless measures of the agreement between the two datasets. To address uncertainty in model evaluation, hypothesis testing for the NSE metric was conducted using bootstrapping. This method involved resampling the data to generate an

approximate probability density function for NSE (Ritter and Muñoz-Carpena, 2013). For time series with autocorrelated values, block bootstrapping was applied to account for temporal dependencies. The null hypothesis (NSE < 0.65) was tested against a one-tailed alternative hypothesis at a significance level (α) of 0.1, a value commonly used for such evaluations. Based on the p-value obtained from the bootstrap analysis, model performance was categorized as Unsatisfactory (NSE < 0.65), Acceptable ($0.65 \leq$ NSE < 0.80), Good ($0.80 \leq$ NSE < 0.90), or Very Good (NSE ≥ 0.90). Time series analysis was performed to evaluate the temporal behavior of flux measurements, allowing for the identification of potential biases or deviations over time. Separate time series were analyzed for EBR-corrected and uncorrected EC fluxes to investigate the impact of energy balance closure on the sensor's performance. Finally, uncertainty in the data and predictions was addressed using FITEVAL's implemented methods. The Probable Error Range (PER) was calculated to quantify the uncertainty in observations and predictions, while the Correction Factor (CF) method was applied to adjust goodness-of-fit indicators for model uncertainty under realistic assumptions about data variability.

3. Results

3.1. Meteorological conditions

Across all four cropping systems (almonds, processing tomatoes, pistachios, and citrus), the meteorological variables exhibit a pronounced seasonal cycle characteristic of California's Mediterranean climate (Fig. 2). Solar radiation ranges from below 200 W m^{-2} in early spring to 400–500 W m^{-2} at its mid-summer peak, before gradually declining in the fall. Air temperature ranges from around 5–15°C in winter to 25–35°C in summer, increasing the vapor pressure deficit from less than 2 kPa in the cooler months to 6–8 kPa at the height of the dry season. This drop in moisture availability lowers relative humidity from around 60–80 % in winter to 20–40 % during the hottest part of the year. Wind speed remains more episodic throughout, generally varying between about 1–3 m s^{-1} and occasionally spiking to 4–6 m s^{-1} during transitional or storm-related events. By late fall, cooler temperatures and scattered rains ease vapor pressure deficit levels, increase relative humidity, and return solar radiation to values closer to those of early spring.

3.2. Energy balance closure analysis

The energy balance closure for the two different ET measurement systems, the full eddy covariance (EC) method and the LI-710 ET sensor, is shown in Figs. 3 and 4, respectively. The relationship between available energy (R_n-G) and combined turbulent fluxes (H+LE) was analyzed for each crop type, with linear regression applied to quantify the degree of energy balance closure.

At the processing tomato site, both the EC system and the LI-710 sensor demonstrated high energy balance closure. The EC system yielded a regression slope of 0.91 with an R^2 value of 0.96, indicating a strong alignment between available energy and combined turbulent fluxes. The LI-710 ET sensor performed comparably well, with a slope of 0.94 and an R^2 of 0.92, showing similar reliability in capturing ET dynamics. The uniform canopy structure in the processing tomatoes likely contributed to the consistency observed with both systems, suggesting that both the EC and LI-710 systems are effective for ET measurement in environments with similar crop structures. At the almond orchard site, both systems also showed strong energy balance closure, though with some differences in slope. The EC system produced a slope of 0.93 and an R^2 of 0.90, indicating a reliable capture of available energy by the combined turbulent fluxes. The LI-710 sensor, on the other hand, exhibited a slightly higher slope of 1.08 with an R^2 of 0.88, indicating a slight overestimation. This difference could be attributed to sensor sensitivity or environmental factors specific to the almond orchard.

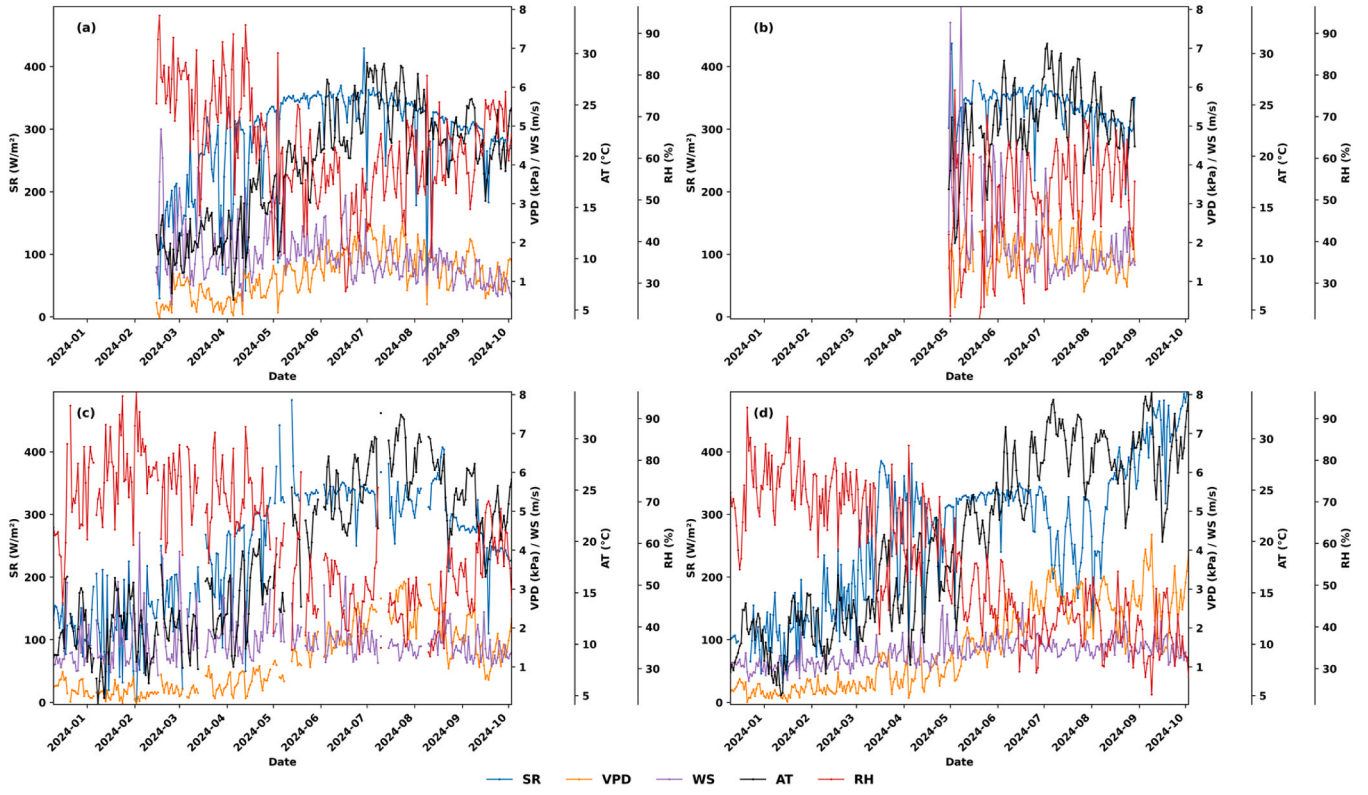


Fig. 2. Time series of key meteorological variables observed in different cropping systems: (a) Almond, (b) Processing Tomato, (c) Pistachio, and (d) Citrus. The variables include solar radiation (SR, blue), vapor pressure deficit (VPD, orange), wind speed (WS, purple), air temperature (AT, black), and relative humidity (RH, red).

