

Tracking Crop Evapotranspiration and Water Stress Across Seasons Using Multi-sensor UAV Observations

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Abstract: Accurate estimation of crop evapotranspiration (ET) requires resolving how canopy structure and physiological activity regulate land–atmosphere energy exchange. This study applies the Priestley–Taylor Two-Source Energy Balance (TSEB-PT) model using very-high-resolution UAV multi-sensor observations (~15 cm) to estimate ET over a 10-hectare field across three seasons (sugar beet, potato, winter wheat). Thermal infrared data provided land surface temperature (LST), while multispectral (MS) and LiDAR data were used to characterize canopy properties, including a fusion-based estimate of the fraction of green LAI (f_g) from MS-derived GAI and LiDAR-derived PAI. Results showed strong sensitivity to LST, highlighting the importance of thermal calibration, and demonstrated that while GAI and PAI performed similarly during peak growth, GAI better captured functional decline during stress and senescence, particularly in dense canopies. Incorporating dynamic f_g improved ET estimates across crops and conditions. Modeled instantaneous ET showed good agreement with eddy covariance (EC) measurements, with RMSE ranging from 0.08 mm h⁻¹ to 0.31 mm h⁻¹ and R² values from 0.28 to 0.97 (highest performance excluding senescence). High-resolution UAV data also enabled early detection of spatial stress patterns not captured by structural or spectral metrics alone. Upscaling instantaneous ET using a reference ET fraction approach produced daily ET estimates with RMSE ranging from 0.96 to 2.30 mm d⁻¹ and R² ranging from 0.27 to 0.80 across crops, with improved consistency under energy-balance–closed EC conditions. These daily estimates also enabled assessment of crop water stress ($K_s = ET/ET_0$) and improved delineation of sub-field variability compared to coarser-resolution methods. These findings demonstrate the value of integrating UAV multi-sensor data with TSEB-PT for robust, high-resolution ET monitoring and practical applications in precision irrigation and water management.

Keywords: UAS; Drone; Thermal-IR; LiDAR; Multi-sensor; Water use

1. Introduction

Evapotranspiration (ET), the combined loss of water through soil evaporation and plant transpiration, is the second-largest flux in the hydrological cycle after precipitation (Allen et al., 1998). ET plays a critical role in water resource allocation and irrigation scheduling (Wang et al., 2014). Plant health and biomass production is closely linked to transpiration, which depends on soil water availability and is regulated by stomatal and environmental conditions. Accurate, timely estimation of ET at the field scale is essential for optimizing irrigation schedules, improving water use efficiency (WUE) (Pereira and Pires, 2011), and supporting sustainable agriculture amid increasing water scarcity and climate variability (Colaizzi, 2016).

Conventional ET measurement methods, such as lysimeters, sap flow sensors, and eddy covariance (EC) systems (Yang et al., 2019), offer high temporal resolution but are limited in spatial coverage, making them inadequate for capturing within-field variability critical to precision irrigation (Yao et al., 2017). Additionally, these systems are costly, making large-scale monitoring impractical (Yao et al., 2017). Satellite and airborne remote sensing approaches improve spatial coverage but often lack the resolution needed for dynamic crop monitoring. Manned aircraft, while capable of very-high-resolution observations, are costly and operationally demanding (Bellvert et al., 2020; Hunt Jr. & Daughtry, 2018).

Recent advances in unmanned aerial vehicles (UAV) and lightweight, very-high-resolution uncooled thermal infrared (TIR) sensors now enable on-demand, field-scale ET monitoring. UAV platforms offer both high spatial and temporal resolution, allowing for detailed detection of crop water stress and rapid changes in canopy function (Niu et al., 2020). TIR remote sensing in the 8–14 μm range is a key component of energy balance models, as land surface temperature (LST) serves as a direct proxy for canopy transpiration and stomatal regulation if crop aerodynamics are known (Tanner, 1963). Anderson et al. (2024) further reviewed the development of TIR based energy balance models, which link vertical temperature gradients to sensible heat flux by modeling resistance, surface, and vegetation interactions.

Popular and widely used models such as SEBAL and METRIC estimate ET using TIR derived LST and LAI data (Mohan et al., 2020), but their one-source energy balance formulations treat the land surface as a single layer. They rely on hot/cold (not transpiring/ fully transpiring) anchor pixels to infer ET extremes, with no explicit representation of soil–canopy interactions or functional canopy condition. This oversimplification can lead to inaccuracies (Niu et al., 2020), especially in heterogeneous or partially senescent fields, where vegetation structure and function vary spatially. However, even though these models are typically used with satellite based remote sensing, they have also been applied with UAV studies (Chandel et al., 2020; Mokhtari et al., 2021; Niu et al., 2019). Some UAV based studies have applied simplified alternatives such as the Deriving Atmosphere Turbulent Transport Useful To Dummies Using Temperature (DATTUTDUT) (Ellsäßer et al., 2020) or the Simple Algorithm for Evapotranspiration Retrieving (SAFER) (de Lima et al., 2024) but have similar constraints for very-high-resolution data at field scale.

Alternatively, Two-Source Energy Balance (TSEB) models partition energy fluxes between soil and vegetation, each with distinct resistances (Norman et al., 1995). It is considered one of the most robust and widely used approaches

(Nieto, 2022; Nassar et al., 2020), often outperforming OSEB models such as SEBAL or METRIC (Guzinski et al., 2020; Brenner et al., 2018; Jaafar et al., 2022; Tao et al., 2024; Xia et al., 2016), especially in variable and sparse vegetation cover (García-Santos et al., 2022; Derardja et al., 2024). Although TSEB was originally developed for satellite observations representing spatially integrated land–atmosphere exchanges, recent studies have demonstrated that high-resolution UAV data can improve model input characterization (Jaafar and Sujud, 2025) by reducing mixed soil and vegetation signals and better resolving within-field heterogeneity, a primary source of uncertainty at coarser spatial resolutions (Hoffmann et al., 2016; Nassar et al., 2020). Multi-scale analyses further show that pixel mixing strongly influences model performance, as aerodynamic and radiative properties become increasingly spatially averaged at larger grid sizes (Burchard-Levine et al., 2021). There are several versions but the most commonly used is the Priestley–Taylor version (TSEB-PT) (Colaizzi et al., 2014). Additionally, TSEB-PT incorporates fraction of green LAI (f_g) within the Priestley–Taylor formulation which allows the model to dynamically scale transpiration based on the fraction of functioning canopy. This makes it especially suitable for modeling at high spatial resolution with heterogeneous canopy covers from partial stress and senescence conditions. Furthermore, the TSEB-PT version avoids uncertainties tied to vapor pressure compared to the Penman–Monteith (TSEB-PM) version, simplifying deployment for UAV-based applications (Colaizzi et al., 2014). The TSEB model has been used with several UAV crop studies including wheat (Gómez-Candón et al., 2021), barley (Hoffmann et al., 2016), sorghum (Tunca et al., 2023a), and pomegranate (Niu et al., 2019), though many applications focus on vineyards (Gao et al., 2021, 2023; Nassar et al., 2020, 2021, 2022; Nieto et al., 2019; Ortiz et al., 2019; Xia et al., 2016). While the TSEB-2T version has been often used in high-resolution and sparse canopies, like vineyards, where soil and canopy temperatures can be separated. However, its performance has shown mixed results and may decline with increasing canopy closure (Kool et al., 2021; Gao et al., 2023). This is largely due to uncertainties in temperature separation under dense, structurally complex canopies. In contrast, TSEB-PT avoids explicit temperature separation and likely provides more stable performance across varying canopy conditions, suggesting it may be better suited for crops with dynamic vegetation–soil fractions

Recently, machine learning (ML) methods have been applied to ET estimation using multispectral, thermal, and auxiliary data (Amani et al., 2023; Liyew et al., 2025). ML models often depend on large, high-quality ground data such as lysimeters (Kavya and Mahadevaiah et al., 2024) or eddy covariance systems (Liu et al., 2021), resources that are expensive, sparse, and highly site-specific, limiting their scalability for field-scale operational use (Hirschi et al., 2017) and are time consuming (García-Santos et al., 2022). Moreover, ML models struggle to transfer accurately to different locations or crop systems (Shi, 2024). In contrast, physically based models such as TSEB-PT provide robust, interpretable, and transferable ET estimates because they are grounded in physically constrained land–atmosphere interactions rather than site-specific training data. The increasing availability of UAV-based multi-sensor observations further enhances these approaches by enabling more detailed characterization of canopy structure, temperature, and surface conditions, opening new opportunities for high-resolution process-based monitoring of crop water use.

Building on these developments, UAV platforms now provide an opportunity to combine physically based energy balance modeling with detailed observations of canopy structure and surface temperature at field scale. In this study we apply the TSEB-PT model for robust, multi-season UAV based ET estimation using very-high-resolution thermal infrared (TIR), multispectral (MS), and LiDAR data. However, small-uncooled TIR sensors are prone to radiometric drift and environmental noise, often requiring ground references to correct LST biases (Kelly et al., 2019). Modeling canopy resistance also hinges on reliable LAI estimates. MS derived green area index (GAI), which reflects pigment concentration, is widely used but susceptible to saturation in dense canopies (Bukowiecki et al., 2020; Zheng & Moskal, 2009). In contrast, LiDAR is increasingly being used for crop LAI type estimations (Bates et al., 2021; Hütt et al., 2022; Dreier et al., 2025). LiDAR derived plant area index (PAI) captures structural canopy density and reduces saturation-related errors (Bates et al., 2021; Ma et al., 2021). The fraction of green LAI (f_g), an indicator of photosynthetically active canopy, is rarely used in UAV based TSEB-PT studies. When included, it is typically assumed spatially constant (Hoffmann et al., 2016) or derived from sparse ground samples (Li et al., 2019) or NDVI based estimates, which lack structural depth (Nassar et al., 2022; Mendiguren et al., 2017). In this study, we leverage the complementary strengths of MS (GAI) and LiDAR (PAI) to generate dynamic, spatially explicit f_g estimates at pixel level. This has the potential to improve transpiration modeling that accounts for both canopy structure and physiological function.

Our study expands UAV-based TSEB-PT applications across three crop types, sugar beet, potato, and winter wheat, spanning full growing seasons and validated against eddy covariance (EC) measurements. In particular, combining multispectral and LiDAR observations enables independent characterization of canopy physiological condition and structural density, providing a framework to evaluate how functional and structural canopy information influence energy balance partitioning within TSEB. Beyond model validation, we examine the model's ability to capture field-scale evapotranspiration variability and detect early signals of water stress. Specifically, we assess the sensitivity of ET estimates to thermal calibration, compare GAI and PAI as alternative LAI inputs, and evaluate the impact of incorporating the fraction of green LAI (f_g) derived from MS–LiDAR fusion. By testing these components under operational UAV conditions, this work advances the application of TSEB-PT toward high-resolution, process-based monitoring of crop water use using UAV observations.

2. Methods

2.1. Study area

The study was conducted at the ICOS Class 1 ecosystem site DE-RuS within the TERENO Eifel Rur observatory in Selhausen, Germany (50°51'56"N, 6°27'03"E) (<https://ddp.tereno.net/ddp/>). The 10-hectare field is situated at 101–103 m above mean sea level with the soil consisting of Pleistocene loess, Holocene translocated loess, with sand and gravel at deeper levels (Brogi et al., 2020). The western section has shallower sand and gravel deposits, creating spatial variability in crop growth, especially during water-scarce periods. Weather conditions including precipitation and air temperature, during the experiment periods can be found in the appendix (see Tab. D1 & Fig. D6).

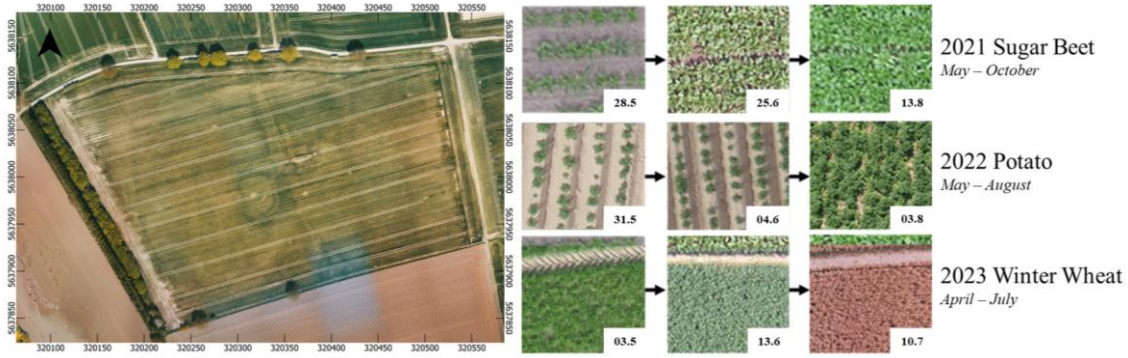


Figure 1: The field experiment site (left) with the EC and meteorological station located in the center of the field. The different crop cover type for each year (right) with example images of plant structure and fraction of vegetation coverage over the field throughout each growing season.

The field experiment site, shown in Fig. 1, was monitored over three growing seasons with different crops each year. In 2021, sugar beet was planted from May to October, starting with 20% vegetation cover and reaching 98% by harvest. In 2022, potatoes were grown from May to August, beginning with 5% cover and closing at 87%, with ridges between rows. In 2023, winter wheat was planted from April to July, maintaining 94-98% cover, with senescence marked by visible leaf browning. Only the potato crop was irrigated, receiving three 30 mm applications in July. These crop and soil variations provide a basis to evaluate the robustness of very-high-resolution UAV data in ET models like TSEB-PT.

2.2. UAV measurements and processing

Two DJI Matrice 600 UAV were used, one carrying a LiDAR payload and the other a combined MS and TIR setup (Fig. 2). The LiDAR system included a YellowScan Surveyor with a Velodyne VLP-16 scanner and Applanix APX15 GNSS-IMU, capturing 300,000 pulses/sec at 903 nm with ~4 cm precision. Flights were conducted at 50 m altitude and 8 m/s with 50% side overlap. A Septentrio Altus NR3 GNSS base station was used for georeferencing. LiDAR data were processed using POSpac (v8.6) and YellowScan's CloudStation.

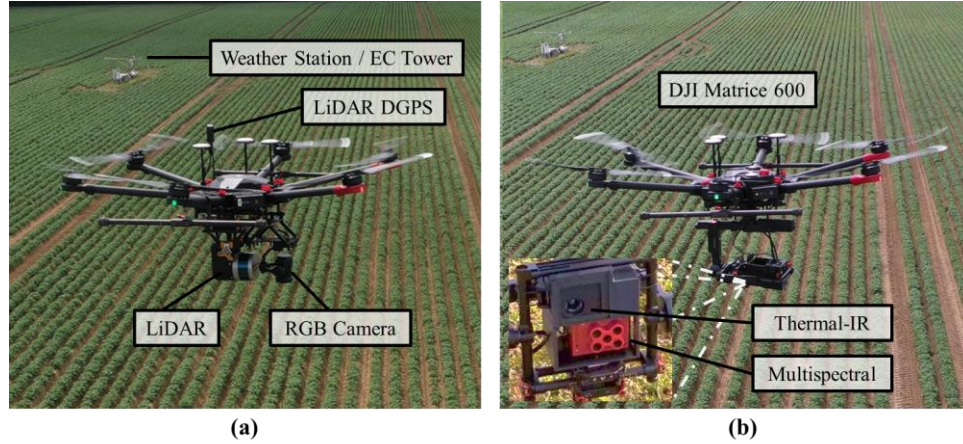


Figure 2: View of the DJI Matrice 600 UAV platforms that were used while flying over the field experiment site. (a) The M600 mounted with the YellowScan LiDAR Surveyor and DJI Zenmuse X1 RGB sensor. (b) The M600 with the FLIR Vue Pro R thermal IR modified with a ThermalCapture external heated shutter and Micasense Red-edge M multispectral sensors mounted on a 3-axis gyro system for nadir imagery.

The TIR sensor, a FLIR Vue Pro R 640 (13 mm), covered the 7.5–13.5 μm range with $\pm 5^\circ\text{C}$ accuracy and was modified with a heated shutter (ThermalCapture, AirRobot® GmbH & Co.) for improved inflight calibration. The MS sensor, a MicaSense RedEdge-M (AgEagle Aerial Systems Inc.), captured five spectral bands; red (663–673 nm) and NIR (820–860 nm) bands were used to calculate NDVI. Both sensors were mounted on a 3-axis gimbal and flown at 100 m altitude and 6 m/s, with approximately 90% image overlap. TIR calibration used internal corrections and ground temperature reference targets, while MS data were calibrated using a reflectance panel. Data from both platforms were processed in Pix4D. Flight campaign details are in the appendix (Tab. D1).

2.4. UAV data products and model implementation

TSEB-PT inputs were grouped into two categories: (1) surface boundary conditions derived from UAV data, including land surface temperature (LST), fractional cover (f_c), leaf area index (LAI), canopy height (h_c), and fraction of green LAI (f_g); and (2) meteorological forcing variables, including air temperature (T_a), wind speed (u), vapor pressure (e_a), and incoming shortwave irradiance (S_{dn}). UAV-derived variables were processed and calibrated using ground measurements, with detailed methods provided in Sections 2.4.1–2.4.5. Data processing and raster analysis were conducted in R using the raster and lidR packages, and all datasets were resampled to a common 15 cm ground sampling distance (GSD). The overall workflow is illustrated in Fig. 3.

