

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

Jordan Steven Bates^{1,2}, Carsten Montzka², Harry Vereecken², François Jonard¹

¹Earth Observation and Ecosystem Modeling (EOSystM) Laboratory, SPHERES Research Unit, University of Liege, Liege, Belgium

²Institute of Bio- and Geosciences: Agrosphere (IBG-3), Forschungszentrum Jülich GmbH, 52428 Jülich, Germany

Correspondence to: Jordan Steven Bates (j.bates@uliege.be)

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 values up 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).

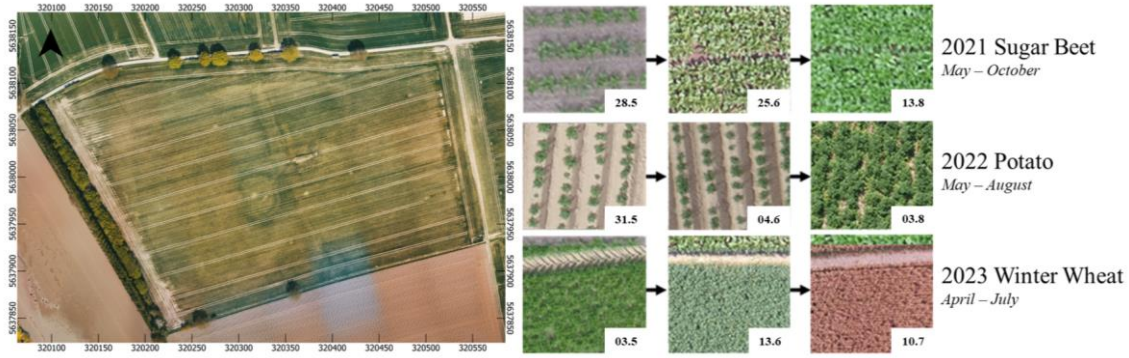


Figure 1: The field experiment site (left) with the EC and meteorological station located in the center of the field. The different crop cover type for each year (right) with example images of plant structure and fraction of vegetation coverage over the field throughout each growing season.

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.

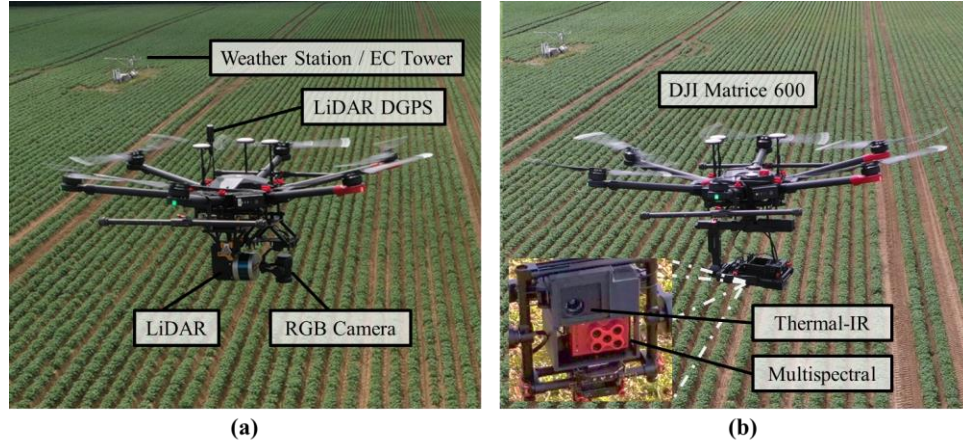


Figure 2: View of the DJI Matrice 600 UAV platforms that were used while flying over the field experiment site. (a) The M600 mounted with the YellowScan LiDAR Surveyor and DJI Zenmuse X1 RGB sensor. (b) The M600 with the FLIR Vue Pro R thermal IR modified with a ThermalCapture external heated shutter 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.