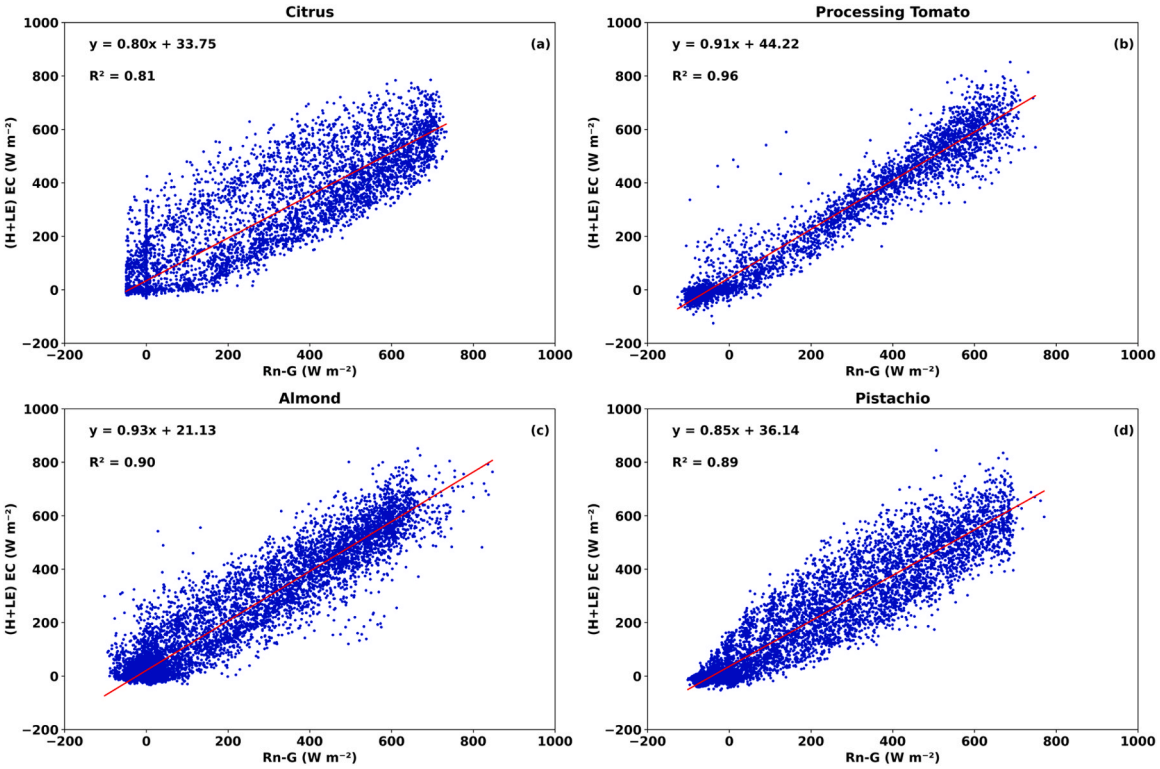


Fig. 3. Linear regressions of available energy (Rn−G) against the sum of sensible heat (H) and latent heat (LE) measured from eddy covariance flux tower data for four different crops: (a) Citrus, (b) Processing Tomato, (c) Almond, and (d) Pistachio. The red line represents the regression line, with the regression equation and coefficient of determination (R^2) values shown for each crop.

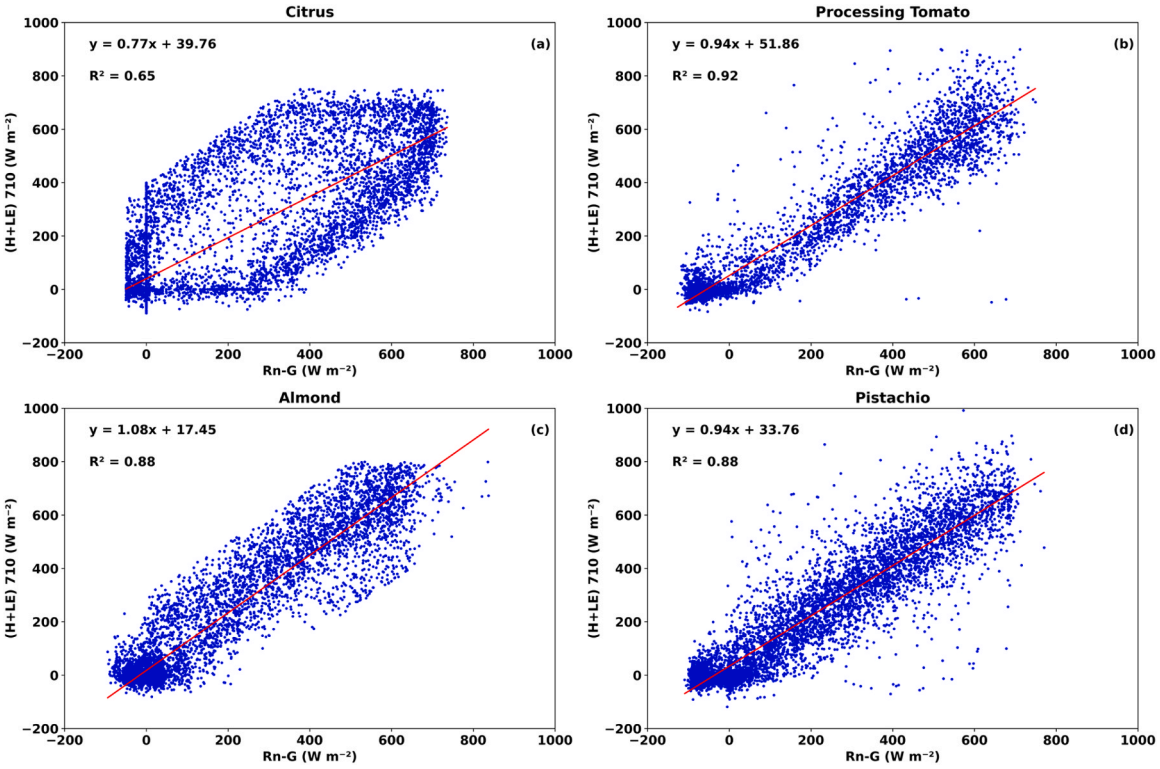


Fig. 4. Linear regressions of available energy (Rn−G) against the sum of sensible heat (H) and latent heat (LE) measured using the LI-710 ET sensor for four different crops: (a) Citrus, (b) Processing Tomato, (c) Almond, and (d) Pistachio. The red line represents the regression line, with the regression equation and coefficient of determination (R^2) values shown for each crop.