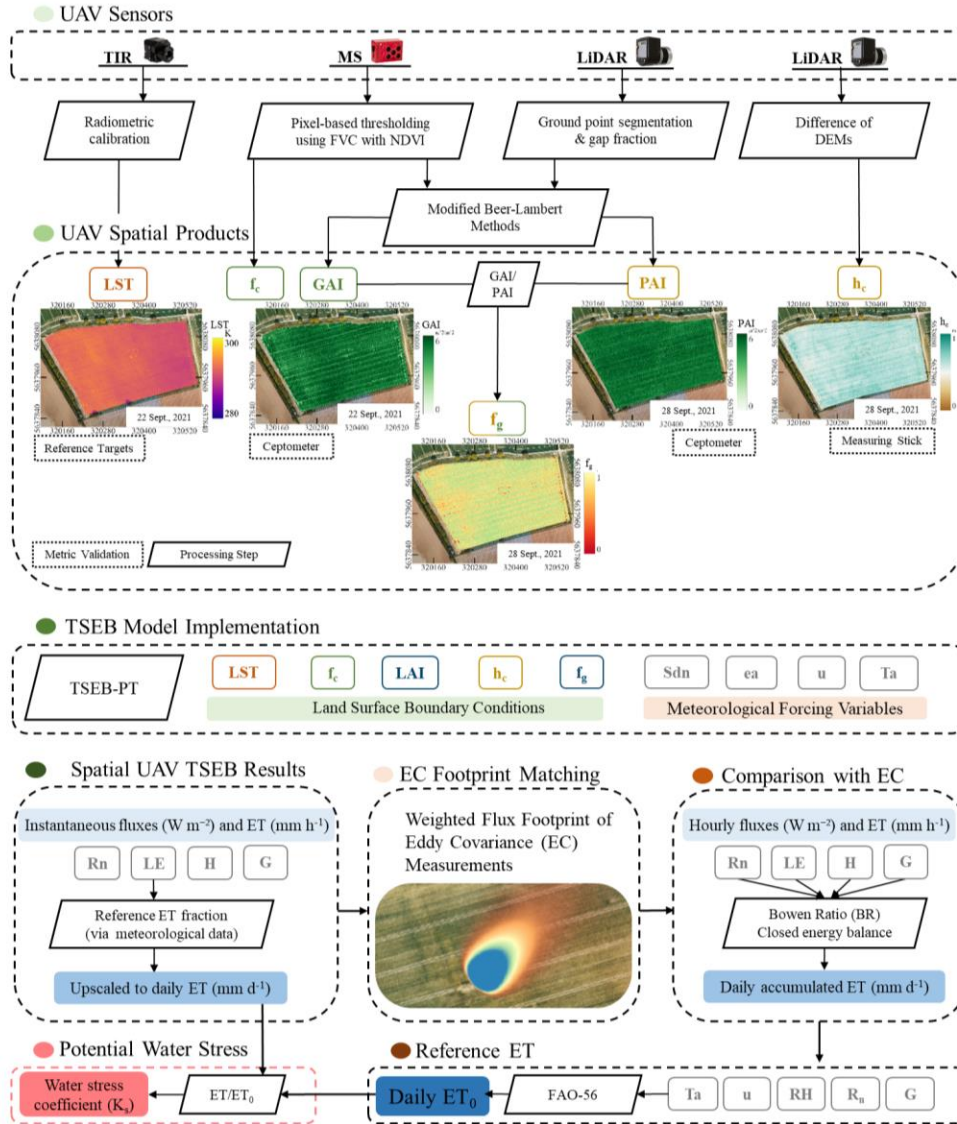


Figure 3: Workflow of the study, showing UAV sensor and eddy covariance (EC) data integration and inputs used in the TSEB-PT model. The model incorporates two categories of inputs: (1) surface boundary conditions and (2) meteorological forcing variables. Key UAV-derived inputs, LST (original vs. corrected), LAI (LiDAR-derived PAI vs. MS-derived GAI), and f_g (default = 1 vs. UAV-derived GAI/PAI), were varied across model runs to assess their impact. Instantaneous ET estimates ($mm h^{-1}$) were upscaled to daily ET ($mm d^{-1}$) and validated against EC fluxes at the UAV overpass time, while cumulative EC daily ET was used for daily comparisons within the modeled EC footprint. Reference ET (ET_0) was computed from EC station meteorological data (FAO-56) to represent atmospheric demand and derive potential water stress (K_s). Meteorological inputs from the EC station included incoming shortwave radiation (Sdn), vapor pressure (ea), wind speed (u), air temperature (Ta), and relative humidity (RH).

Model runs were designed to assess the impact of key inputs, including LST (original vs. corrected), LAI (MS-derived GAI vs. LiDAR-derived PAI), and f_g (default $f_g = 1$ vs. UAV-derived $f_g = GAI/PAI$), on instantaneous fluxes and ET derived from UAV observations. These outputs were compared with eddy covariance (EC) fluxes and ET within the

modeled EC footprint. The analysis was conducted sequentially by first evaluating LST configurations, followed by comparisons of LAI inputs (GAI vs. PAI) with f_g held constant ($f_g = 1$), and finally incorporating dynamic f_g (GAI/PAI) with PAI as the structural LAI input.

Following identification of the optimal configuration, instantaneous UAV-based ET estimates were upscaled to daily ET using the reference ET fraction (ET_rF) approach and compared with daily EC ET. Reference ET (ET_o) was calculated using the FAO-56 method with EC meteorological data and used to represent atmospheric demand and derive potential water stress (K_s) from both UAV and EC-derived ET estimates.

2.4.1. Land surface temperature (LST) maps

To convert incoming longwave radiance from the TIR microbolometer sensor into land surface temperature (LST), surface emissivity and atmospheric correction parameters were required. Prior to each flight, radiometric calibration parameters, including emissivity, object distance (flight altitude), air temperature, and relative humidity, were updated in the FLIR Vue Pro R camera settings using in-field measurements. These parameters are incorporated within the camera's internal radiometric processing to correct apparent surface temperature for emissivity and atmospheric attenuation effects. Previous studies have demonstrated that LST retrieval from small UAV uncooled sensor microbolometers is highly sensitive to these inputs and requires careful calibration (Kelly et al., 2019; Han et al., 2020; Virtue et al., 2021). Constant emissivity values were assigned to each crop type based on literature, and differences between vegetation and bare soil emissivity were considered negligible due to the limited extent of soil exposure.

Uncooled thermal sensors on UAV platforms, such as the FLIR Vue Pro R, are prone to radiometric instability, largely due to inconsistencies in the internal non-uniformity correction (NUC) applied to the microbolometer focal plane array. To improve calibration consistency, an external heated shutter was employed, which has been shown to substantially improve temperature measurement stability (Virtue et al., 2021). Additional radiometric uncertainty may arise from sensor self-heating and environmental interactions, as temperature drift in uncooled microbolometer arrays can degrade non-uniformity correction and lead to substantial increases in fixed pattern noise, in some cases up to fourfold (Budzier & Gerlach, 2015; Gogler et al., 2014; Sagan et al., 2019). Wind exposure can further destabilize sensor readings (Kelly et al., 2019). To mitigate these effects, the thermal sensor was housed within a custom 3D-printed enclosure providing thermal insulation and wind shielding, and flights were conducted at reduced speeds to minimize wind-induced temperature fluctuations.

Following radiometric correction and sensor stabilization, LST accuracy was evaluated using ground-based reference targets during the 2021 field season. Two reference targets were deployed for each flight: (1) a high-emissivity metallic "hot" plate and (2) a "cold" water target. Target temperatures were measured at the beginning and end of each flight using calibrated contact thermometry (a contact probe attached to the back of the metal plate and an immersion probe for the water container). These measurements were treated as reference temperatures and compared with radiometric temperatures extracted from the UAV thermal imagery over the same targets (Fig. D2).

Despite applying radiometric correction parameters within the camera, a systematic temperature offset remained and varied with meteorological conditions. Consistent with previous findings for uncooled UAV thermal sensors, this residual bias is linked to environmental forcing (Kelly et al., 2019; Han et al., 2020; Virtue et al., 2021). Therefore, a multiple linear regression model was developed using the 2021 reference dataset to relate temperature offsets to air temperature, wind speed, and relative humidity measured at the site. The fitted regression model was subsequently applied to later campaigns (2022–2023) to estimate and correct LST offsets without requiring repeated deployment of reference targets. Two LST inputs were ultimately used in the TSEB model, the original temperature (OG), based solely on the internal radiometric calibration of the sensor, and (2) the target-corrected temperature (TC), which incorporates the regression-based offset correction derived from reference target measurements.

2.4.2. Leaf area index (LAI)

Two representations of canopy density were evaluated as LAI inputs for the TSEB-PT model: multispectral (MS)–derived green area index (GAI) and LiDAR-derived plant area index (PAI). GAI is derived from spectral reflectance and represents the photosynthetically active (green) component of the canopy (Park et al., 2021; Wei et al., 2023), whereas PAI is derived from LiDAR returns and represents total canopy structure independent of pigment content (Bates et al., 2021). Prior to senescence, both metrics act as effective proxies for LAI, as canopy density derived from LiDAR (PAI) and greenness from multispectral indices co-vary with vegetation development and soil–vegetation contrast, until peak growth when structural persistence diverges from declining leaf pigment content (Bates et al., 2021).

GAI and PAI were estimated using modified Beer–Lambert formulations describing radiation attenuation within plant canopies (Ali et al., 2015; Thorp et al., 2010). GAI was derived from multispectral fractional vegetation cover (FVC), calculated from NDVI using a pixel-based thresholding approach (Jia et al., 2017; Yue et al., 2021; Zhang et al., 2019), while PAI was derived from LiDAR gap fraction (GF), defined as the proportion of laser pulses reaching the ground relative to total returns within each raster cell. In this framework, FVC served both as an intermediate remote-sensing variable for estimating GAI and as the fractional cover (f_c) input to pyTSEB for sugar beet and potato, which exhibited partial canopy cover, particularly during early development.

The extinction coefficient (k) was calibrated using in-field SunScan ceptometer LAI measurements (Oguntunde et al., 2012) and applied inversely to estimate GAI and PAI (Eq. B2–B4). Given the limited number of ground samples per date (four control zones), this semi-empirical approach provided a balance between physical realism and available validation data. Because canopy architecture changes rapidly during early development, 2–3 seasonal k values were assigned per growing season following recommendations of Brogi et al. (2020) and Bates et al. (2021). After canopy closure, k was held constant through peak growth and harvest.

2.4.3. Fraction of green LAI (f_g)

To separate canopy structure from physiological activity, the fraction of green LAI (f_g) was computed by combining GAI and PAI. The parameter f_g represents the proportion of total canopy structure that remains photosynthetically active and actively contributing to transpiration within the TSEB-PT framework.

$$f_g = GAI/PAI = \left(\frac{-\log(1-FVC)}{k_{max}} \right) / \left(\frac{-\cos(\underline{\theta}) \ln(GF)}{k_{max}} \right) \quad (1)$$

where $\underline{\theta}$ is the LiDAR scan angle, and k_{max} is the extinction coefficient derived under peak canopy conditions. This formulation allows f_g to dynamically capture divergence between pigment-based canopy function and structural canopy persistence during stress or senescence.

Before senescence, f_g was set to 1, assuming a fully functional canopy. After senescence onset, f_g decreased according to relative differences between GAI and PAI, allowing transpiration potential to scale with canopy physiological status. Senescence timing was identified using field observations supported by seasonal GAI trends. Sugar beet senescence began after 13 August 2021, potato after 3 August 2022, and winter wheat after 13 July 2023. In winter wheat, early transitions to senescence occurred with notable spatial variability, with the western portion of the field exhibiting earlier onset. Accordingly, f_g was applied from 13 May to capture functional canopy dynamics across most of the growing season.

2.4.4. Fractional cover (f_c)

Fractional cover (f_c) characterizes the horizontal distribution of vegetation and contributes to the representation of canopy spatial heterogeneity and clumping within TSEB-PT (Norman et al., 1995; Kustas & Norman, 1999). For the sugar beet and potato growing seasons, multispectral NDVI-derived fractional vegetation cover (FVC), as described in Section 2.4.2, was used as the spatially varying f_c input to account for partial canopy cover, particularly during early development. For winter wheat, canopy cover remained nearly complete throughout the UAV observation period (94–98%), and f_c was therefore retained at the pyTSEB default value of 1.0.

Within pyTSEB, the supplied f_c contributes together with LAI to the representation of canopy clumping and the directional vegetation fraction used for soil–canopy radiometric temperature decomposition (Eqs. A10 and A13–A14). This allows horizontal canopy cover to be represented separately from canopy density and physiological status. Accordingly, structural PAI was used as the LAI input when implementing f_g , while f_g independently represented the fraction of plant area that remained green and contributed to canopy transpiration.

2.4.5. Crop height (h_c)

Crop height (h_c), also referred to as the canopy height model (CHM), was derived using a difference of digital elevation models (DoD) approach (Eq. B5, Appendix B). A pre-emergence UAV LiDAR flight was conducted to

obtain a bare-soil digital terrain model (DSM_d). Subsequent flight campaigns captured crop surface structure and were used to generate date-specific digital surface models (DSM_d). Crop height was calculated as the difference between DTM_0 and DSM_d for each campaign. Using a dedicated bare-soil terrain model rather than ground returns extracted from individual campaigns reduces interpolation uncertainty and improves height accuracy, particularly under dense canopy conditions (Cao et al., 2019). For each raster cell, h_c was defined as the maximum canopy elevation above the terrain surface following subtraction of DTM_0 from DSM_d .

2.4.6 TSEB-PT model and contributions of UAV Derived Inputs

The TSEB-PT model partitions net radiation (R_n) into latent (LE), sensible (H), and ground (G) heat fluxes, with LE converted to evapotranspiration (ET). The model was implemented using the pyTSEB library (Nieto et al., 2018). UAV-derived inputs described in Sections 2.4.1–2.4.5 constrain key components of the energy balance by influencing radiative partitioning, aerodynamic exchange, and canopy transpiration processes. Figure 4 and Table 1 summarize how each variable contributes to surface–atmosphere interactions within TSEB-PT. Model equations are detailed in Eq. A1–A13 in the appendix and Norman et al., (1995).

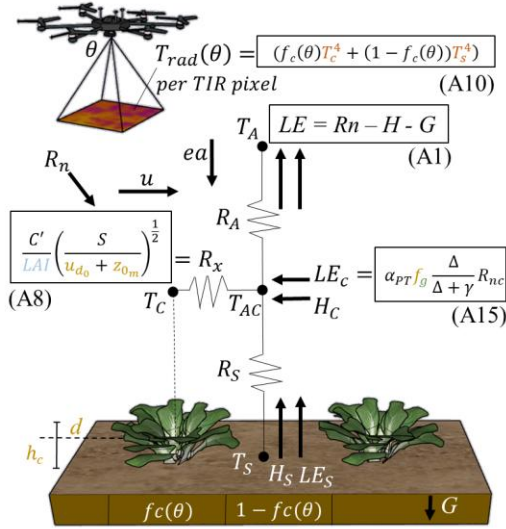
Table 1. UAV-derived model inputs, their roles and interactions within TSEB-PT, and the corresponding equations in which they are used. Equations are provided in Appendix A and the model framework is illustrated in Figure 4.

UAV Input	Role in Model	Equation(s)
Surface temperature (T_c, T_s)	Drives partitioning and energy balance	A5, A6, A10
Fractional cover (f_c)	Horizontal canopy cover	A10
Leaf Area Index (LAI)	Effective canopy area contributing to attenuation, canopy resistances and clumping calculations	A8, A11
Fraction of Green LAI (f_g)	Scales potential canopy transpiration	A15
Crop height (h_c)	Aerodynamic roughness and turbulent transport	A8, A9 (via d_0, z_0)

Land surface temperature (LST) directly controls sensible heat flux through surface–air temperature gradients. Because TSEB estimates latent heat as the residual of the energy balance after solving for sensible and ground heat fluxes, small changes in LST strongly influence energy partitioning and therefore modeled evapotranspiration (ET). Leaf area index (LAI), represented here by either multispectral-derived GAI or LiDAR-derived PAI, influences both canopy radiative attenuation and resistance terms, including aerodynamic resistance (R_a) and canopy resistance (R_x). Increasing LAI generally enhances canopy interception of radiation and reduces the relative contribution of the soil to the surface energy balance. The f_c provides complementary information on horizontal canopy distribution and contributes, together with LAI, to canopy clumping and the directional vegetation fraction used for soil–canopy radiometric temperature decomposition (Appendix A4). The f_g regulates canopy transpiration within the Priestley–Taylor formulation by scaling the effective Priestley–Taylor coefficient (α_{PT}). In model runs incorporating f_g , reductions in f_g decrease canopy latent heat flux without altering the prescribed structural LAI or fractional-cover inputs, allowing ET to decline during stress or senescence even when canopy structure remains dense. This distinction is particularly important in dense canopies, where reduced transpiration may otherwise be masked by structural cooling effects (Elfarkh et al., 2020; Kustas et al., 2016). Crop height (h_c) affects aerodynamic roughness length (z_0)

and displacement height (d), thereby influencing aerodynamic resistance and turbulent heat exchange between the surface and atmosphere. Together, these inputs enable TSEB-PT to separately represent structural controls on radiation exchange and physiological controls on transpiration, improving interpretation of spatial and seasonal variability in ET.