Nevertheless, both systems showed strong correlations with available energy, supporting the suitability of both methods for measuring evapotranspiration (ET) in almond orchards.

In the pistachio orchard, the EC system achieved a slope of 0.85 with an R^2 value of 0.89, while the LI-710 sensor produced a slope of 0.94 with an R^2 of 0.88. These results suggest a strong relationship between available energy and combined turbulent fluxes for both systems, though the EC system showed a slightly lower slope. The complex canopy structure in pistachio orchards may introduce variability in measurements, but both systems performed well overall, capturing most of the available energy in the pistachio orchard. The citrus orchard presented more variability in energy balance closure between the two systems. The EC system had a regression slope of 0.80 and an R^2 value of 0.81, indicating reasonable, though not perfect, energy closure. In

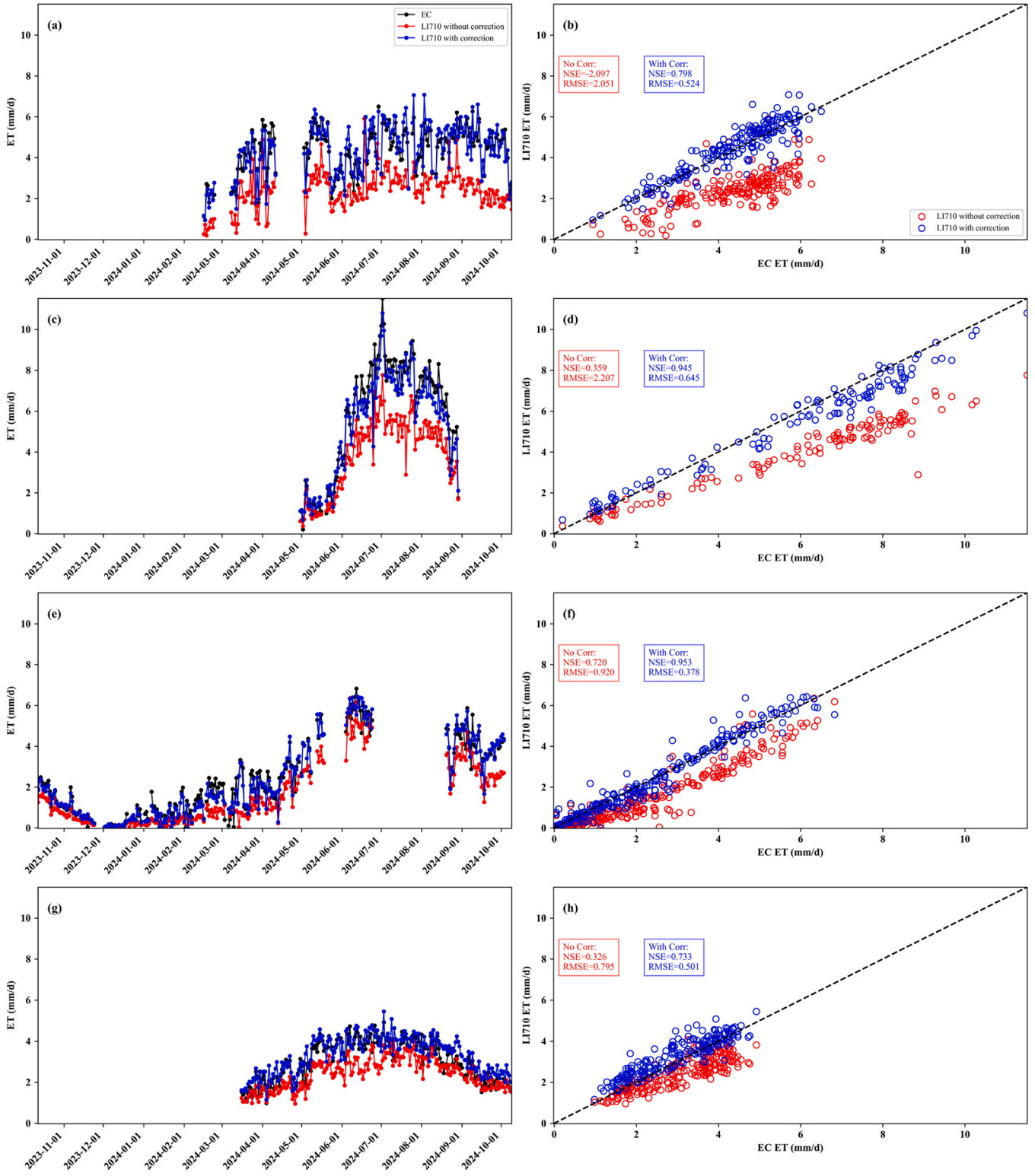


Fig. 5. Time series and scatter plots comparing daily evapotranspiration (ET) measurements from eddy covariance (EC) and LI-710 ET sensors for almond (a, b), processing tomato (c, d), pistachio (e, f), and citrus (g, h) crops.

contrast, the LI-710 sensor showed a lower slope of 0.77 with an R^2 of 0.65, suggesting less alignment between available energy and combined turbulent fluxes. The complex canopy structure in the citrus orchard characterized by pruning citrus trees (Fig. S1) likely affected the LI-710 sensor's performance, leading to a weaker correlation compared to the EC system. This discrepancy highlights that while the LI-710 sensor is effective in simpler canopy structures, it may face challenges in accurately capturing ET in more complex environments, such as hexagonal pruned citrus orchards. Overall, both the EC system and the LI-710 sensor demonstrated strong energy balance closure in the processing of tomatoes, almonds, and pistachio orchards, with comparable slopes and R^2 values. However, in the citrus orchard, the EC system provided more consistent results than the LI-710 sensor, likely due to the influence of canopy complexity.

3.3. Evapotranspiration comparisons between the eddy covariance system and the LI-710 ET sensor

Fig. 5 presents the daily ET measurements from the EC system and the LI-710 ET sensors across almond, processing tomato, pistachio, and citrus cropping systems. The time series plots (Figs. 5a, 5c, 5e, 5g) illustrate the variations in ET over the study period, while the scatterplots (Figs. 5b, 5d, 5f, 5h) depict the relationships between EC and LI-710 measurements, with and without energy balance residual (EBR) correction. Table 1 summarizes the statistical performance of the LI-710 ET sensor, including NSE, NRMSE, KGE, p-values, and model bias classification.

In all cases, the uncorrected LI-710 sensor underestimated daily ET relative to the EC system, resulting in low or negative NSE values, high RMSE, and underprediction biases of up to 43.7 %. The largest discrepancy was observed in almonds, where the uncorrected LI-710 sensor produced an NSE of −2.09 and RMSE of 2.05 mm d^{-1} , with a model bias of 43.7 % underestimation. Processing tomatoes had an NSE of 0.35 and RMSE of 2.20 mm d^{-1} , with an underprediction bias of 33.1 %. In pistachios, the uncorrected sensor achieved an NSE of 0.72 and RMSE of 0.92 mm d^{-1} , with an underprediction bias of 31.7 %. The citrus dataset exhibited the lowest NSE (0.32) and an RMSE of 0.79 mm d^{-1} , with a 20.1 % underprediction bias. The p-values for the uncorrected measurements were 1.000 for almonds, processing tomatoes, and citrus, indicating that the null hypothesis (NSE $<$ 0.65) could not be rejected, confirming poor model performance. In pistachios, the p-value was 0.015, showing marginal agreement but still indicating substantial deviation. KGE values further confirmed poor performance, ranging from 0.42 in almonds to 0.65 in citrus.

Applying the EBR correction substantially improved the agreement with the EC system in all cropping systems, as indicated by higher NSE values, reduced RMSE, increased KGE, and a notable decrease in model bias. Processing tomatoes showed the highest NSE improvement, increasing from 0.35 to 0.94, with RMSE decreasing from 2.20 to 0.64 mm d^{-1} and bias dropping to 6.2 %. In almonds, the NSE improved to 0.79, RMSE decreased to 0.52 mm d^{-1} , and bias was reduced to 2.0 % overprediction. Pistachios exhibited the strongest agreement after correction, with NSE increasing to 0.95, RMSE dropping to 0.37 mm d^{-1} , and bias reducing to 1.1 %. In citrus, NSE improved to 0.73, RMSE decreased to 0.50 mm d^{-1} , and bias shifted to a 9.6 % overprediction. KGE values also improved significantly across all cropping systems, reaching 0.87 in almonds, 0.87 in processing tomatoes, 0.95 in pistachios, and 0.84 in citrus. The p-values for the corrected dataset indicate statistically significant improvements, with values of 0.000 for almonds, processing tomatoes, and pistachios, confirming a statistically significant strong agreement with the EC data. In Citrus, the p-value of 0.017 indicates statistically significant improvement, though it was slightly lower than in other cropping systems.

The classification of model performance based on NSE indicates that uncorrected LI-710 measurements were consistently categorized as unsatisfactory for all crops. After correction, performance improved to acceptable in almonds (52.7 %) and good in processing tomatoes (100 %) and citrus (97.2 %), while in pistachios, the corrected LI-710 achieved very good performance (100 %). The scatterplots in Fig. 5 confirm that the uncorrected LI-710 sensor consistently underestimated ET, as indicated by the data points (red) clustering below the 1:1 line. However, after EBR correction, the points (blue) show much closer alignment with EC measurements, clustering tightly around the 1:1 line with reduced dispersion. These results demonstrate that the application of the EBR correction consistently mitigates the systematic underestimation in raw LI-710 observations, delivering daily ET estimates that closely match those obtained from the EC method across diverse cropping systems.

3.4. Sensible heat flux comparisons between the eddy covariance system and the LI-710 ET sensor

Fig. 6 presents the daily average H measurements obtained from the EC system and the LI-710 ET sensor across almond, processing tomato, pistachio, and citrus cropping systems. The time series plots (Figs. 6a, 6c, 6e, 6g) illustrate the temporal variations in H, while the scatterplots (Figs. 6b, 6d, 6f, 6h) depict the relationships between EC and LI-710 measurements, with and without EBR correction. Table 2 summarizes the statistical performance of the LI-710 sensor for H, including NSE, NRMSE, KGE, p-values, and model bias classification.

In all cropping systems, the uncorrected LI-710 ET sensor generally underpredicted daily H, as indicated by low NSE values, high RMSE, large negative biases, and elevated NRMSE. In almonds, the uncorrected NSE was −0.35, with an RMSE of 44.88 W m^{-2} and an NRMSE of 68.5 %, showing the highest error among all crops. Processing tomatoes showed better agreement with the EC system in the uncorrected dataset, with an NSE of 0.86 and an RMSE of 23.30 W m^{-2}; however, the bias analysis still indicated a 31.7 % underprediction. In pistachios, the uncorrected LI-710 ET sensor achieved an NSE of 0.20, RMSE of 28.71 W m^{-2}, and NRMSE of 49.0 %, with a bias of 32.6 % underestimation. The citrus dataset had the lowest NSE of 0.13 and an RMSE of 31.47 W m^{-2}, with an underprediction bias of 22.9 %. The p-values for the uncorrected

Table 1
Comparison of evapotranspiration (ET) measurements from eddy covariance and LI-710 ET sensors across different crops. Table 1 shows model performance with and without correction using statistical metrics: Nash-Sutcliffe Efficiency (NSE), Normalized Root Mean Square Error (NRMSE), Kling-Gupta Efficiency (KGE), and p-value. Model bias is categorized based on the percentage of underprediction or overprediction. Performance classification includes unsatisfactory (U), acceptable (A), good (G), and very good (VG) predictions.

Crop	Correction	NSE	NRMSE (%)	KGE	p	U (%)	A (%)	G (%)	VG (%)	Model Bias
Almond	Without	−2.09	47.7	0.42	1.000	100	0	0	0	Underprediction by 43.7 %
Almond	With	0.79	12.2	0.87	0.000	0	52.6	47.3	0	Overprediction by 2.0 %
Processing tomato	Without	0.35	37.9	0.52	1.000	100	0	0	0	Underprediction by 33.1 %
Processing tomato	With	0.94	11.1	0.87	0.000	0	0	0	100	Underprediction by 6.2 %
Pistachio	Without	0.72	41.2	0.64	0.014	1.4	98.6	0	0	Underprediction by 31.7 %
Pistachio	With	0.95	16.9	0.95	0.000	0	0	0	100	Underprediction by 1.1 %
Citrus	Without	0.32	26.3	0.65	1.000	100	0	0	0	Underprediction by 20.1 %
Citrus	With	0.73	16.6	0.84	0.017	2	96.8	1.2	0	Overprediction by 9.6 %