TSEB-PT Model Concept and UAV Data Contributions



UAV-Derived Spatial Inputs to TSEB-PT

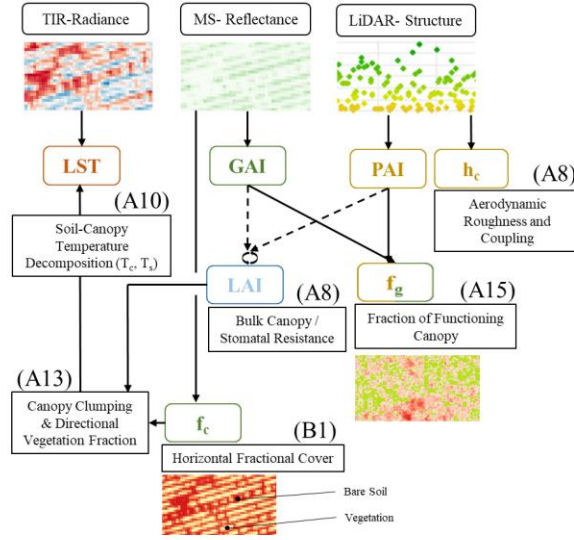


Figure 4. Conceptual schematic and example data illustrating how UAV-derived inputs constrain energy-balance partitioning within the TSEB-PT model. The left panel shows the model architecture, highlighting the partitioning of net radiation (R_n) into latent (LE), sensible (H), and ground (G) heat fluxes and the pathways through which UAV-derived variables influence these components. Key inputs include land surface temperature (LST), leaf area index (LAI), fractional cover (f_c), fraction of green LAI (f_g), and canopy height (h_c). The right panel illustrates the corresponding UAV-derived spatial inputs and their roles within pyTSEB. Spatially varying multispectral NDVI-derived fractional cover was supplied as the f_c input for sugar beet and potato, whereas f_c was retained at the pyTSEB default value of 1.0 for winter wheat. Within pyTSEB, LAI and f_c contribute to canopy clumping and the directional vegetation fraction $f_c(\theta)$ used for soil–canopy radiometric temperature decomposition (Appendix A4). The f_g input represents the fraction of functioning green canopy within the Priestley–Taylor canopy transpiration formulation, while LiDAR-derived h_c contributes to aerodynamic roughness and turbulent coupling. Example spatial data are shown for sugar beet. Abbreviations: R_a ($s\ m^{-1}$), aerodynamic resistance; R_x ($s\ m^{-1}$), canopy resistance; R_s ($s\ m^{-1}$), soil resistance; T_c and T_s (K), canopy and soil temperatures; z_0 (m), roughness length; d (m), displacement height; and α_{PT} (–), Priestley–Taylor coefficient.

2.4.7 Weather station, EC ET, and flux footprints validations

Ground measurements were collected to support UAV data validation and model calibration. Eddy covariance (EC) flux data, processed according to ICOS standards, were used to evaluate UAV-derived evapotranspiration (ET) estimates (Schmidt et al, 2025a; Schmidt et al, 2025b). EC measurements of wind speed, wind direction, and water vapor concentration were used to compute vertical turbulent fluxes associated with ET (Ghiat et al., 2021).

The spatial representativeness of EC observations was addressed through flux footprint modelling. Flux footprints were estimated using the footprint prediction model (FPP) implemented in R (Kljun et al., 2015), which accounts for micrometeorological conditions and surface roughness characteristics. Footprints were calculated for the duration of each UAV flight, and UAV-based TSEB-PT ET estimates were compared with EC measurements by extracting weighted averages of raster pixels within the 90 % cumulative footprint extent. Individual footprint examples are provided in Appendix C (Fig. D1). This approach reduces scale mismatch between point-based EC observations and spatially distributed UAV flux estimates by accounting for the dynamic source area contributing to measured turbulent fluxes.

Energy balance closure was addressed using the Bowen-ratio-preserving correction of Twine et al. (2000), consistent with previous UAV-based TSEB studies (e.g., Hoffmann et al., 2016; Brenner et al., 2017, 2018; Gao et al., 2023). Model evaluation primarily relied on comparisons with open EC fluxes to avoid introducing additional assumptions related to closure corrections (Mokhtari et al., 2021; Nassar et al., 2021). Nevertheless, comparisons using energy-balance-closed fluxes are also presented to assess the sensitivity of model performance to EC energy balance correction.

3. Results

3.1. UAV data derived model inputs

UAV thermal infrared (TIR) observations consistently underestimated ground-surface temperature relative to in-field reference targets during 2021. Uncorrected TIR data had an RMSE of 4.19 °C but maintained strong temporal agreement across dates ($R^2 = 0.97$). Ground-target correction reduced the seasonal RMSE to 2.78 °C. Thermal error was most strongly associated with air temperature ($r = 0.74$), followed by wind speed ($r = 0.55$) and relative humidity ($r = 0.34$). These relationships were used in a multiple linear regression model to correct sensor bias in subsequent seasons, producing an average LST increase of 2.2 °C across acquisitions. Correction relationships and validation are presented in Fig. D2, while seasonal differences between original (LST_{OG}) and corrected (LST_{TC}) field-average LST are shown in Fig. 5.

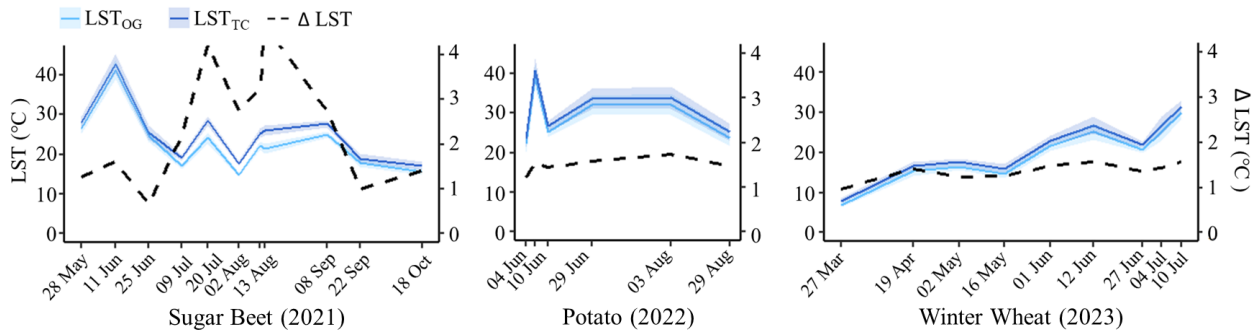


Figure 5: Field-averaged land surface temperature (LST) before (LST_{OG}) and after temperature correction (LST_{TC}). The dashed line represents the temperature difference between the two LST estimates.

Multispectral-derived green area index (GAI) and LiDAR-derived plant area index (PAI) were evaluated against ground-based ceptometer LAI measurements (Fig. 6). PAI showed closer agreement with ground observations across crops, with $R^2 = 0.99$ and an overall RMSE of $0.27 \text{ m}^2 \text{ m}^{-2}$, compared with $R^2 = 0.88$ and $\text{RMSE} = 1.02 \text{ m}^2 \text{ m}^{-2}$ for GAI, based on a limited number of calibration samples. Differences between GAI and PAI were greatest during senescence, when GAI declined while LiDAR-derived PAI retained higher canopy structural values.

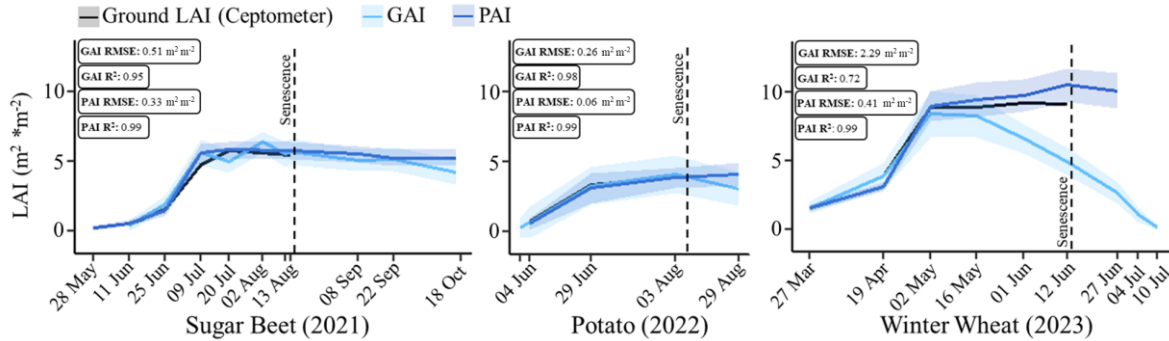


Figure 6: Field averaged UAV derived green area index (GAI) and plant area index (PAI) compared to ground based ceptometer LAI measurements across each campaign for three growing seasons. Ground measurements conclude prior to the onset of senescence, during which divergence between GAI and PAI becomes more pronounced due to declining pigment content in the canopy.

UAV-derived canopy height (h_c) also showed strong agreement with ground measurements (Fig. 7), with an overall RMSE of 0.06 m and $R^2 = 0.90$ across crops. Winter wheat showed the highest agreement ($\text{RMSE} = 0.01 \text{ m}$; $R^2 = 0.99$), while potato showed greater error ($\text{RMSE} = 0.12 \text{ m}$), potentially reflecting ridge planting and heterogeneous canopy closure within sampled areas.

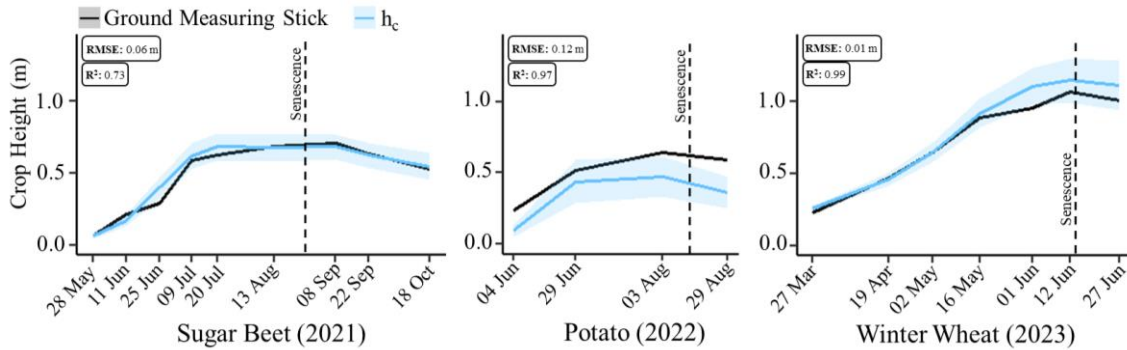


Figure 7: Comparison of UAV LiDAR derived canopy height (h_c) and ground based measuring stick data for each season. UAV derived values represent field wide averages, while ground measurements reflect averages within designated control point (CP) zones.

3.2. Accuracy and sensitivity of TSEB-PT ET estimates from UAV thermal corrections

To assess the impact of radiometric calibration on model performance, TSEB-PT estimates derived from original (LST_{OG}) and target-corrected (LST_{TC}) UAV thermal imagery were compared with EC fluxes under open and closed energy balance conditions across all three crop seasons (Fig. 8). Thermal correction generally produced slightly lower modeled net radiation (R_n) and latent heat flux (LE) and higher sensible heat flux (H), with the largest responses in sugar beet (2021) and winter wheat (2023) and more moderate changes in potato (2022). Soil heat flux (G) changed comparatively little. Overall, LST_{TC} improved agreement with EC observations, particularly for LE and under closed energy balance conditions.

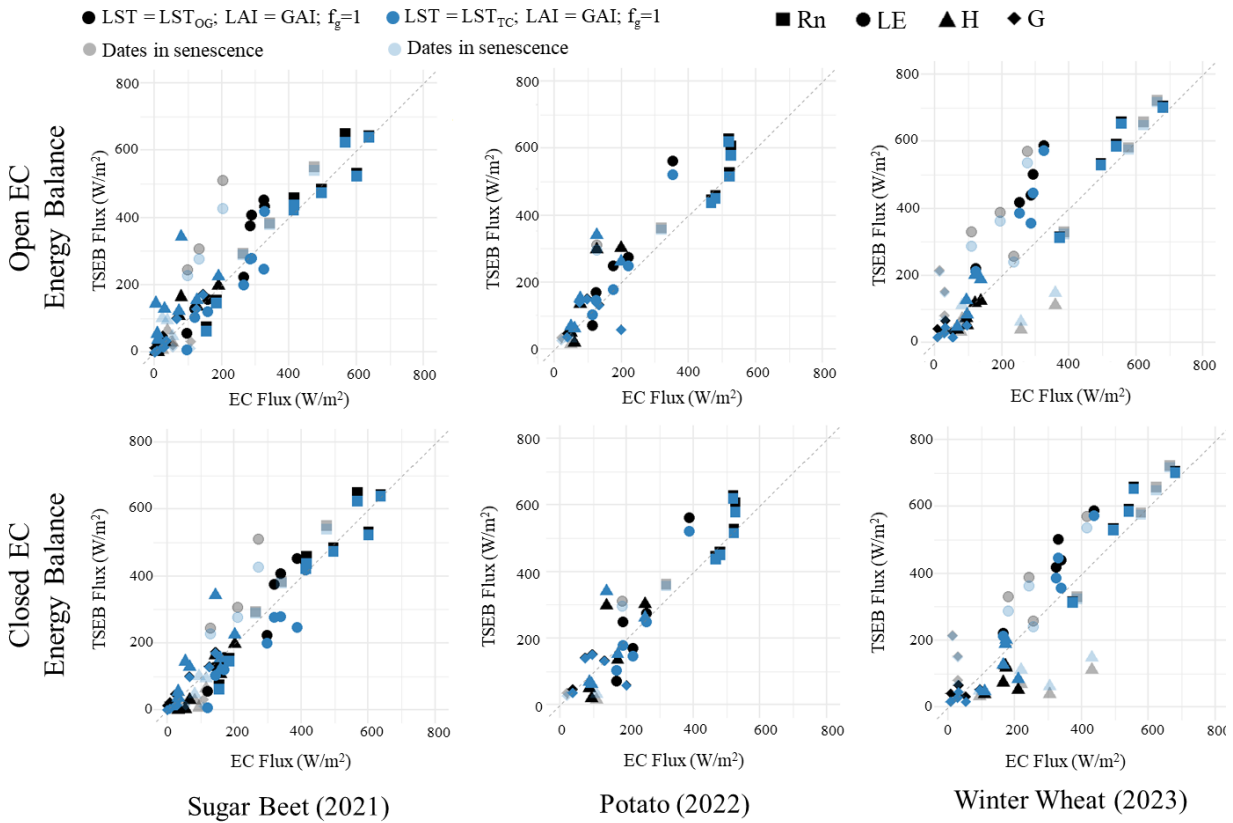


Figure 8. Comparison of modeled TSEB-PT energy fluxes (R_n , LE , H , and G) with eddy covariance (EC) observations across three crop seasons. Upper panels show comparisons using open EC energy balance fluxes, while lower panels show closed EC energy balance fluxes. Colors indicate land surface temperature inputs (original, LST_{OG} ; target-corrected, LST_{TC}), symbols indicate flux components, and shaded points represent observations acquired during senescence.

RMSE and R^2 statistics (Table D2) supported these patterns. Thermal correction generally reduced LE RMSE across crops, with the largest improvements for winter wheat and sugar beet, whereas responses in H were less consistent. R_n showed minimal sensitivity and G generally exhibited smaller and crop-dependent responses. Excluding senescence dates strengthened agreement, particularly for LE . Across configurations, closed EC energy balance comparisons generally produced higher R^2 and lower RMSE than open EC comparisons.

Because LE represents evapotranspiration within the energy balance, estimates were converted to ET (mm h^{-1}) for direct evaluation at UAV acquisition times (Fig. 9). Under open EC conditions, LST_{TC} reduced RMSE from 0.21 to 0.16 mm h^{-1} for sugar beet, 0.14 to 0.11 mm h^{-1} for potato, and 0.31 to 0.26 mm h^{-1} for winter wheat. Thermal correction did not always improve temporal correspondence; for sugar beet, R^2 decreased from 0.50 to 0.32 despite the lower RMSE. Excluding senescence dates further strengthened agreement, with the largest improvement in sugar beet (RMSE 0.16 to 0.11 mm h^{-1} ; R^2 0.32 to 0.79). Closed EC comparisons generally produced higher R^2 and slightly lower RMSE across crops.

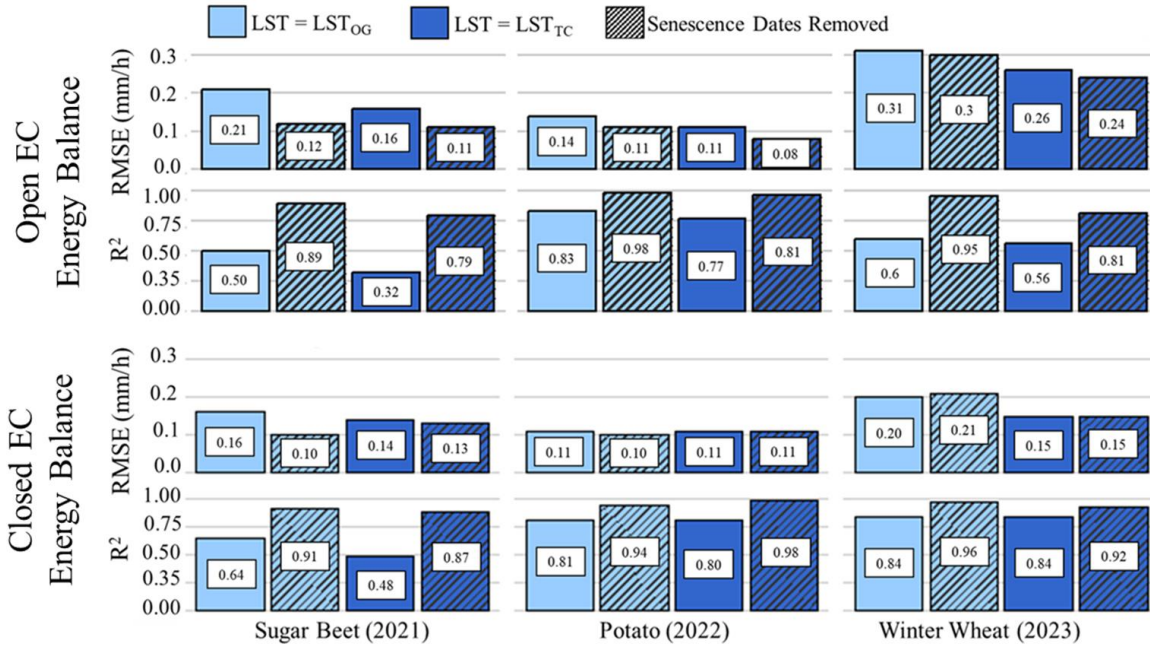


Figure 9. RMSE and R^2 between modeled TSEB-PT ET and EC-derived ET under open and closed energy balance conditions, averaged over the EC flux footprint. Model runs are compared using original (LST_{OG}) and target corrected (LST_{TC}) land surface temperature inputs. Metrics are shown for the full growing season and with senescence periods excluded.

3.3. Accuracy and sensitivity of TSEB-PT ET estimations from different UAV based LAI inputs

Building on the thermal correction analysis, we evaluated the influence of multispectral-derived GAI, LiDAR-derived PAI, and dynamic fractional green LAI ($f_g = \text{GAI}/\text{PAI}$) on TSEB-PT flux estimates (Fig. 10; Table D3). Differences between GAI and PAI configurations were generally small during early- to mid-season conditions when canopy structure and greenness were closely aligned, with similar agreement with EC observations under both open and closed energy balance comparisons.

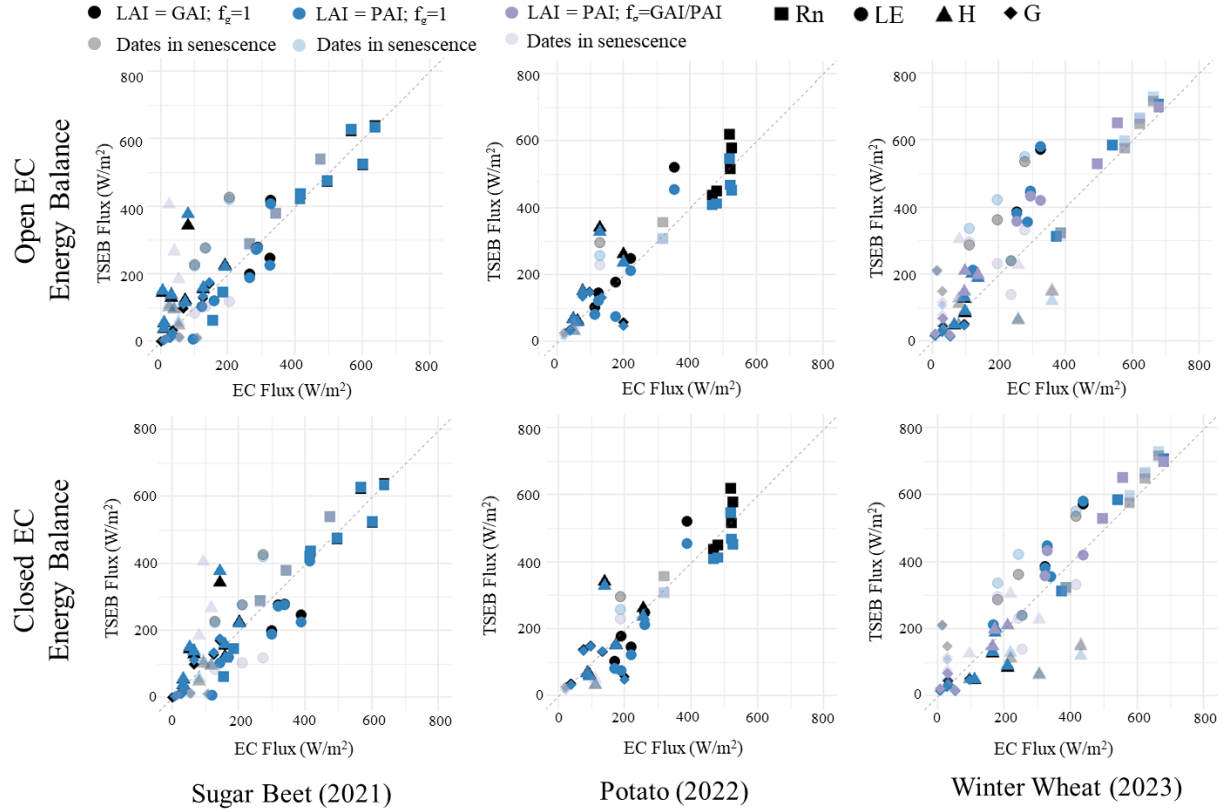


Figure 10. Comparison of modeled TSEB-PT energy fluxes (Rn, LE, H, and G) with eddy covariance (EC) observations across three crop seasons under different LAI and f_g parameterizations. Upper panels show comparisons using open EC fluxes, and lower panels show closed EC energy balance fluxes. Colors indicate model configurations (GAI; PAI; PAI with

Differences became more pronounced during senescence, particularly in winter wheat. Using PAI with $f_g = 1$ resulted in greater LE overestimation, whereas GAI improved agreement with EC observations. Using PAI together with dynamic f_g further reduced this bias and shifted modeled fluxes closer to the 1:1 relationship (Fig. 10; Table D3). Similar but smaller responses were observed for sugar beet and potato. Across crops, LAI configuration had comparatively small effects on Rn and G, while LE and H showed greater sensitivity. Closed EC comparisons generally produced higher R^2 and lower RMSE than open EC comparisons.

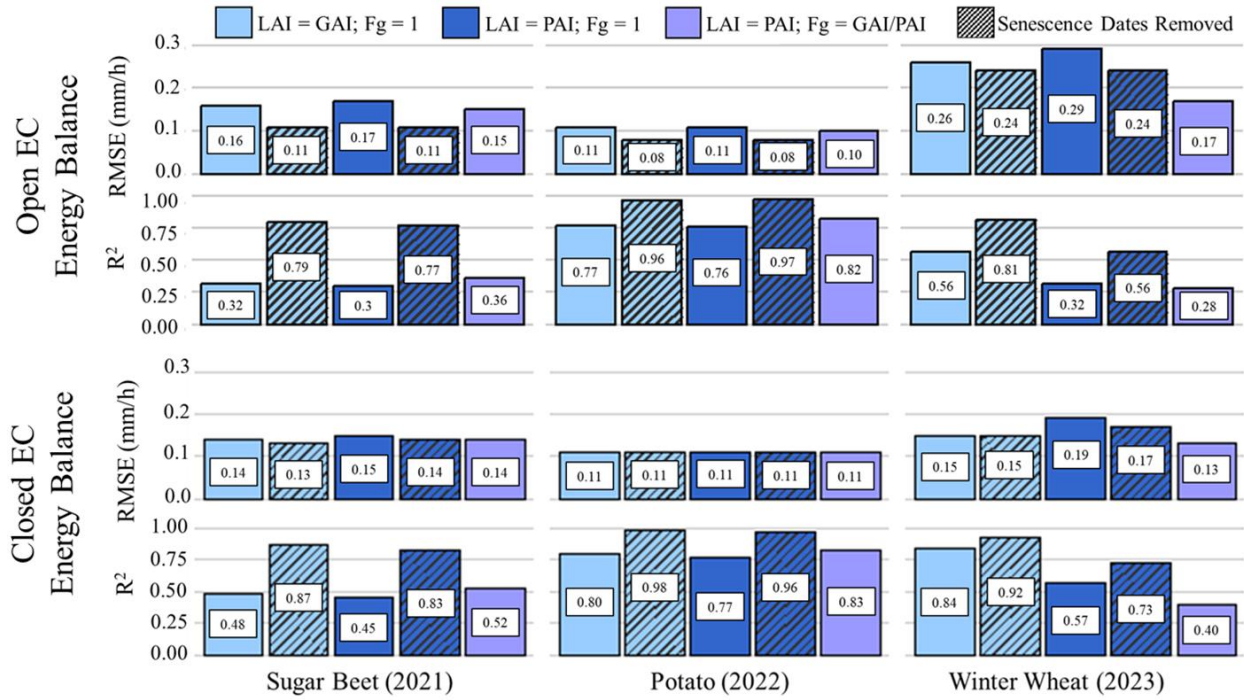


Figure 11. RMSE and R^2 between TSEB-PT modeled ET and EC-derived ET under open and closed energy balance conditions, averaged over the EC flux footprint. Green area index (GAI) and plant area index (PAI) were evaluated as LAI inputs for all campaign dates and with senescence dates excluded. A third configuration using PAI with dynamic fractional green LAI ($f_g = \text{GAI}/\text{PAI}$) was evaluated during senescence to account for changes in green canopy fraction.

ET comparisons further demonstrated these differences (Fig. 11). For winter wheat, under open EC energy balance conditions, PAI with $f_g=1$ produced greater ET overestimation ($\text{RMSE} \approx 0.29 \text{ mm h}^{-1}$; $R^2 \approx 0.32$) than GAI ($\text{RMSE} \approx 0.26 \text{ mm h}^{-1}$; $R^2 \approx 0.56$), while incorporating dynamic f_g , with $\text{LAI} = \text{PAI}$, reduced RMSE to approximately 0.17 mm h^{-1} and improved agreement. Across crops, comparisons with closed EC ET generally showed similar or improved performance based on R^2 and RMSE. Excluding senescence dates reduced differences among LAI configurations across all crops, with differences between GAI and PAI becoming minimal, indicating similar performance before senescence.

3.4. Input impacts on ET magnitude and spatial variability

TSEB-PT ET varied in both magnitude and spatial distribution depending on the UAV-derived inputs. To assess their influence on spatial variability, changes in the coefficient of variation (CV) of ET were compared with differences in input CV for LST (TIR_{OG} vs. TIR_{TC}), LAI (GAI vs. PAI), and f_g ($f_g=1$ vs. GAI/PAI-derived f_g) (Fig. D4). LST correction produced substantial changes in ET spatial variability despite the largely uniform temperature offset, while differences between GAI and PAI had a comparatively smaller influence. In contrast, dynamic f_g substantially altered ET spatial variability, demonstrating a stronger influence on the spatial representation of ET than LAI source alone.

The spatial effects of LST correction were further examined for potato under early- and late-season canopy conditions (Fig. D5). During early development, when fractional cover was lower, LST correction increased spatial contrasts associated with soil and vegetation contributions to ET. Later in the season, ET reductions following LST correction were greater in areas exhibiting vegetation stress, increasing the contrast between stressed and non-stressed zones. Thus, thermal correction affected not only ET magnitude but also the spatial representation of modeled crop water use.

3.5. Precise early identification of crop water stress with high-res ET maps

One of the most practical advantages of TIR based UAV derived ET modeling is its capacity to detect early signals of crop water stress before structural or spectral changes manifest in traditional vegetation indices. In the 2022 potato and 2023 winter wheat seasons, this capability was clearly demonstrated as seen in Fig. 12 & 13.

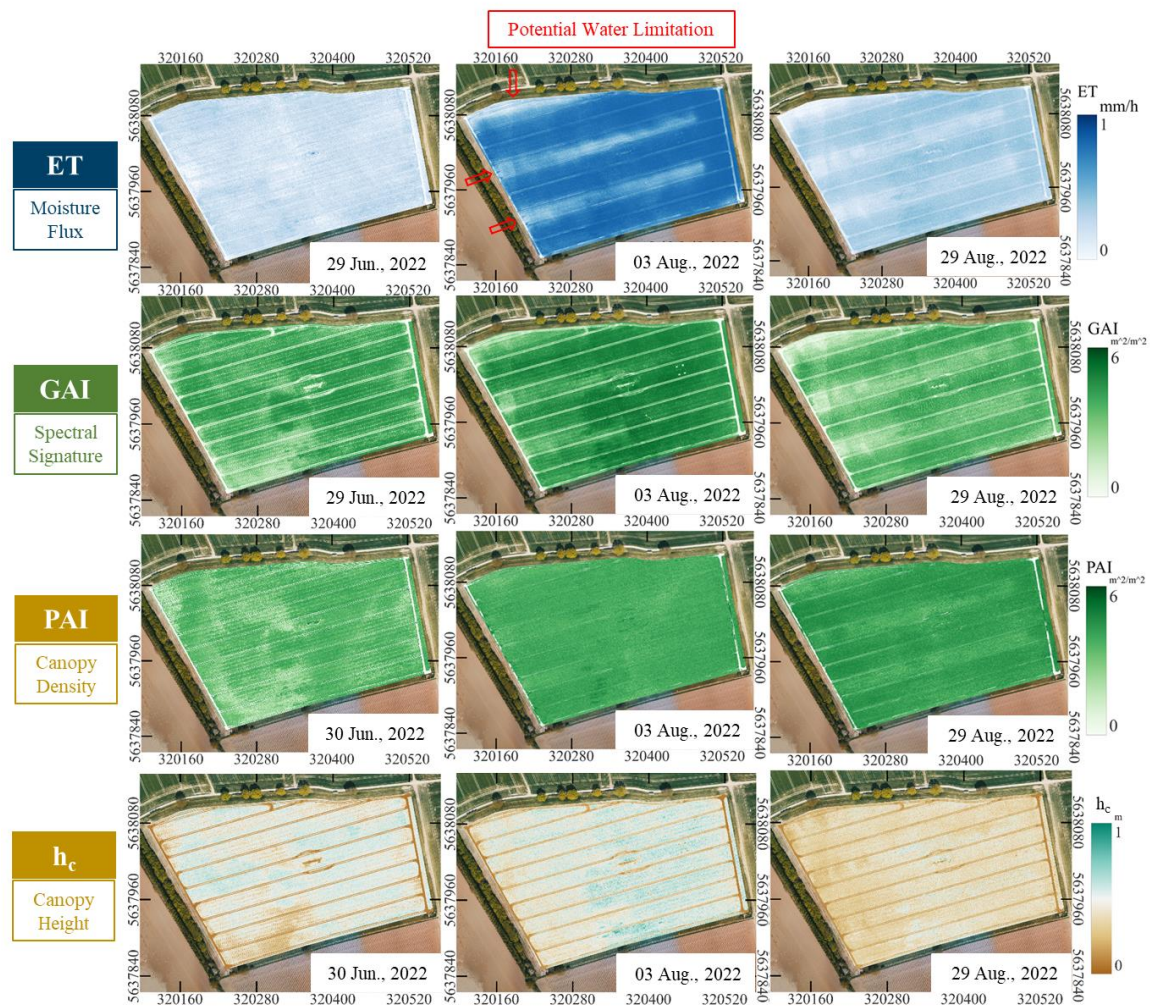


Figure 12: Particular dates in the potato 2022 season of Evapotranspiration (ET), green area index (GAI), plant area index (PAI) comparisons around moments of potential water related stress. ET map shows clear structures within field related

to irrigation patterns on the 3rd of August more so than with GAI and PAI. On the 29th of August, consequences in pigment and canopy structure can be seen with GAI and PAI.

Comparisons between the August 3 and August 29 UAV campaigns in 2022 revealed that, despite minimal changes in both GAI and PAI, the ET maps captured pronounced declines in water use across specific sections of the field. These reductions aligned with known zones of reduced irrigation coverage caused by limitations of the hose reel sprinkler system. Notably, areas along the northwest corner and adjacent to irrigation lanes exhibited significant ET suppression, even though they remained structurally intact in LiDAR and multispectral imagery.

A similar pattern was observed in 2023 with winter wheat, though in this case the stress was most likely attributed to known underlying soil–root interactions that have caused water stress in the past. On June 13, the ET map revealed broader and more pronounced spatial structures of suppressed transpiration that were not yet visible in the GAI or PAI maps. By June 28, however, similar spatial patterns emerged in both GAI and PAI, confirming physiological and structural canopy decline.