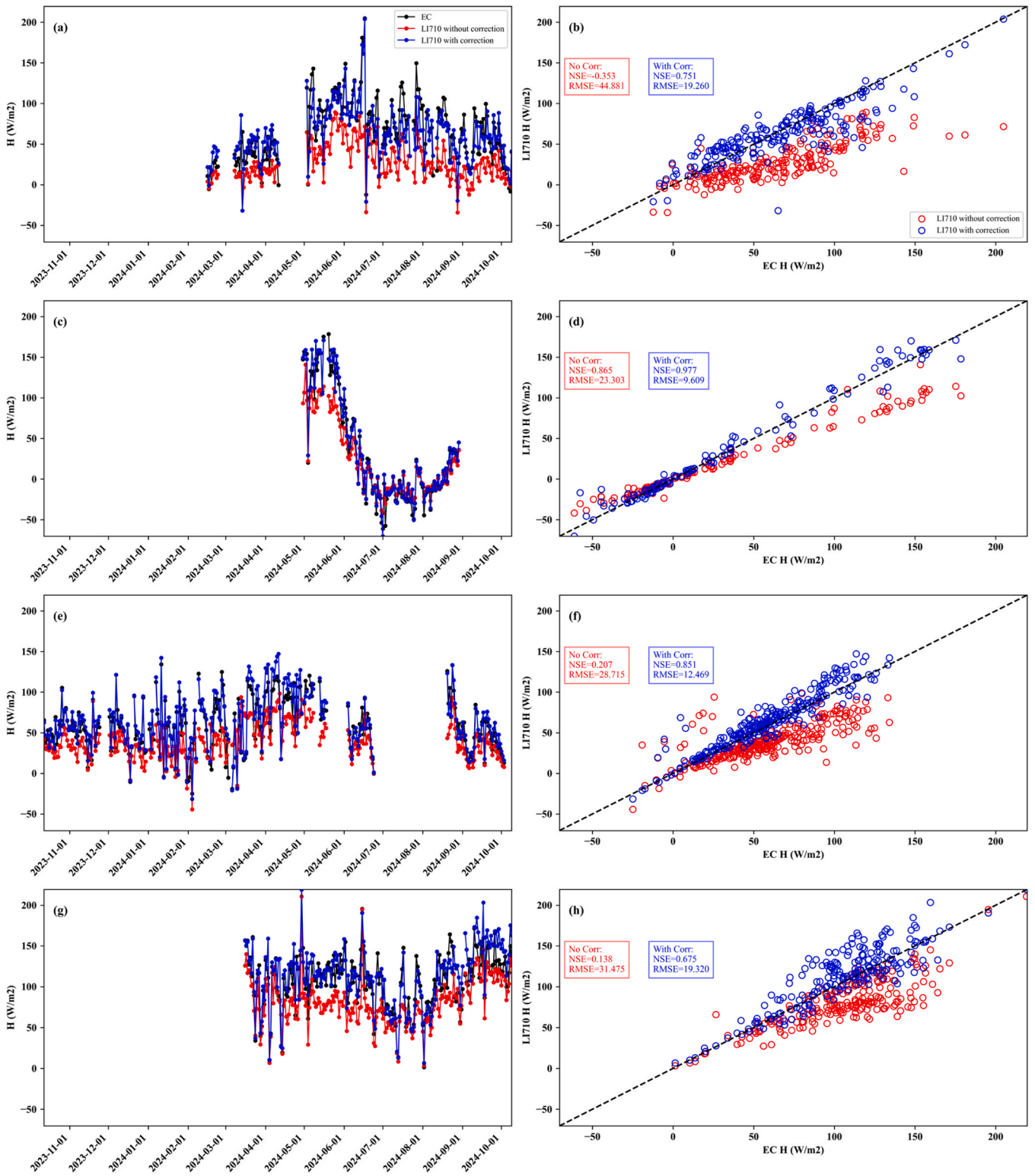


Fig. 6. Time series and scatter plots comparing daily sensible heat flux (H) measurements from eddy covariance (EC) and LI-710 ET sensors for almond (a, b), processing tomato (c, d), pistachio (e, f), and citrus (g, h) crops.

measurements were 1.000 for almonds, pistachios, and citrus, indicating that the null hypothesis (NSE $<$ 0.65) could not be rejected, confirming poor model performance. In processing tomatoes, the p-value was 0.000, suggesting significant agreement despite the underestimation. KGE values in the uncorrected dataset remained low, ranging from 0.28 in almonds to 0.66 in citrus, reinforcing the need for correction.

Applying the EBR correction significantly improved alignment with EC measurements in all cropping systems, as evidenced by increased NSE values, lower RMSE and NRMSE, and improved KGE. In processing tomatoes, the NSE increased to 0.97, RMSE decreased to 9.60 W m^{-2}, and bias reduced to 7.4 % overprediction, demonstrating strong agreement. In almonds, the NSE improved to 0.75, RMSE decreased to 19.26 W m^{-2}, and bias reduced to 4.9 % underprediction. Pistachios exhibited notable improvement with NSE increasing to 0.85, RMSE

Table 2
Comparison of sensible heat flux (H) measurements from eddy covariance and LI-710 ET sensors across different crops. Table 2 shows model performance with and without correction using statistical metrics: Nash-Sutcliffe Efficiency (NSE), Normalized Root Mean Square Error (NRMSE), Kling-Gupta Efficiency (KGE), and p-value. Model bias is categorized based on underprediction or overprediction percentages. Performance classification includes unsatisfactory (U), acceptable (A), good (G), and very good (VG) predictions.

Crop	Correction	NSE	NRMSE (%)	KGE	p	U (%)	A (%)	G (%)	VG (%)	Model Bias
Almond	Without	−0.35	68.5	0.28	1.000	100	0	0	0	Underprediction by 57.6 %
Almond	With	0.75	29.4	0.79	0.036	3.9	82	14.1	0	Underprediction by 4.9 %
Processing tomato	Without	0.86	71.6	0.56	0.000	0	0	99.9	0.1	Underprediction by 31.7 %
Processing tomato	With	0.97	29.5	0.92	0.000	0	0	0	100	Overprediction by 7.4 %
Pistachio	Without	0.20	49	0.48	1.000	100	0	0	0	Underprediction by 32.6 %
Pistachio	With	0.85	21.3	0.88	0.000	0	2.2	97.6	0.3	Overprediction by 9.2 %
Citrus	Without	0.13	29.8	0.66	1.000	100	0	0	0	Underprediction by 22.9 %
Citrus	With	0.67	18.3	0.83	0.040	13.9	85.9	0.2	0	Overprediction by 7.0 %