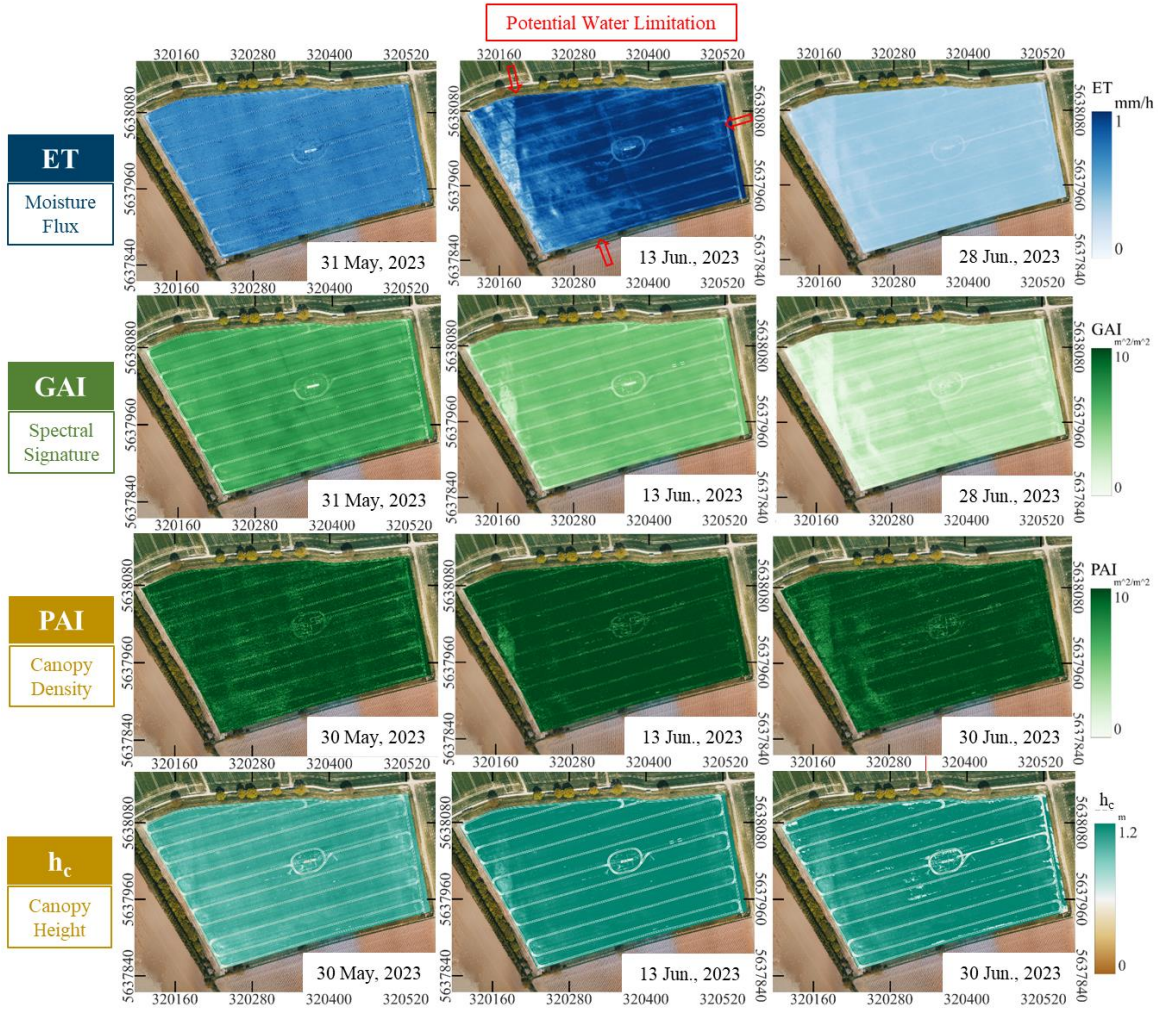


Figure 13: Particular dates in the winter wheat 2023 season of Evapotranspiration (ET), green area index (GAI), plant area index (PAI) comparisons around moments of potential water related stress. ET map shows clear structures within field related to soil layer properties and root depth on the 13th of June. On the 30th of June, stress reaction in pigment and canopy structure can be seen with GAI and PAI.

3.6. Upscaling Instantaneous UAV ET to Daily Values for Agricultural Water Management

To evaluate the operational applicability of UAV-derived ET, instantaneous estimates were upscaled to daily values and compared with daily EC ET under open and closed energy balance conditions and with FAO-56 reference ET (ET_0) (Allen et al., 1998; Appendix C3). Upscaling followed Cammalleri et al. (2014) using the best-performing TSEB-PT configuration ($LST = LST_{TC}$, $LAI = PAI$, $f_g = GAI/PAI$, and LiDAR-derived h_c). A daily relative ET stress proxy ($K_s = ET/ET_0$) was additionally calculated to characterize crop water use relative to atmospheric demand.

Figure 14 presents daily EC ET, ET_0 , and upscaled UAV ET aggregated over the field, EC flux footprint, and potential water-limitation zones (PWLZ; Figs. 12–13). UAV-derived daily ET generally followed the temporal patterns of EC

ET and ET_0 across crops, while PWLZ estimates frequently differed from field and footprint averages. Correspondingly, K_s declined below 0.7 and 0.5 during several periods, particularly within PWLZs, indicating substantially reduced ET relative to atmospheric demand.

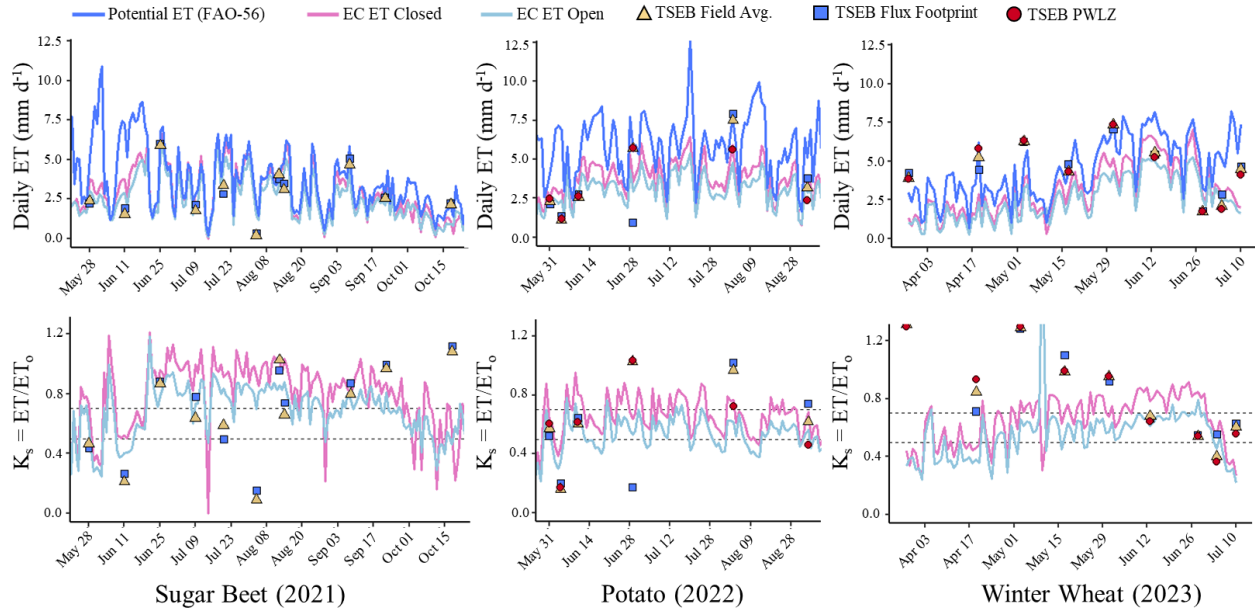


Figure 14. Daily evapotranspiration (ET) time series and relative ET stress proxy derived from UAV–TSEB and EC measurements. Top panels show upscaled UAV ET compared with daily EC ET (open and closed energy balance) and FAO-56 reference ET (ET_0). Bottom panels show the relative ET stress proxy ($K_s=ET/ET_0$). Dashed lines indicate K_s thresholds of 0.7 (possible water stress) and 0.5 (likely water stress relative to atmospheric demand). Symbols distinguish UAV ET aggregated over the field, EC flux footprint, and potential water-limitation zones (PWLZ; Figs. 12–13).

Daily UAV-derived ET performance against EC observations is summarized in Fig. 15. Agreement varied among crops and EC energy balance treatments. Sugar beet showed moderate agreement ($RMSE = 0.96\text{--}1.30\text{ mm d}^{-1}$; $R^2 = 0.57\text{--}0.61$), while potato showed the strongest agreement ($RMSE = 1.53\text{--}1.61\text{ mm d}^{-1}$; $R^2 \approx 0.80$). Winter wheat showed the weakest agreement ($RMSE = 1.90\text{--}2.30\text{ mm d}^{-1}$; $R^2 = 0.27\text{--}0.30$).

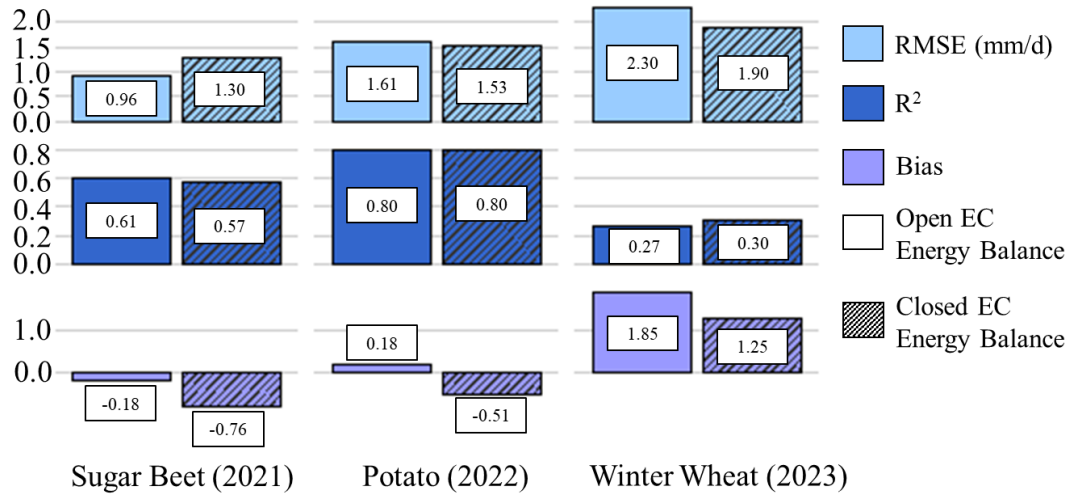


Figure 15. Comparison of daily UAV-derived TSEB ET against EC measurements for sugar beet (2021), potato (2022), and winter wheat (2023). Performance is evaluated using RMSE (mm d^{-1}), R^2 , and bias (mm d^{-1}) under open and closed EC energy balance conditions. Closed EC estimates are shown with hatched bars.

Bias was also crop dependent, ranging from -0.18 to -0.76 mm d^{-1} for sugar beet, $+0.18$ to -0.51 mm d^{-1} for potato, and $+1.25$ to $+1.85 \text{ mm d}^{-1}$ for winter wheat. Differences between open and closed EC comparisons demonstrate the influence of energy balance treatment on model evaluation and the uncertainty associated with EC-derived ET as a reference.

4. Discussion

4.1. Thermal accuracy and impacts on spatial ET distribution

TSEB-PT's strong sensitivity to land surface temperature (LST) is well established (e.g., Hoffmann et al., 2016), but this study extends those findings using very-high-resolution UAV based thermal imagery under uniform crop cover. Uncorrected LST exhibited a significant underestimation, consistent with prior UAV studies (e.g., Kelly et al., 2019; Han et al., 2020; Wan et al., 2024; Tunca et al., 2023b; Liu et al., 2024). This bias led to systematic ET overestimation. While R^2 declined slightly after correction, the improved thermal realism enhanced physical consistency in ET estimates, particularly important for cumulative ET tracking and water balance assessments.

Thermal bias was most severe under high air temperature and wind speed, precisely when crops face peak transpiration demand and are most vulnerable to stress. This trend aligns with Sagan et al. (2019), who reported increased UAV TIR underestimation under warmer conditions. In our results, stressed areas showed amplified ET deviations with LST correction, indicating greater sensitivity to thermal accuracy. Underestimated LST muted ET suppression signals, reducing contrast between stressed and non-stressed zones and potentially misleading irrigation responses. In addition, corrected LST sharpened spatial gradients in ET by enhancing energy balance contrast, particularly under dominant water or energy limitation conditions. This raised the standard deviation of ET values across the field and improved spatial differentiation of stress signals.

Despite onboard radiometric correction and a heated shutter for non-uniformity calibration, ground based reference targets remained essential for accurate LST and ET retrieval. When such targets are unavailable, alternate approaches like the Dual-Temperature Difference (DTD) variant of TSEB-PT has shown to improve estimations (Hoffman et al., 2016). Although in our case, DTD yielded only moderate improvements compared to ground-calibrated correction when used for the 2021 campaign (results not shown).

Finally, LST accuracy could be further improved through spatially dynamic emissivity correction. While constant emissivity values are appropriate under full canopy closure during peak growth, they become less valid under partial canopy conditions (e.g., early growth stages in sugar beet and potato) and during senescence, particularly in cereal crops such as winter wheat where strong contrasts between green, functioning vegetation and brown, senescent material introduce greater emissivity variability. Recent work has shown that emissivity can be effectively parameterized using NDVI to distinguish between soil, vegetation, and mixed pixels in high-resolution UAV datasets (e.g., NDVI segmentation or scaling approaches) (Heinemann et al., 2020). Applying such methods could improve LST retrievals in heterogeneous and senescing canopies, thereby enhancing spatial ET estimation and stress detection.

4.2. Implications of LAI and f_c source and sensitivity to plant physiological properties

Both GAI and PAI served as effective LAI inputs for TSEB-PT during peak growth, when structural (PAI) and pigment-based (GAI) indicators were closely aligned, yielding similar ET estimates. This is consistent with a prior one-source energy balance study showing that LiDAR-derived LAI can perform comparably to multispectral-derived LAI for ET estimation (Wei et al., 2023). However, few studies have examined how model performance shifts under stress or senescence, when canopy structure and function can diverge.

When f_g was held at its default value of 1, PAI remained high due to persistent canopy structure and was associated with greater ET overestimation during these periods. In contrast, GAI declined with senescence and produced more conservative ET estimates that better aligned with EC observations, particularly in winter wheat, where structural density persisted as canopy greenness and transpiration declined. Although PAI and ground-based ceptometer LAI showed better agreement in absolute magnitude, they did not reflect the decline in green canopy area to the same extent as GAI. The improved performance of GAI relative to PAI may therefore indicate that its decline indirectly represented part of the reduction in transpiring green vegetation that was otherwise not accounted for when f_g remained at its default value, whereas PAI better retained information on persistent canopy structure.

For sugar beet and potato, spatially varying NDVI-derived f_c accounted for partial canopy cover and soil exposure, providing complementary information on the horizontal distribution of vegetation. Together with LAI, f_c contributes to canopy clumping and the directional vegetation fraction used to decompose radiometric temperature into soil and canopy component temperatures. These component temperatures influence soil–canopy sensible heat partitioning and, consequently, the energy balance from which G is estimated (Appendix A4). The crop-specific differences in ground heat flux (Table D2) therefore suggest that the relative performance of GAI and PAI may depend partly on canopy architecture. PAI may have improved G estimates in winter wheat by better representing canopy density and structural

shading in the tall, closed canopy, whereas GAI performed better in the lower, more open sugar beet and potato canopies with greater vegetation–soil contrast, suggesting that the relative benefits of multispectral and LiDAR inputs may depend on canopy architecture. However, these interpretations are inferred from the model behavior observed in this study, and targeted sensitivity testing is needed to establish the underlying mechanisms.

4.3. Role of f_g in differentiating functional transpiration from passive cooling

Distinguishing passive canopy cooling from actual transpiration is critical in dense canopies like winter wheat, where structure remains even as physiological function declines. Unlike eddy covariance systems, which directly measure vapor flux, TSEB-PT relies on LST as a proxy. Without accounting for canopy function, models may incorrectly attribute radiative cooling to transpiration. In this study, combining LiDAR based structural LAI (PAI) and MS derived pigment-sensitive LAI (GAI) enabled the calculation of a spatially dynamic f_g , allowing canopy transpiration within the Priestley–Taylor formulation to be scaled according to physiological status, improving ET agreement with EC observations, particularly during early stress and senescence.

The dynamic f_g also improved model performance before pronounced visible senescence, indicating sensitivity to periods when transpiration was suppressed due to stress. Although f_g is an available TSEB-PT input, it is frequently omitted and retained at its default value of 1 in applications. Comparable explicit structural–functional scaling is absent from single-source models such as SEBAL and METRIC. More broadly, these approaches were developed primarily for conventional remote-sensing applications, where detailed characterization of canopy structure and function is more limited than with current UAV observations. UAV platforms provide an opportunity to better exploit this distinction by combining high-resolution three-dimensional structural information from LiDAR with spectral information related to canopy greenness.

Previous UAV-based TSEB-PT studies that did not dynamically parameterize f_g also reported ET overestimation under conditions of declining canopy function. Gómez-Candón et al. (2021) reported ET overestimation in wheat (RMSE = 0.24 mm h⁻¹), particularly later in the season during senescence. Similarly, Tunca et al. (2023a) reported overestimation in stressed sorghum and suggested adjustment of the Priestley–Taylor coefficient (α) as a potential solution. The present results indicate that dynamic f_g provides a spatially explicit means of scaling the Priestley–Taylor canopy transpiration estimate instead of relying on a uniform adjustment of α_{PT} . Bozorgi et al. (2024) likewise identified assumptions concerning the green fraction of LAI as a potential source of TSEB bias, further supporting the importance of representing changes in green canopy fraction.

As shown in Figure D4, f_g influenced spatial ET variability more strongly than LAI type alone, demonstrating the sensitivity of modeled ET to f_g and the importance of accurately representing this variable. This sensitivity was greater for sugar beet and potato than for winter wheat. The high LAI of winter wheat may have contributed to its reduced response, as exponential radiation attenuation in dense canopies results in diminishing changes in radiation interception with increasing LAI (Campbell and Norman, 1998; Kustas and Norman, 1999); however, the mechanisms underlying the observed crop-specific sensitivity to f_g require further investigation.

UAV LiDAR methods can now provide purely structural, high-resolution information that complements multispectral estimates of canopy function, helping to reduce pigment-related biases inherent in reflectance-only approaches (Chirouze et al., 2014). Unlike maximum NDVI methods, which may not fully capture structural changes during senescence, combining LiDAR-derived structure with MS-based greenness allows f_g to better represent the green fraction relative to total canopy structure. This integrated approach can improve ET partitioning and may be beneficial for broader application in UAV-based TSEB-PT and other ET modeling workflows.

4.4. Upscaling instantaneous UAV TSEB to daily ET and performance

To support applications in irrigation management and water balance assessment, instantaneous evapotranspiration (ET) estimates derived from UAV-based TSEB-PT were upscaled to daily totals. TSEB provides flux estimates corresponding to the time of thermal acquisition, requiring temporal upscaling for daily ET estimation. In this study, daily ET was derived using the ETrF approach (Section 3.6; Eq. C2) based on the best-performing instantaneous configuration ($LST = LST_{TC}$, $LAI = PAI$, $f_g = GAI/PAI$). This approach enabled direct comparison with EC-derived daily ET and with reported daily ET estimates from previous studies.

The resulting daily ET estimates showed good agreement with EC observations across crops, although winter wheat remained the most challenging. Relatively few studies report daily field-scale TSEB performance for the crops examined here, and the available studies are predominantly satellite-based. For winter wheat, reported daily ET RMSE values are approximately 1.5–2.0 mm d⁻¹ (Hazdour et al., 2025). Other satellite-based energy-balance approaches have reported similar errors; for example, Zoratipour et al. (2023) obtained daily winter wheat ET RMSEs of 2.15 and 1.53 mm d⁻¹ for SEBAL and SEBS, respectively. These comparisons place the present UAV-based TSEB-PT results within the range reported for other remote-sensing ET approaches, while UAV observations provide greater spatial detail and acquisition flexibility. This is consistent with Nassar et al. (2020), who showed that increasing model grid size had a comparatively smaller effect on field-scale mean fluxes than on within-field variability, while Mokhtari et al. (2021) demonstrated the value of higher-resolution UAV data for resolving fine-scale spatial variability in ET. However, direct comparisons between studies should be interpreted cautiously because of differences in spatial and temporal resolution, crop conditions, and validation and EC-processing methods.

Crop-specific behavior further illustrates differences in model performance. Winter wheat showed a tendency toward ET overestimation, consistent with previous studies reporting positive bias under dense canopy conditions (Hazdour et al., 2025), where structural persistence may lead to overestimation of transpiration when physiological activity declines. In contrast, studies on sugar beet (Acharya & Sharma, 2021) and potato (Ebert et al., 2022) have reported slight underestimation of ET, which may be associated with higher soil exposure during early growth stages. Greater soil exposure increases the contribution of the soil component to radiometric temperature and influences soil–canopy energy partitioning within TSEB (Norman et al., 1995; Kustas & Norman, 1999). Consistent with this interpretation, the largest underestimations in this study occurred during early growth stages of sugar beet and potato, when soil fractions were highest (Fig. 16).

Future improvements in daily ET estimation could involve both alternative upscaling formulations and improved temporal sampling. Evaporative-fraction, radiation-based, and other scaling approaches can exhibit different performance depending on phenology, environmental conditions, and acquisition time (Nassar et al., 2021). Recent developments include improved evaporative-fraction-based temporal scaling (Wei et al., 2025) and machine-learning approaches for instantaneous-to-daily flux upscaling (Tunca, 2026). UAV platforms also provide flexibility in acquisition timing and the potential for repeated observations within a day. Together, these developments suggest that improved daily ET estimation may require a combination of appropriate temporal-scaling methods, optimized acquisition timing, and, where feasible, multi-temporal observations that better characterize the diurnal ET cycle.

4.5. Future considerations with UAV TSEB model implementation

Additional UAV sensor capabilities could further improve TSEB parameterization. Multi-layer LiDAR gap-fraction profiles could improve characterization of vertical canopy structure (Bates et al., 2022), while LiDAR intensity has shown relationships with crop LAI (Hütt et al., 2022) and biomass (Montzka et al., 2023), potentially extending LiDAR from a purely structural measurement toward a dual-purpose source of structural and intensity-based canopy information. Ground-classified LiDAR observations could also provide information on soil-surface roughness, potentially helping to guide the selection or adjustment of soil roughness and resistance parameters, which have been shown to influence TSEB performance (Li et al., 2019). Additional information on canopy and surface moisture could be provided by emerging UAV radar systems, including synthetic aperture radar (SAR) and ground-penetrating radar (GPR) (Wu and Lambot, 2022), while integration of surface soil moisture has been shown to improve TSEB transpiration estimates (Song et al., 2022). Hyperspectral UAV observations offer another complementary source of physiological information, potentially enabling retrieval of SIF and PRI, with SIF providing information linked to photosynthetic activity and transpiration and PRI providing sensitivity to changes in photosynthetic light-use efficiency and stress responses (Jonard et al., 2020; Zheng et al., 2024). Together, these sensors offer opportunities to move beyond using UAVs solely as higher-resolution substitutes for satellite inputs toward explicitly exploiting three-dimensional structure, moisture status, and canopy function in ET modeling.

Another important consideration is the influence of shadowing on remote sensing inputs. Studies have shown that shadow pixels can introduce bias in LST and ET estimation, as shaded surfaces exhibit lower temperatures that may lead to artificially elevated modeled ET under some conditions (Mokhtari et al., 2021). Additional work has demonstrated that shadowing can significantly affect vegetation indices and the retrieval of f_c and LAI, thereby providing an additional pathway through which illumination conditions can influence TSEB flux partitioning (Lu et al., 2022; Gao et al., 2023). These effects may be particularly important in discontinuous canopies with greater soil exposure (Duran-Gomez et al., 2026). However, shaded pixels form part of the composite radiometric signal, and their removal may not necessarily improve flux estimation; recent work instead supports approaches that retain or compensate for shadow effects (Aboutaleb et al., 2019; Duran-Gomez et al., 2026). LiDAR-derived structural inputs provide an advantage in this context because they are substantially less dependent on illumination conditions than passive sensor observations. Although shadow effects were likely reduced in this study by near-solar-noon

acquisitions and predominantly developed canopies, future UAV-TSEB studies should further evaluate shadow-compensation strategies for both multispectral and thermal inputs.

UAV acquisition flexibility also provides opportunities to improve temporal representation. Flights can be targeted near optimal acquisition periods or repeated throughout the day to characterize diurnal ET variability and changing illumination conditions, including the movement and influence of shadows. This flexibility may also complement satellite observations by supporting temporal interpolation between satellite overpasses (Hazdour et al., 2025), as well as high-resolution validation and spatial sharpening of satellite-derived products (Jaafar et al., 2022). Combining the spatial detail and acquisition flexibility of UAV observations with the broader spatial and temporal coverage of satellite systems may therefore improve both within-field characterization and temporal continuity of ET estimates.

Finally, further improvements may arise from testing alternative resistance formulations and soil heat flux parameterizations. Modified resistance schemes have improved TSEB performance under particular canopy conditions (Li et al., 2019; Lun et al., 2026), while simplified G parameterizations remain an important source of uncertainty (Hoffmann et al., 2016). In this study, G was sensitive to LAI representation, with GAI performing better in the more open sugar beet and potato canopies and PAI in dense winter wheat, further motivating targeted testing of how UAV-derived structural and spectral canopy information can best parameterize these model inputs. Model configuration may also be adapted to canopy conditions. Preliminary application of TSEB-2T to the 2021 sugar beet campaign (data not shown) indicated improved performance during early development under low vegetation cover, whereas TSEB-PT was more robust under dense canopy conditions. Future work could therefore examine how model configuration, parameterization, and UAV-derived canopy inputs can be adapted according to canopy architecture and phenological stage.

4.6. Practical impacts and considerations for farming practices, water stress, and irrigation

Moving toward practical farm management applications, physically based models such as TSEB-PT offer advantages by explicitly representing land–atmosphere energy exchange without requiring the extensive training datasets typically needed for data-driven approaches such as machine learning. In this study, TSEB-PT provided ET estimates across three crop seasons with relatively limited ground inputs, consisting primarily of a small number of control plots for LAI and canopy height calibration and early-season thermal reference targets. This demonstrates the potential of combining physically based modeling with UAV observations, with complementary sensor information improving characterization of canopy structure, function, and surface temperature.

The high spatial resolution of UAV ET mapping enables detection of sub-field variability that may not be resolved by conventional scouting or coarser satellite observations. In this study, TIR-derived ET revealed crop water stress patterns before corresponding changes became evident in multispectral GAI or LiDAR-derived PAI and h_c . In potato, ET maps revealed zones of reduced ET following irrigation events, consistent with under-irrigation (Fig. 14), while persistently low ET in winter wheat corresponded with shallow gravel layers and areas exhibiting potential water

stress and earlier senescence (Fig. 15). Such spatial information can help identify zones of contrasting crop water use and support targeted irrigation management.

A daily water stress proxy ($K_s = ET/ET_0$), based on atmospheric demand (FAO-56), further supported identification of water-limited conditions by relating actual crop water use to atmospheric demand, consistent with previous approaches (Giardina et al., 2019). Comparisons among field averages, EC footprints, and delineated stress zones (Fig. 14) demonstrate how spatial aggregation can mask localized stress signals, particularly in potato during 3–29 August when within-field variability was greatest.

Previous studies similarly support energy-balance approaches for crop water-stress assessment. TSEB-derived transpiration and stomatal conductance have provided robust stress indicators compared with temperature-based indices alone (Nieto et al., 2022), while combining ET-related information with CWSI has improved discrimination of irrigation treatments and water deficits in UAV applications (Sánchez-Virosta et al., 2025). Operationally, UAV-derived ET could be combined with rainfall and irrigation records to estimate spatial crop water deficits and support irrigation scheduling. Additional integration with gross primary productivity (GPP) and water-use efficiency (WUE) could further connect crop water use with productivity (Elfarkh et al., 2023). High-resolution ET information has consequently been identified as valuable for agricultural water management (Wanniarachchi and Sarukkalige, 2022), with UAV-based approaches offering opportunities for spatially targeted interventions (Ankela et al., 2026).

Despite these advantages, operational implementation requires consideration of spatial scale. The 15 cm GSD outputs generated here exceed the resolution typically required for irrigation decisions, which are generally implemented at irrigation-sector or management-zone scales (von Hebel et al., 2021). Such zones can be defined by soil, yield, crop, and ET variability and typically operate at meter- to tens-of-meter scales or as a limited number of homogeneous field units (Serrano et al., 2020; Flint et al., 2023). The principal value of very-high-resolution UAV ET may therefore lie not in managing individual pixels, but in identifying meaningful within-field heterogeneity that can subsequently be aggregated into actionable management zones. This provides a multi-scale framework in which fine-resolution observations support stress detection and characterization, while aggregated information supports irrigation planning and decision-making.

5. Conclusion

This study demonstrates the potential of integrating very-high-resolution UAV multi-sensor observations with TSEB-PT for field-scale evapotranspiration (ET) estimation across sugar beet, potato, and winter wheat over full growing seasons. With relatively limited ground calibration of UAV inputs, modeled ET showed good agreement with eddy covariance (EC) observations, although performance varied among crops and winter wheat remained the most challenging. Agreement was largely maintained when instantaneous estimates were upscaled to daily ET using a reference ET fraction (ET_rF) approach, supporting the application of UAV-based TSEB for crop water-use assessment. Reference ET was further used to contextualize modeled ET relative to atmospheric demand, enabling identification of potential water stress conditions. High-resolution UAV ET maps revealed clear spatial patterns of

reduced ET associated with likely water-limited zones, which would not be apparent from coarser-scale observations. Comparisons of stress proxies across spatial scales demonstrated how aggregation to field-average and EC-footprint scales can mask localized reductions in crop water use.

Among the UAV inputs, thermal infrared observations were both highly influential and an important source of uncertainty. The uncooled thermal sensor underestimated LST under high-temperature and high-VPD conditions, contributing to ET overestimation, while ground-based thermal correction improved ET magnitude and spatial representation. Vegetation inputs showed similarly important crop- and phenology-dependent behavior. LiDAR-derived PAI and multispectral-derived GAI performed comparably when canopy structure and greenness were closely aligned, but diverged during stress and senescence as PAI retained persistent canopy structure while GAI declined with green canopy area. Combining these complementary sensitivities through dynamic f_g (GAI/PAI) substantially improved ET performance, particularly when structural and functional canopy properties diverged.

Overall, the results highlight the value of combining thermal, multispectral, and 3D LiDAR observations rather than relying on a single UAV sensor. The physically based TSEB framework provides a means of integrating these complementary observations while requiring relatively limited ground information and remaining applicable across different crop types. Together with flexible acquisition timing and very-high spatial resolution, this approach provides opportunities for identifying within-field water-use variability and supporting spatially targeted crop-water management.

Key contributions of this study include:

- Demonstrating the robustness of UAV-based TSEB-PT across three crop types with limited ground calibration, while identifying crop-specific modeling challenges, particularly in dense winter wheat canopies.
- Underscoring the importance of accurate TIR calibration for ET estimation, particularly under high-temperature conditions.
- Demonstrating comparable performance of LiDAR-derived PAI and multispectral-derived GAI when canopy structure and greenness were closely aligned, and their divergence during stress and senescence.
- Proposing a LiDAR–MS fusion approach to derive dynamic f_g for transpiration scaling and demonstrating its value for improving ET estimates across changing physiological conditions.
- Demonstrating the potential of UAV TIR-based ET mapping to detect early patterns of potential water stress before corresponding changes became evident in other sensor-derived canopy metrics, supporting targeted irrigation management.

Future improvements should focus on advancing thermal calibration and dynamic emissivity characterization, improving representation of $LAI-f_c-f_g$ interactions, and further integrating structural and physiological UAV observations. Combining UAV and satellite observations through spatial fusion and temporal interpolation could extend these high-resolution estimates across broader spatial and temporal scales, strengthening their application to crop-water monitoring and irrigation management.

Appendix A: Description of the TSEB-PT model implementation

The Two-Source Energy Balance model with Priestley-Taylor formulation (TSEB-PT; Norman et al., 1995) was used to estimate surface energy fluxes, particularly latent heat flux (LE), by partitioning soil and canopy contributions based on radiometric surface temperature. The model was implemented in Python using the open-source pyTSEB package (Nieto et al., 2018). For more detailed description of TSEB, please refer to Norman et al. (1995) and W. P. Kustas & Norman (1999).

A1. Energy balance equations

$$R_n = LE + H + G \quad (A1)$$

Fluxes are partitioned into canopy and soil components:

$$R_{nc} = H_c + LE_c \quad (A2)$$

$$R_{ns} = H_s + LE_s + G \quad (A3)$$

Soil heat flux GGG is parameterized as a fraction of R_{ns} :

$$G = c_g R_{ns} \quad (A4)$$

Where $c_g=0.35$ is an empirical constant (Choudhury et al., 1987; Kustas & Daughtry, 1990).

A2. Sensible heat partitioning and air temperature

The total sensible heat flux H is calculated as:

$$H = H_c + H_s = \rho C_p \left[\frac{T_{ac} - T_c}{R_a} \right] = \rho C_p \left[\frac{T_c - T_{ac}}{R_x} + \frac{T_s - T_{ac}}{R_s} \right] \quad (A5)$$

Where T_{ac} = within-canopy air temperature (Kelvin); T_c and T_s = canopy and soil surface temperature components derived from UAV thermal imagery; ρ = air density (kg m^{-3}); C_p = heat capacity of the air at constant pressure (J/kg/K); R_a , R_s , and R_x = aerodynamic resistances (s m^{-1}).

The in-canopy air temperature is:

$$T_{AC} = \frac{\frac{T_A}{R_a} + \frac{T_c}{R_x} + \frac{T_s}{R_s}}{\frac{1}{R_a} + \frac{1}{R_x} + \frac{1}{R_s}} \quad (A6)$$

A3. Resistance parameterizations

Soil boundary layer resistance (Kustas & Norman, 1999):

$$R_s = \frac{1}{c(T_s - T_A)^{\frac{1}{3}} + bu_s} \quad (A7)$$

With the semi-empirical constants, b and c left at their default values. u_{su} represents wind speed near the soil surface.

Canopy resistance (Norman et al., 1995):

$$R_x = \frac{C'}{LAI} \left(\frac{S}{u_{d_0} + z_{0m}} \right)^{\frac{1}{2}} \quad (A8)$$

Where $C' (s^{1/2} m^{-1}) = 90 s^{1/2} m^{-1}$; LAI = leaf area index estimated from either UAV multispectral GAI or LiDAR PAI; S (m) = characteristic leaf size; $u_{d_0} + z_{0m}$ is the wind speed at the height reference height; $d_0 + z_{0m}$ as d_0 is the zero-plane displacement height and z_{0m} is the roughness length for momentum estimated from UAV derived crop height.

$$R_a = \frac{\ln\left(\frac{z_T - d_0}{z_{0H}}\right) - \psi_h\left(\frac{z_T - d_0}{L}\right) + \psi_h\left(\frac{z_{0H}}{L}\right)}{k' u_*} \quad (A9)$$

z_T is the measurement heights for wind speed u (ms^{-1}). d_0 is the zero-plane displacement height, z_{0H} is the roughness length for momentum and heat transport with $z_{0H} = z_{0m} (-kB-1)$. The ψ (ζ) terms in Eqs. 7a and are the adiabatic correction factors for momentum. L being the Monin–Obukhov length (m).