dropping to 12.46 W m^{-2}, and bias shifting to 9.2 % overprediction. In citrus, NSE improved to 0.67, RMSE decreased to 19.32 W m^{-2}, and bias shifted to 7.0 % overprediction. The KGE values also improved significantly across all cropping systems, reaching 0.79 in almonds, 0.92 in processing tomatoes, 0.88 in pistachios, and 0.83 in citrus, demonstrating enhanced agreement with EC data. The p-values for the corrected dataset indicate statistically significant improvements, with values of 0.000 for processing tomatoes and pistachios, confirming strong agreement with EC data. For almonds, the p-value was 0.036, also indicating a statistically significant improvement, while in citrus, the p-value remained relatively low at 0.040, suggesting a significant improvement as well. The classification of model performance based on NSE indicates that uncorrected LI-710 measurements were consistently categorized as unsatisfactory for all crops. After correction, performance improved to acceptable in almonds (82.2 %) and good in processing tomatoes (99.9 %) and citrus (65.2 %), while in pistachios, the corrected LI-710 achieved a very good performance (97.1 %). The scatterplots in Fig. 6 confirm that the uncorrected LI-710 sensor systematically underestimated H, as indicated by the data points (red) clustering below the 1:1 line. However, after EBR correction, the points (blue) align more closely with the EC measurements, clustering around the 1:1 line with reduced dispersion.

3.5. Latent heat flux comparisons between the eddy covariance system and the LI-710 ET sensor

Fig. 7 presents the daily LE measurements from the EC system and the LI-710 sensor across four cropping systems: almond, processing tomato, pistachio, and citrus. The time series plots (Figs. 7a, 7c, 7e, 7g) illustrate the variations in LE over time, while the scatterplots (Figs. 7b, 7d, 7f, 7h) depict the relationships between EC and LI-710 ET sensor measurements, with and without EBR correction. Table 3 summarizes the statistical performance of the LI-710 ET sensor, including NSE, NRMSE, KGE, p-values, and model bias classification.

Across all cropping systems, the uncorrected LI-710 measurements consistently underestimated LE, as indicated by low or negative NSE values, high RMSE, significant negative biases, and elevated NRMSE. Almonds exhibited the largest deviation, with an uncorrected NSE of −1.51, RMSE of 55.57 W m^{-2}, and NRMSE of 44.2 %, with a 39.6 % underprediction bias. Processing tomatoes resulted in an NSE of 0.44, an RMSE of 58.46 W m^{-2}, and an underprediction bias of 30.6 %. In the pistachios, the uncorrected LI-710 sensor achieved an NSE of 0.71, RMSE of 26.62 W m^{-2}, and an underprediction bias of 29.4 %. Citrus showed the lowest NSE of −0.10, RMSE of 26.59 W m^{-2}, and an underprediction bias of 20.0 %. The p-values for the uncorrected measurements were 1.000 for almonds, processing tomatoes, and citrus, confirming that the null hypothesis (NSE < 0.65) could not be rejected, thereby indicating poor LI-710 ET sensor performance. In the case of pistachios, the p-value was 0.058, indicating slightly better agreement but still suggesting substantial errors. KGE values in the uncorrected dataset ranged from 0.47 in almonds to 0.72 in citrus, further confirming the systematic bias in the uncorrected LI-710 data.

After applying EBR correction, agreement with the EC system improved significantly across all crops, with increased NSE, reduced RMSE and NRMSE, improved KGE, and bias values approaching or shifting slightly above zero. In processing tomatoes, NSE increased to 0.95, RMSE decreased to 15.79 W m^{-2}, and bias reduced to 1.9 % underprediction, indicating strong agreement. In almonds, NSE improved to 0.76, RMSE dropped to 17.13 W m^{-2}, and bias changed to 8.2 % overprediction. Pistachios exhibited a significant improvement, with NSE increasing to 0.93, RMSE decreasing to 13.11 W m^{-2}, and bias reducing to 2.7 % underprediction. Citrus showed similar improvements, with NSE rising to 0.77, RMSE decreasing to 11.89 W m^{-2}, and bias reducing to 4.5 % overprediction. KGE values also improved considerably across all cropping systems, reaching 0.86 in almonds, 0.94 in processing tomatoes, 0.92 in pistachios, and 0.89 in citrus, reflecting enhanced agreement with EC data. The p-values for the corrected dataset indicate statistically significant improvements, with values of 0.000 for processing tomatoes and pistachios, confirming strong agreement with EC measurements. In almonds, the p-value was 0.012, confirming a statistically significant improvement, while in citrus, the p-value was 0.008, further demonstrating the effectiveness of the correction. The classification of model performance based on NSE indicates that uncorrected LI-710 measurements were unsatisfactory across all crops. After correction, performance improved to acceptable in almonds (84.4 %) and good in citrus (70.0 %). In contrast, the corrected LI-710 data achieved very good performance in processing tomatoes (100 %) and pistachios (96.5 %). The scatterplots in Fig. 7 confirm that the uncorrected LI-710 sensor systematically underestimated LE, as indicated by the data points (red) clustering below the 1:1 line. However, after EBR correction, the points (blue) aligned more closely with the EC measurements, clustering tightly around the 1:1 line with reduced dispersion.

4. Discussion

The EC system and the LI-710 ET sensor generally exhibited similar patterns in ET, H, and LE fluxes. Both systems use the eddy covariance approach to measure turbulent fluxes but with notable differences. The EC system employs a sonic anemometer to measure wind speed in three directions, which aids in computing LE and H, whereas the LI-710 only measures vertical wind speed. This difference likely contributed to variations observed before energy balance residual (EBR) corrections were implemented. Additionally, site conditions influenced discrepancies. In its raw form, the LI-710 consistently underestimated flux magnitudes, particularly during high flux periods, suggesting an incomplete representation of turbulent energy exchanges. This bias was most pronounced during peak crop growth stages, increasing RMSE and occasionally resulting in negative model efficiency. The primary factor underlying these discrepancies is the challenge of energy balance closure. Like other flux measurement techniques, the LI-710 does not inherently close the surface energy budget, leading to some missing