A4. Radiometric temperature decomposition and canopy clumping

The observed directional radiometric temperature (T_{RAD}) is decomposed into canopy (T_c) and soil (T_s) component temperatures according to their relative contributions to the sensor field of view (Norman et al., 1995):

$$T_{RAD}(\theta) = [f_c(\theta)T_c^4 + (1 - f_c(\theta))T_s^4]^{1/4} \quad (A10)$$

where $f_c(\theta)$ represents the directional fraction of vegetation observed by the sensor at viewing zenith angle θ . Following the theoretical formulation presented for TSEB, this directional vegetation fraction can be expressed as:

$$f_c(\theta) = 1 - \exp[-k_{be}(\theta)LAI] \quad (A11)$$

where $k_{be}(\theta)$ is the canopy extinction coefficient at viewing zenith angle θ , with the leaf-angle distribution function defined by the Campbell (1990) χ parameter:

$$k_{be} = \frac{\sqrt{\chi^2 + \tan^2 \theta}}{\chi + 1.774 (\chi + 1.182)^{-0.733}} \quad (A12)$$

where χ is the Campbell (1990) parameter describing the canopy leaf-angle distribution.

For partially covered or spatially heterogeneous canopies, pyTSEB additionally accounts for canopy clumping when estimating the directional vegetation fraction. The nadir clumping index, $\Omega(0)$, is estimated from LAI and the supplied fractional-cover input (f_c) following Kustas and Norman (1999):

$$\Omega(\theta) = \frac{-\ln(f_c \exp(-k_{be}F) + (1-f_c))}{k_{be}F} \quad (A13)$$

with local LAI (F) defined as:

$$F = \frac{LAI}{f_c} \quad (A14)$$

where LAI is the effective LAI supplied to pyTSEB, f_c is the fractional-cover model input, and F represents the local LAI within the vegetated fraction of the surface. In this study, multispectral NDVI-derived FVC was supplied as f_c for sugar beet and potato, whereas $f_c=1$ was retained for the nearly closed winter wheat canopy. Thus, the fractional-cover input f_c and LAI contribute to the estimation of canopy clumping and, consequently, to the directional vegetation fraction used in Eq. (A10). The fractional-cover input f_c should therefore be distinguished from the directional vegetation fraction $f_c(\theta)$ appearing in Eqs. (A10–A11).

A5. Priestley-Taylor approach to canopy transpiration

The initial estimate of LE_c uses the Priestley-Taylor formulation:

$$LE_c = \alpha_{PT} f_g \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (A15)$$

where $\alpha_{PT}=1.26$ and is iteratively reduced when necessary to obtain a physically plausible solution ($LE_s > 0$) (Kustas and Anderson, 2009); f_g is the fraction of green LAI; Δ is the slope of the saturation vapor pressure curve ($kPa K^{-1}$); γ is the psychrometric constant ($kPa K^{-1}$); and R_{nc} is canopy net radiation.

Appendix B: Sensor derived metrics

B1. Fractional Vegetation Cover and Green area index (multispectral)

$$FVC = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \quad (B1)$$

with $NDVI_s$ being the upper threshold for NDVI values representing soil pixels and $NDVI_v$ representing the upper threshold of healthy vegetation.

$$GAI = \frac{-\log(1-FVC)}{k(\theta)} \quad (B2)$$

$k(\theta)$ = extinction coefficient, parametrized using SunScan ceptometer LAI measurements. k was adjusted once between early and mid-late season and then held constant through senescence.

839 **B2. Plant area index (LiDAR)**

840
$$GF = \frac{n_{ground}}{n} \quad (B3)$$

841 n_{ground} = number of LiDAR returns classified as ground. n = total number of returns (ground + vegetation) in the
842 pixel.

843
$$PAI = -\frac{\cos(\theta) \ln(GF)}{k} \quad (B4)$$

844 θ = LiDAR scan angle ; GF = gap fraction from previous equation; k = extinction coefficient (same as above),
845 adjusted once mid-season and then held constant.

846 **B2. Crop height (LiDAR)**

847
$$h_c = DSM_d - DTM_0 \quad (B5)$$

848 DSM_d = digital surface model from the crop canopy (per flight date); DTM_0 = digital terrain model from the bare soil
849 pre-emergence flight.

850 **Appendix C: EC energy balance closure and daily and potential ET**

851 **C1. Eddy Covariance Closure Method – Bowen ratio (BR)–preserving method**

852 For hourly eddy covariance (EC) flux and the accumulative daily ET, a Bowen ratio–preserving approach following
853 Twine et al. (2000) was used for closed energy balance conditions as follows:

854
$$LE^* = \frac{LE}{H+LE} * (R_n - G) \quad (C1)$$

855
$$H^* = \frac{H}{H+LE} * (R_n - G) \quad (C2)$$

856 **C2. FAO 56 reference ET (Potential ET)**

857 The reference evapotranspiration (ET_0) was calculated using the FAO-56 method (Allen et al., 1998) as follows:

858
$$ET_0 = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T+273} u_2 (u_s - u_a)}{\Delta + \gamma(1+0.34u_2)} \quad (C3)$$

859 With T being the air temperature, u_2 as wind speed at 2m ($m s^{-1}$), e_s as saturation vapor pressure, e_a as actual vapor
860 pressure, Δ as the slope of vapor pressure curve ($kPa ^\circ C^{-1}$), and γ as psychrometric constant ($kPa ^\circ C^{-1}$). This reference
861 ET was used to upscale instantaneous UAV-derived ET estimates to daily values using an ET fraction approach.

862 **C3. TSEB upscaling to Daily ET using reference ET fraction (ETrF)**

$$ET_f F = \frac{ET_{inst}}{ET_{0,inst}} \quad (C4)$$

With $ET_f F$ representing the reference evapotranspiration fraction and ET_{inst} being the UAV derived ET and $ET_{0,inst}$ the calculated instantaneous reference ET during that same time window as the UAV flight. The instantaneous fraction is then multiplied by the produced daily reference ($ET_{0,daily}$) as follows:

$$ET_{daily} = ET_f F * ET_{0,daily} \quad (C5)$$

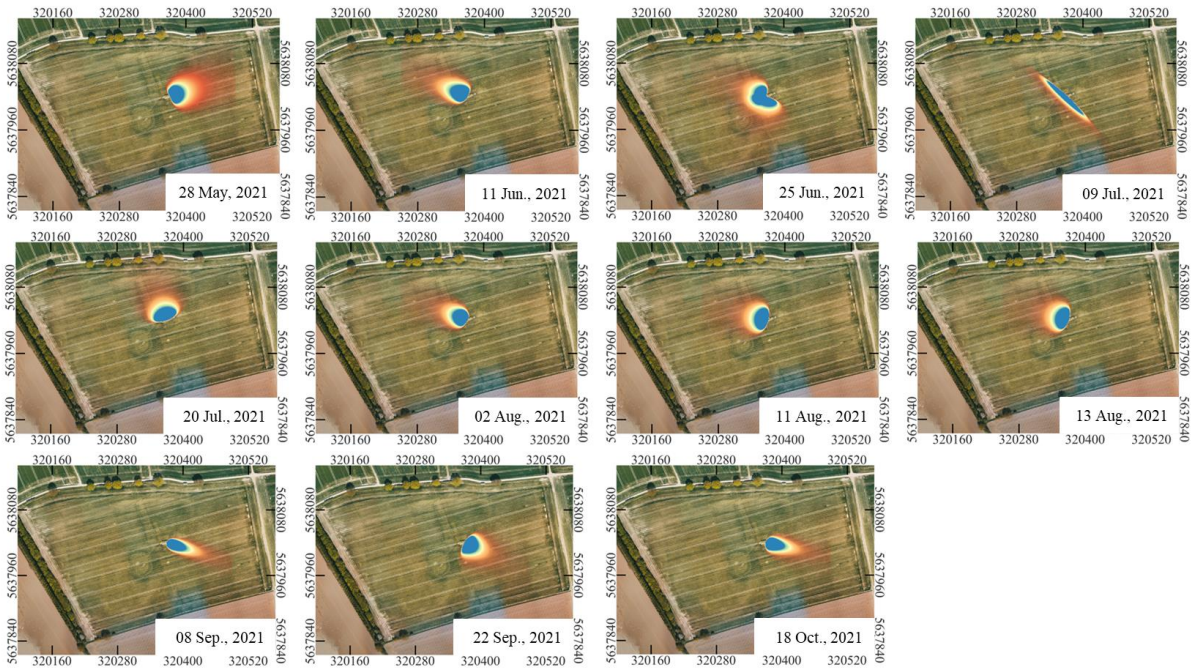
Here, $ET_f F$ differs from the evaporative fraction ($EF = LE/(R_n - G)$) and is used for temporal upscaling following Cammalleri et al. (2014).

870 C4. Water stress coefficient

ET estimations from UAV TSEB and EC were compared relative to atmospheric demand (reference ET) introduced from Allen et al. (1998) as follows:

$$K_s = \frac{ET}{ET_0} \quad (C6)$$

874 Appendix D: Supplemental material



875

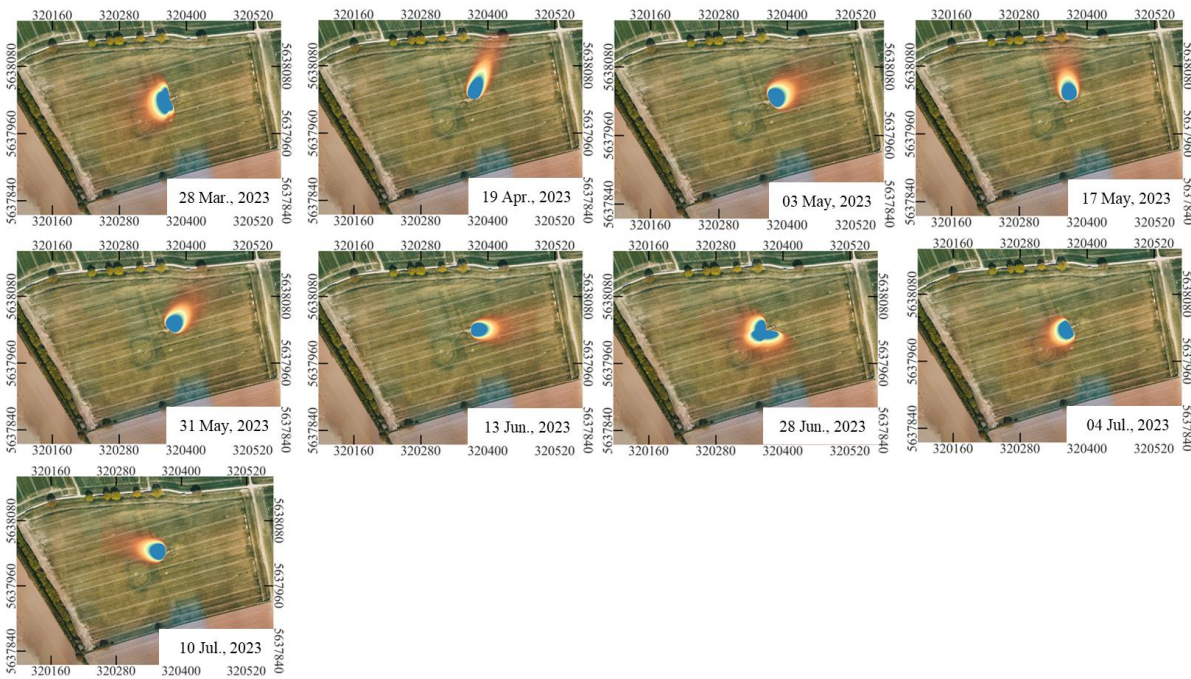
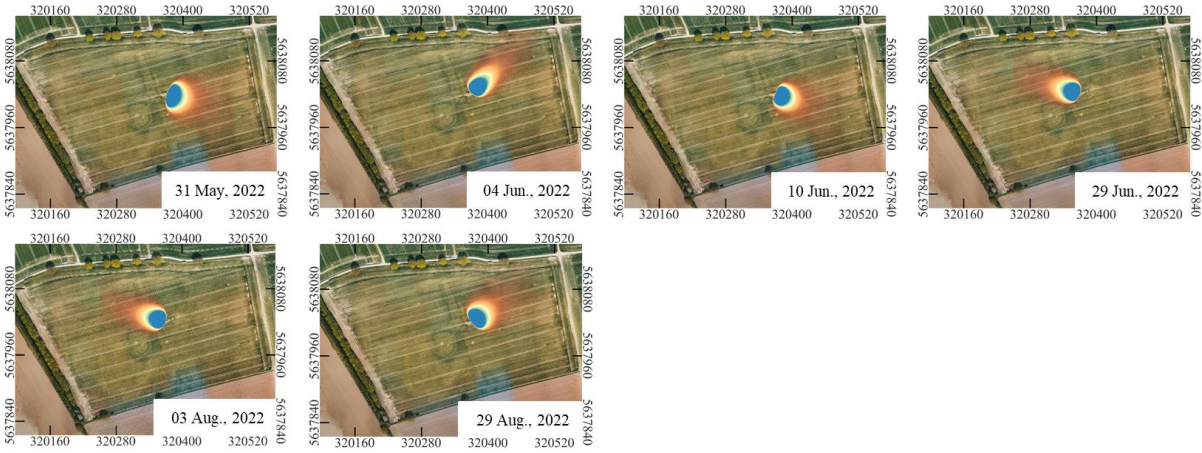


Figure D1: The estimated EC footprints for each TIR campaign flight time interval to be used to compare the TSEB-PT ET values within this spatial extent to the EC ET estimations.

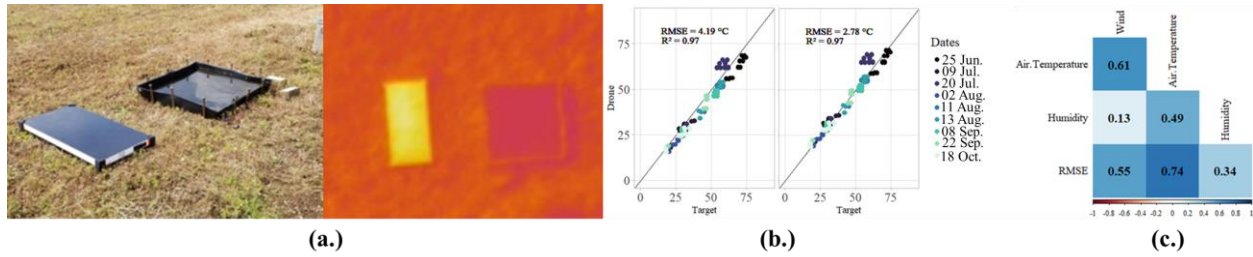


Figure D2 (a.) ground photo and aerial TIR view of the hot and cold temperature ground reference targets (b.) pre-correction and post-correction graphed RMSE of TIR images in the 2021 season (c.) correlation of weather factors with RMSE.

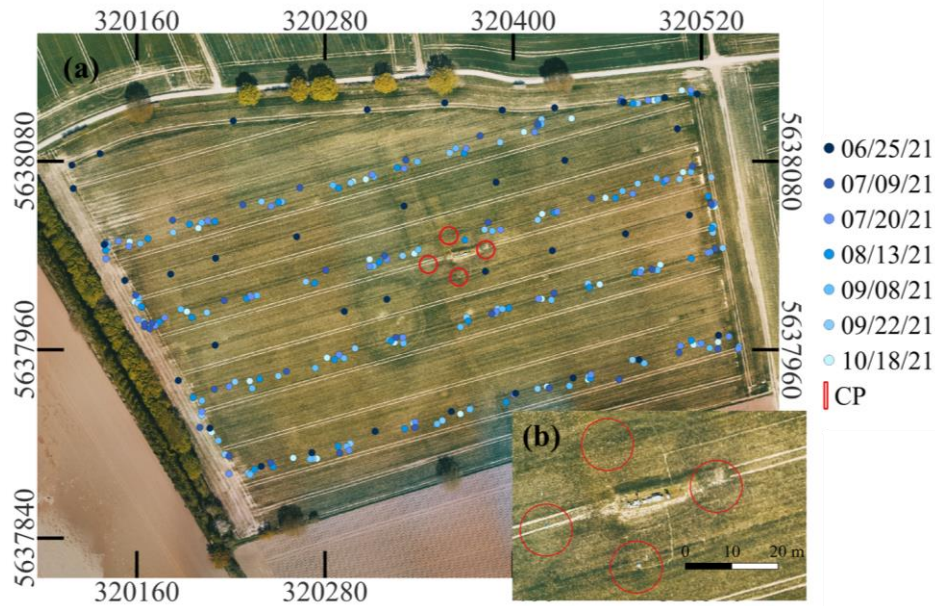


Figure D3: (Left) Location of continuous measurement plots (CP) around climate station in the middle of the experiment field site. (Right) Crop height measuring locations for the listed 2021 campaigns by color.

Table D1: The following TIR and MS collection dates with the relevant weather conditions during each flight that may have contributing factors on the accuracy of the observations.

Date	FLIR/MS Flights	LiDAR Flights	Start Time	End Time	Wind (m/s)	Air_Temp. (°C)	Humidity (%)	Wind_Direction (°)
5/28/2021	X	X	1310	1425	1.4	16.1	8.1	73
6/11/2021	X	X	1514	1619	2.3	25.9	11.9	295
6/25/2021	X	X	1228	1324	1.8	20.2	9.4	260
7/9/2021	X	X	1126	1233	1.2	17.8	13.1	304
7/20/2021	X		1328	1358	1.4	20.9	10	309
7/23/2021	X	X						
8/02/2021	X		1143	1212	0.9	15.4	10.6	299
8/11/2021	X		1400	1430	1.2	22.5	13.6	246
8/13/2021	X	X	1251	1328	2	22.5	12.7	287
9/08/2021	X		1328	1402	2.5	25.5	11.8	123

9/09/2021		X						
9/22/2021	X		1148	1227	0.9	16.7	8.6	133
9/28/2021		X						
10/18/2021	X		1400	1430	1.9	15.5	9.1	102
5/31/2022	X		1209	1251	0.8	15.3	8.2	102
6/04/2022	X	X	1447	1513	2.6	24.3	11.5	46
6/10/2022	X		1419	1448	1.3	22.1	11	226
6/29/2022	X	X	1512	1550	1.4	27.1	9.46	113
8/03/2022	X	X	1503	1533	1.9	31.7	10.7	292
8/29/2022	X	X	1508	1542	1.6	23.0	8.8	46
3/28/2023	X	X	1158	1235	0.9	6.6	3.8	250
4/19/2023	X	X	1323	1356	1.4	14.1	5.5	22
5/03/2023	X	X	1327	1341	1.2	14.3	6.5	55
5/17/2023	X	X	1350	1403	1.3	14.3	6.5	350
5/31/2023	X	X	1208	1240	1.5	22.2	9.4	38
6/13/2023	X	X	1257	1324	1.6	24.8	9.1	90
6/28/2023	X	X	1341	1410	1.4	20.5	11.5	225
7/04/2023	X		1243	1313	1.4	21.1	9.2	235
7/10/2023	X		1220	1251	1.6	24.7	11.3	283

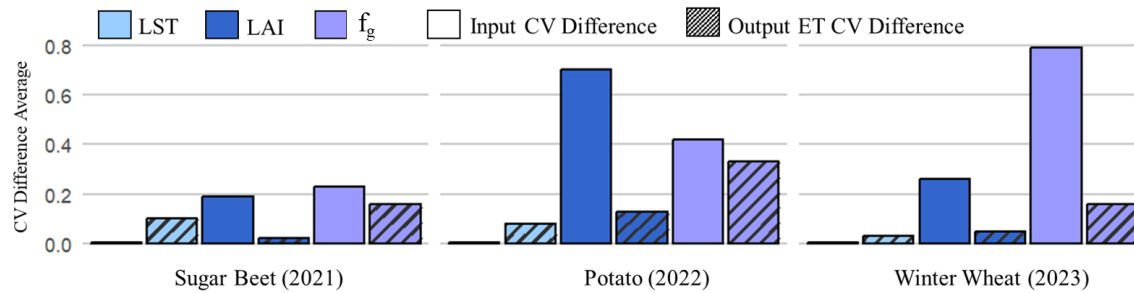


Figure D4: Comparison of average differences in the coefficient of variation (CV) between key TSEB-PT input variables (LST, LAI, f_g) and the resulting ET estimates across three crop types. This highlights how changes in the spatial variability of each input affect the spatial variability of modeled ET. The CV difference for f_g reflects the transition from a uniform value ($f_g = 1$) to a spatially variable product derived from the fusion of GAI and PAI.

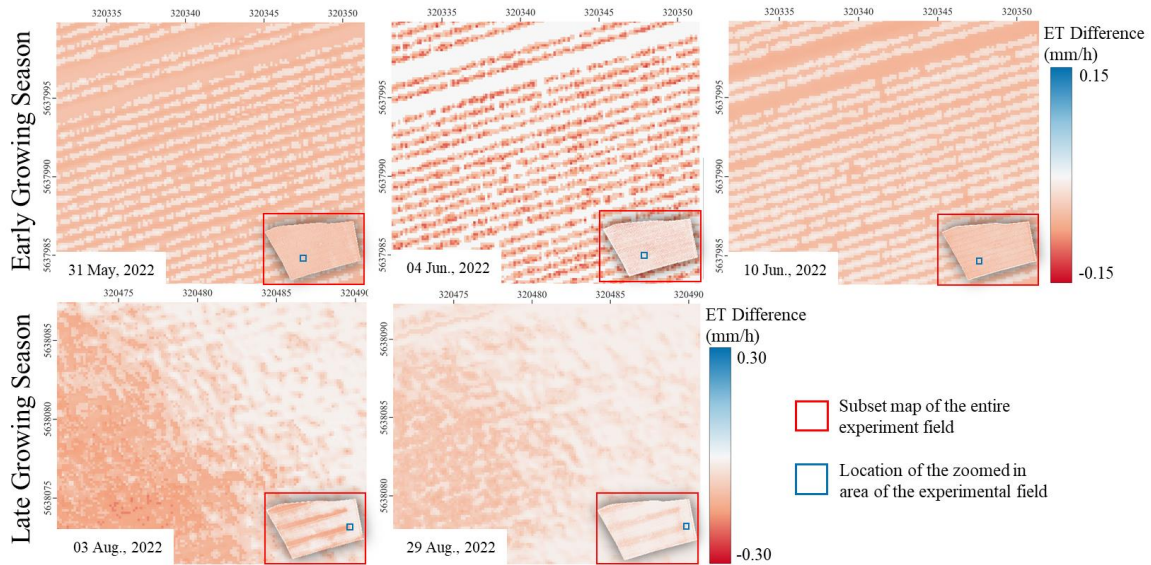


Figure D5: Difference in TSEB-PT ET estimates using original land surface temperature (LST_{OG}) ET minus reference target corrected (LST_{TC} ; $ET_{OG} - ET_{TC}$) ET. The maps illustrate how the magnitude and spatial pattern of ET differences vary with dominant evaporative sources (soil vs. canopy) and crop water stress conditions. The zoomed-in area is outlined in blue within the full experimental field (red). Late-season areas are located along the edge of a potential water-limited zone, highlighting differences in ET response between stressed and non-stressed regions under varying LST inputs.

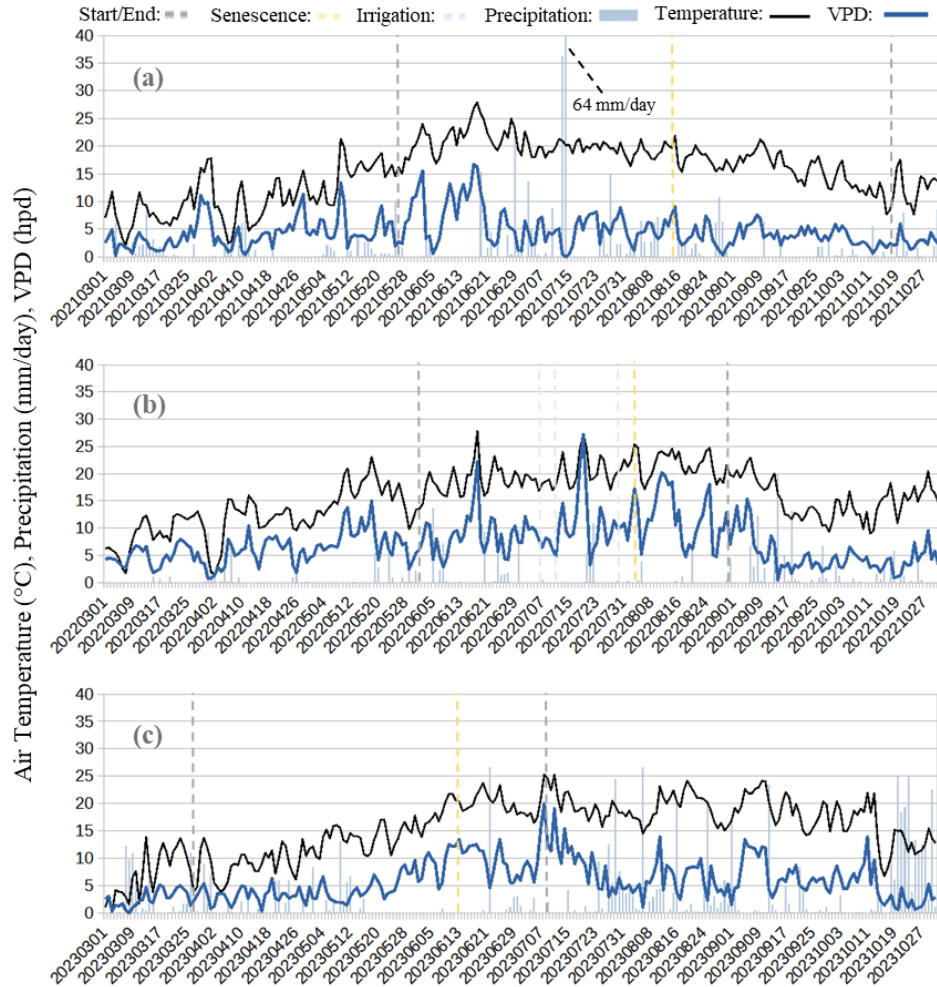


Figure D6: Daily air temperature, precipitation, and vapor pressure deficit (VPD) for the following years (a) 2021 (b) 2022 (c) 2023.

Table D2. Summary of flux comparison statistics for net radiation (Rn), latent heat flux (LE), sensible heat flux (H), and soil heat flux (G) derived from TSEB model runs using UAV-based inputs. Model configurations include original and temperature-corrected LST, with additional inputs of LAI = GAI and $f_g = 1$. Results are presented for three growing seasons: 2021 (sugar beet), 2022 (potato), and 2023 (winter wheat), covering the full growing period. For each season, statistics are shown for both the complete dataset and for periods excluding senescence. Comparisons are provided against eddy covariance (EC) measurements under both open energy balance conditions and Bowen ratio–closed energy balance conditions.

		Sugar Beet (2021)				Potato (2022)				Winter Wheat (2023)			
		LST= LST _{OG}		LST= LST _{TC}		LST= LST _{OG}		LST= LST _{TC}		LST= LST _{OG}		LST= LST _{TC}	
		RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²
Open EC Energy Balance	Rn	52.01	0.92	49.32	0.93	59.37	0.72	51.55	0.72	53.86	0.94	51.39	0.94
	LE	135.05	0.52	102.79	0.34	122.75	0.79	99.05	0.77	196.59	0.62	164.49	0.58
	H	30.26	0.84	102.43	0.31	88.21	0.82	96.88	0.66	112.63	0.11	102.85	0.04
	G	30.02	0.67	34.72	0.66	67.45	0.05	66.97	0.08	83.54	0.11	80.72	0.07
		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence	
	Rn	51.92	0.94	50.88	0.95	62.07	0.77	53.91	0.75	60.03	0.92	56.75	0.92
	LE	82.26	0.91	59.57	0.84	105.82	0.96	77.19	0.98	208.52	0.86	174.88	0.73
	H	32.62	0.86	115.32	0.31	95.29	0.80	105.82	0.61	24.01	0.84	44.44	0.82
	G	19.22	0.95	16.13	0.96	73.62	0.01	73.32	0.001	34.40	0.001	29.58	0.07
		Sugar Beet (2021)				Potato (2022)				Winter Wheat (2023)			
Closed EC Energy Balance		LST= LST _{OG}		LST= LST _{TC}		LST= LST _{OG}		LST= LST _{TC}		LST= LST _{OG}		LST= LST _{TC}	
		RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²	RMSE (W/m ²)	R ²
	Rn	52.02	0.92	49.34	0.93	59.37	0.72	51.55	0.72	53.86	0.94	51.39	0.94
	LE	96.50	0.65	90.49	0.48	102.16	0.75	81.74	0.77	126.23	0.84	93.97	0.84
	H	45.15	0.86	71.61	0.40	87.17	0.58	90.40	0.39	163.79	0.11	139.10	0.04
	G	30.02	0.67	34.72	0.66	67.45	0.05	66.97	0.08	83.54	0.11	80.72	0.07
		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence	
	Rn	51.92	0.94	50.88	0.95	62.07	0.77	53.91	0.75	60.03	0.92	56.75	0.92
	LE	53.45	0.92	80.57	0.87	96.86	0.9	74.72	0.96	128.50	0.96	94.05	0.92
	H	33.89	0.93	82.70	0.42	85.28	0.56	92.64	0.35	105.14	0.02	75.5804	0.05
	G	19.22	0.95	16.13	0.96	73.62	0.01	73.32	0.001	34.40	0.001	29.58	0.07

Table D3. Summary of flux comparison statistics for net radiation (Rn), latent heat flux (LE), sensible heat flux (H), and soil heat flux (G) derived from TSEB model runs using UAV-based inputs. Model configurations include (i) variation in LAI input (GAI vs. PAI) with $LST = LST_{TC}$ and $f_g = 1$, and (ii) implementation of a dynamic f_g (GAI/PAI) with $LST = LST_{TC}$ and $LAI = PAI$. Results are presented for three growing seasons: 2021 (sugar beet), 2022 (potato), and 2023 (winter wheat), covering the full growing period. For each season, statistics are shown for both the complete dataset and for periods excluding senescence. Comparisons are provided against eddy covariance (EC) measurements under both open energy balance conditions and Bowen ratio–closed energy balance conditions.

		Sugar Beet (2021)				Potato (2022)				Winter Wheat (2023)			
		LAI =GAI; $f_g = 1$		LAI =PAI; $f_g = 1$		LAI =GAI; $f_g = 1$		LAI =PAI; $f_g = 1$		LAI =GAI; $f_g = 1$		LAI =PAI; $f_g = 1$	
		RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Open EC Energy Balance	Rn	49.34	0.93	49.46	0.93	51.55	0.72	53.88	0.76	51.39	0.94	55.19	0.95
	LE	102.79	0.34	102.61	0.31	99.05	0.77	80.41	0.68	164.49	0.58	182.44	0.45
	H	102.43	0.31	112.03	0.26	96.88	0.66	89.29	0.61	102.85	0.04	109.53	0.002
	G	34.72	0.66	38.02	0.64	66.97	0.08	69.32	0.07	80.72	0.07	73.29	0.07
		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence	
	Rn	50.88	0.95	50.96	0.95	53.91	0.75	58.86	0.51	56.75	0.92	59.61	0.93
	LE	59.57	0.84	62.95	0.81	77.19	0.98	65.69	0.90	174.88	0.73	180.63	0.71
	H	115.32	0.31	126.22	0.25	105.8 2	0.61	97.52	0.55	44.44	0.82	46.92	0.77
	G	16.13	0.96	21.65	0.94	73.32	0.001	75.92	0.004	29.58	0.07	26.52	0.20
		LAI =PAI; $f_g = GAI/PAI$				LAI =PAI; $f_g = GAI/PAI$				LAI =PAI; $f_g = GAI/PAI$			
Closed EC Energy Balance		RMSE	R^2			RMSE	R^2			RMSE	R^2		
	Rn	48.94	0.93			54.02	0.77			53.14	0.94		
	LE	60.03	0.81			73.57	0.73			106.70	0.38		
	H	176.24	0.04			89.02	0.61			116.19	0.01		
	G	36.27	0.66			69.31	0.06			77.38	0.10		
		Sugar Beet (2021)				Potato (2022)				Winter Wheat (2023)			
		LAI =GAI; $f_g = 1$		LAI =PAI; $f_g = 1$		LAI =GAI; $f_g = 1$		LAI =PAI; $f_g = 1$		LAI =GAI; $f_g = 1$		LAI =PAI; $f_g = 1$	
		RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
	Rn	49.34	0.93	49.46	0.93	51.55	0.72	53.88	0.76	51.39	0.94	55.19	0.95
	LE	90.49	0.48	93.55	0.45	81.40	0.77	82.85	0.77	93.97	0.84	114.04	0.71
	H	71.61	0.40	81.32	0.34	90.40	0.39	86.11	0.35	139.11	0.04	142.69	0.01
	G	34.72	0.66	38.01	0.64	66.97	0.08	69.32	0.07	80.72	0.07	73.29	0.07
		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence		No Senescence	
	Rn	50.88	0.95	50.96	0.95	53.91	0.75	58.86	0.51	56.75	0.923	59.61	0.93
	LE	80.57	0.87	87.06	0.83	74.72	0.96	85.02	0.98	94.04	0.92	99.57	0.91
	H	82.70	0.42	94.53	0.35	92.67	0.35	87.81	0.31	75.58	0.05	68.72	0.10
	G	16.13	0.96	21.65	0.94	73.32	0.001	75.92	0.004	29.58	0.07	26.52	0.20
		LAI =PAI; $f_g = GAI/PAI$				LAI =PAI; $f_g = GAI/PAI$				LAI =PAI; $f_g = GAI/PAI$			

		<i>RMSE</i>	R^2			<i>RMSE</i>	R^2			<i>RMSE</i>	R^2		
	Rn	48.95	0.93			54.02	0.7			53.14	0.94		
	LE	94.12	0.80			79.68	0.83			73.36	0.47		
	H	135.19	0.174			83.84	0.35			102.88	0.11		
	G	36.27	0.66			69.31	0.06			77.38	0.10		

Data availability

Eddy covariance fluxes, meteorological observations, and ground-based vegetation measurements, including ceptometer LAI and crop height, are publicly available through the ICOS Carbon Portal. The ICOS datasets for the Selhausen site used in this study are cited in the manuscript with their corresponding persistent identifiers (Schmidt et al., 2025a, b). UAV-derived datasets underlying the analyses will be archived in a FAIR-aligned repository, with the corresponding persistent identifier added to the final manuscript.

Code availability

TSEB-PT simulations were performed using the open-source pyTSEB package developed by Nieto et al. (2019), which is publicly available through the pyTSEB GitHub repository. Eddy covariance footprint calculations were performed using the open-source implementation of the Kljun et al. (2015) flux-footprint parameterization available through the Flux Footprint Prediction repository

Credit authorship contribution statement

Jordan Steven Bates: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Carsten Montzka:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Harry Vereecken:** Writing – review & editing, Methodology. **Francois Jonard:** Funding Acquisition, Writing – review & editing, Methodology, Investigation, Conceptualization, Supervision.

Declaration of competing interest

There is no conflict of interest.

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