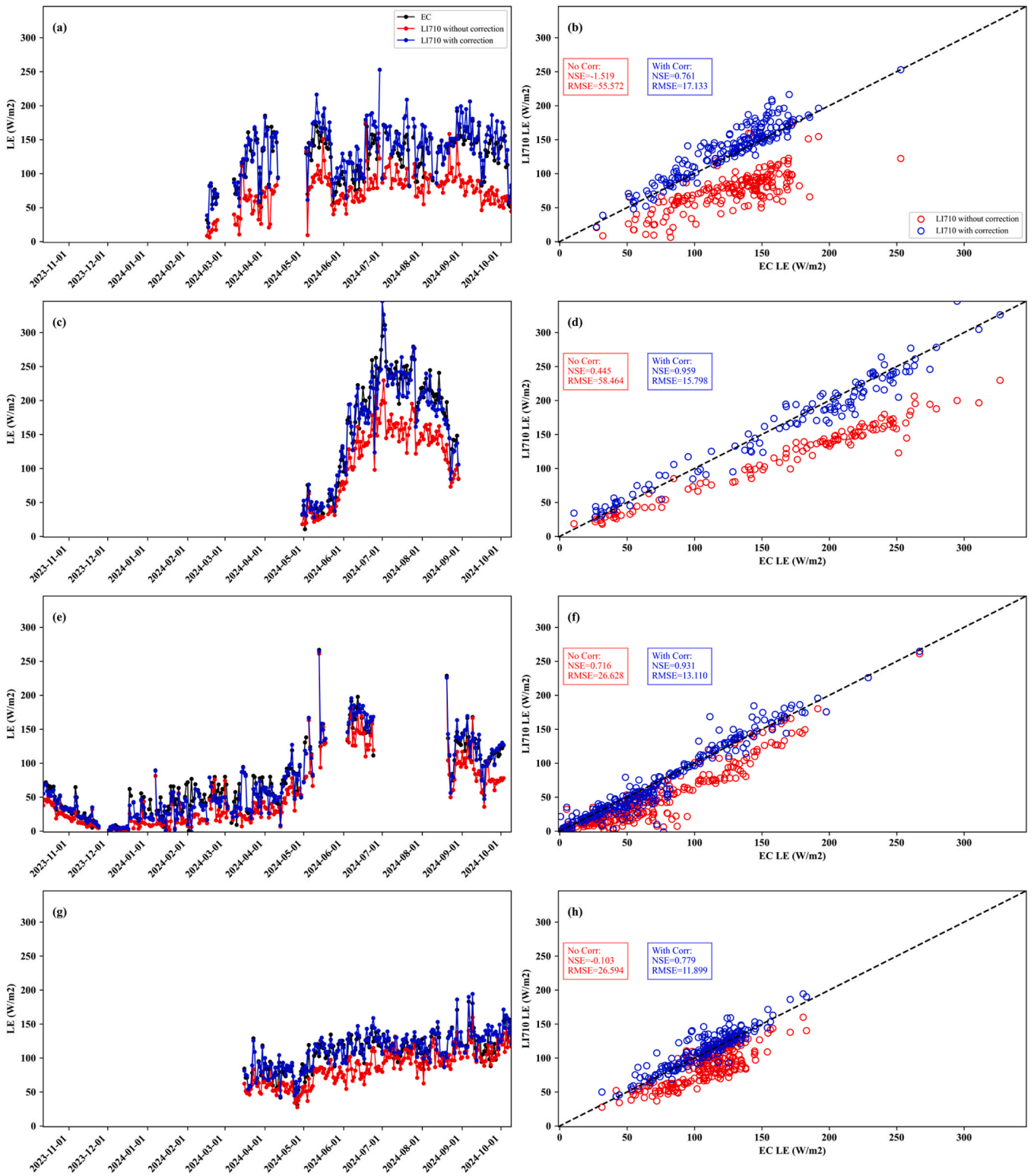


Fig. 7. Time series and scatter plots comparing daily latent heat flux (LE) measurements from eddy covariance (EC) and LI-710 ET sensors for almond (a, b), processing tomato (c, d), pistachio (e, f), and citrus (g, h) crops.

energy contributions to sensible and latent heat fluxes. Even EC systems often report lower-than-expected LE values due to unresolved large-scale turbulent structures and advective fluxes (Tang et al., 2019). Applying EBR corrections improved agreement between the LI-710 and EC reference, enhancing measurement reliability.

Site-specific factors also contributed to discrepancies. Frequency response and sensor dynamics played a role, as the EC setup, with its research-grade 3D sonic anemometer and infrared gas analyzer, captures a broader spectrum of turbulent scales (Baldocchi, 2003; Burba, 2013). The integrated design of the LI-710 may miss certain high-frequency fluctuations or large-eddy contributions, leading to underestimation of H and LE fluxes, particularly during sudden gusts or

Table 3
Comparison of latent heat flux (LE) measurements from eddy covariance and LI-710 ET sensors across different crops. Table 3 shows model performance with and without correction using statistical metrics: Nash-Sutcliffe Efficiency (NSE), Normalized Root Mean Square Error (NRMSE), Kling-Gupta Efficiency (KGE), and p-value. Model bias is categorized based on the percentage of underprediction or overprediction. Performance classification includes unsatisfactory, acceptable, good, and very good predictions.

Crop	Correction	NSE	NRMSE (%)	KGE	p	U (%)	A (%)	G (%)	VG (%)	Model Bias
Almond	Without	−1.51	44.2	0.47	1.000	100	0	0	0	Underprediction by 39.6 %
Almond	With	0.76	13.6	0.86	0.012	1.2	86.3	12.5	0	Overprediction by 8.2 %
Processing tomato	Without	0.44	34.8	0.55	1.000	100	0	0	0	Underprediction by 30.6 %
Processing tomato	With	0.95	9.4	0.94	0.000	0	0	0	100	Underprediction by 1.9 %
Pistachio	Without	0.71	38	0.69	0.058	5.8	93.6	0.6	0	Underprediction by 29.4 %
Pistachio	With	0.93	18.7	0.92	0.000	0	0	3.9	96.1	Underprediction by 2.7 %
Citrus	Without	−0.10	24.5	0.72	1.000	100	0	0	0	Underprediction by 20.0 %
Citrus	With	0.77	11	0.89	0.008	0.8	69.2	30	0	Overprediction by 4.5 %

small-scale turbulence. Differences also emerged during stable or low-turbulence conditions, such as at night or in the early morning when fluxes were minimal. Both systems occasionally recorded spurious values, but the LI-710, lacking standard EC corrections like coordinate rotation or density adjustments, exhibited greater drift. We mitigated these discrepancies by applying uniform data filtering and corrections across datasets. Additionally, advection and heterogeneous fetch conditions influence flux measurements. During California summers, hot, dry air advection elevated ET fluxes recorded by the EC system as crops evaporated the additional energy (Bambach et al., 2022).

In the almond orchard, both systems exhibited similar diurnal and seasonal ET, H, and LE patterns. However, initial discrepancies arose due to the orchard's complex canopy structure and advective conditions. The raw LI-710 measurements underestimated fluxes during peak midday periods in midsummer, reflecting incomplete turbulent energy capture influenced by canopy roughness and external hot air advection (Arriga et al., 2017; Kivalov et al., 2023; Wang et al., 2024). Post-EBR corrections, agreement improved significantly (daily ET NSE ≈ 0.8–0.9), confirming energy balance closure as the primary limitation. Residual differences early in the season or after irrigation events may have resulted from variations in sensor responses to brief soil evaporation pulses or midday stomatal regulation (Sperling et al., 2023; Vanella et al., 2022). Nevertheless, cumulative ET values closely matched by season-end, validating the LI-710's reliability in almond orchards when properly calibrated.

In processing tomato fields, an annual row crop with a homogeneous canopy, the LI-710 performed exceptionally well post-correction, closely matching EC fluxes throughout rapid canopy development and peak ET periods (daily ET NSE ≈ 0.94). Minor late-season differences emerged during canopy senescence, likely due to reduced sensor sensitivity to small evaporation fluxes and EBR correction limitations under extreme conditions (Hanson and May, 2006; Peddinti et al., 2025). However, overall seasonal performance demonstrated the sensor's suitability for precision irrigation in annual crops.

For the pistachio orchard, characterized by a taller (7 m) pruned uniform canopy, post-correction agreement was exceptionally high (ET NSE ~0.95), indicating minimal daily flux discrepancies. The sensor reliably tracked seasonal ET dynamics, suggesting that orchard homogeneity and predominantly transpiration-driven fluxes facilitated accurate measurements (Bellvert et al., 2018; Marino et al., 2019). Minor midday divergences during extreme heat were likely due to physiological responses smoothed by EBR corrections but had negligible effects overall (Mauder et al., 2024; Wanner et al., 2024). In the evergreen citrus orchard, initial differences were moderate due to clumped canopy structure, uneven soil evaporation from irrigation, and year-round transpiration activity (Villalobos et al., 2009). Following EBR corrections, agreement improved (daily ET NSE ≈ 0.73), with remaining variability linked to short-term weather changes and sub-canopy fluxes. The LI-710 effectively captured seasonal ET trends, though optimal accuracy required careful calibration and periodic maintenance. Despite these challenges, the sensor demonstrated sufficient accuracy for practical water management, validating its versatility across orchard systems.

Compared to the low-cost eddy covariance system tested by Markwitz and Siebicke, (2019), which showed ET deviations of −14 % to 8 % and R^2 values between 0.71 and 0.94, the LI-710 after energy balance correction performed comparably or better across all four crops: NSE improved from −2.09 to 0.79 in almonds (RMSE = 0.52 mm/day), from 0.72 to 0.95 in pistachios (RMSE = 0.37 mm/day), from 0.35 to 0.94 in processing tomatoes (RMSE = 0.64 mm/day), and from 0.32 to 0.73 in citrus (RMSE = 0.50 mm/day). Compared to the chamber-based low-cost system tested by Macagga et al. (2024), which showed reliable performance in a single cropping system under challenging African conditions, the LI-710 demonstrated more consistent accuracy across a diverse range of perennial and annual crops under California conditions. Callejas-Rodelas et al., (2024) reported LE regression slopes between 0.78 and 0.99 and R^2 of 0.70–0.85 using RH-based EC systems; the LI-710 met or exceeded this range in all tested crops after correction, particularly excelling in pistachio and tomato, and showing solid performance even in more structurally complex systems like citrus and almond.

The LI-710 sensor significantly enhances irrigation management by providing reliable ET data at a fraction of the cost and complexity of traditional EC systems. Its affordability enables widespread deployment across multiple fields, capturing spatial ET variations influenced by soil texture or microclimate—details often missed by single weather-based estimates (Kang et al., 2025). This capability supports precision irrigation methods such as variable rate irrigation (Corbari et al., 2024; Li et al., 2023), optimizing water distribution within fields. Additionally, the LI-710 facilitates regulated deficit irrigation in crops like pistachios by providing real-time ET data for monitoring water stress and dynamically adjusting irrigation to maximize efficiency and productivity (Gijón et al., 2009; Kandhway et al., 2025; Rozenstein et al., 2023). By directly measuring actual crop water use, rather than relying solely on reference ET and crop coefficients, the LI-710 improves accuracy, helping growers comply with regulations and enhance water productivity (López-Urrea et al., 2020; Machakaire et al., 2021; Tunalı et al., 2023).

Despite some maintenance challenges, the LI-710's lower cost facilitates broader adoption with minimal operational disruption. Local support and training are essential to ensure effective sensor use. Integration with modern irrigation management platforms, including cloud-based dashboards, enhances data utilization by combining ET measurements with soil moisture and weather data. By bridging research insights with practical applications, the LI-710 enables optimized water management, enhances drought resilience, and supports sustainable agricultural practices amid increasing water scarcity. This advancement represents a step toward climate-smart irrigation, crucial for ensuring agricultural sustainability.

Overall, our findings indicate that the LI-710 ET sensor is a viable and cost-effective alternative to EC systems, with the potential to expand flux monitoring coverage and reduce data scarcity in precision

agriculture. Broader coverage would improve land-atmosphere exchange research (Ciais et al., 2022), refine regional water budgets (Huang et al., 2025), and enhance spatially resolved flux measurements for weather and climate models (Huang et al., 2025; Kumar et al., 2022). Moreover, the LI-710 supports non-invasive ET measurements crucial for regulatory compliance, particularly in water-restricted regions like California. Future research should explore multi-year deployments in extreme environments and integrate additional sensing techniques, such as sap flow or canopy temperature, to improve the partitioning of soil evaporation and crop transpiration. By combining accessibility, improved accuracy, and potential for grower-led monitoring networks, the LI-710 ET sensor advances sustainable water management, precision irrigation, and agroecosystem research.

5. Conclusions

The LI-710 sensor, when adjusted with energy-balance-residual (EBR) corrections, offers a practical and cost-effective solution for evapotranspiration (ET) monitoring in perennial (almond, pistachio, citrus) and annual cropping (processing tomato) systems. Key findings underscore that raw LI-710 measurements systematically underestimate turbulent fluxes, but EBR adjustments align its output closely with conventional eddy covariance (EC), achieving NSE values exceeding 0.73 for ET across all crops. This improvement enables accurate monitoring of crop water use, particularly during peak demand periods, essential for precision irrigation in water-scarce regions like California's Central Valley. The sensor's lower cost and operational simplicity make it accessible for widespread adoption, facilitating real-time data integration into farm management systems to optimize water productivity and comply with regulatory use regulations. However, performance variability in complex canopies (e.g., citrus) suggests the need for site-specific calibration. Future research should explore multi-year deployments, integration of sensors with complementary technologies (e.g., remote sensing), and the implementation of automated energy balance ratio (EBR) corrections to enhance measurement robustness. Additionally, if the LI-710 sensor can be modified to reduce its underprediction of fluxes, it may further improve accuracy across diverse environmental conditions. By bridging the gap between research-grade systems and on-farm applications, the LI-710 ET sensor holds strong potential for advancing climate-smart agriculture and promoting sustainable water management.

CRediT authorship contribution statement

Peddinti Srinivasa Rao: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Kisekka Isaya:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2025.109501.

Data availability

Data will be made available on request.

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