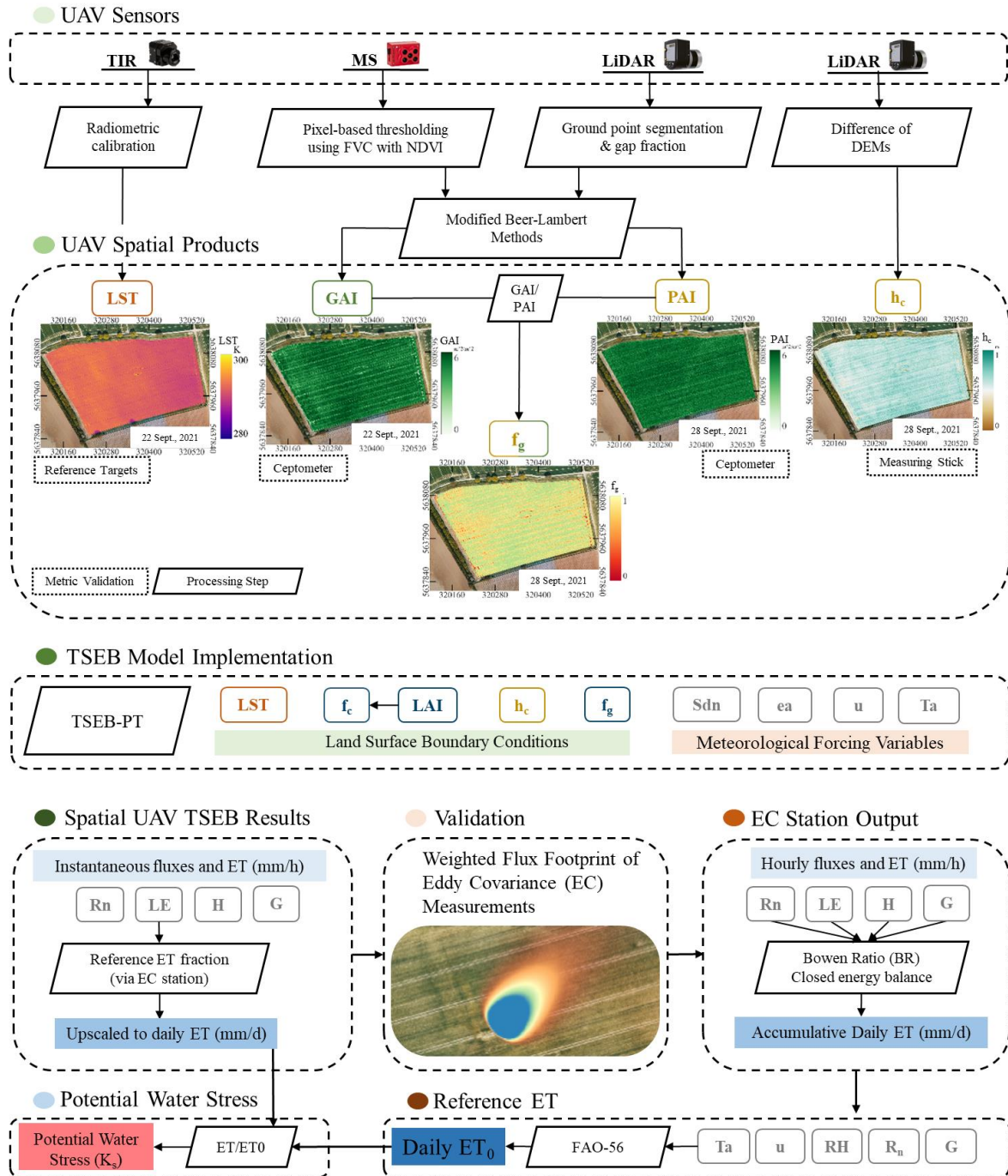


Figure 3: Workflow of the study, showing UAV sensor and eddy covariance (EC) data integration and inputs used in the TSEB-PT model. The model incorporates two categories of inputs: (1) surface boundary conditions and (2) meteorological forcing variables. Key UAV-derived inputs, LST (original vs. corrected), 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 (S_{dn}), vapor pressure (e_a), wind speed (u), air temperature (T_a), 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 $f_g = \text{GAI}/\text{PAI}$), 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-based 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 solely as an intermediate remote-sensing variable for estimating GAI and was not used directly as the fractional cover (f_c) input within TSEB.

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.

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

where θ 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)

Within TSEB-PT, fractional cover (f_c) represents the proportion of ground shaded by canopy and governs radiative partitioning between soil and vegetation (Norman et al., 1995; Kustas & Norman, 1999). Unlike the multispectral fractional vegetation cover (FVC) used in Section 2.4.2 as an intermediate variable for estimating GAI, f_c is not prescribed directly in this study. Instead, when LAI is provided, the pyTSEB implementation internally computes f_c using a Beer–Lambert formulation (Eq. A11), ensuring consistency between canopy density and modeled radiation exchange.

From the TSEB perspective, f_c should represent physical canopy structure, as it controls shading and soil energy exposure (Chirouze et al., 2014). Therefore, structural LAI (PAI) was used as the LAI input when implementing f_g , allowing internally derived f_c to reflect actual canopy geometry, while f_g independently scales transpiration according to canopy physiological function.

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).

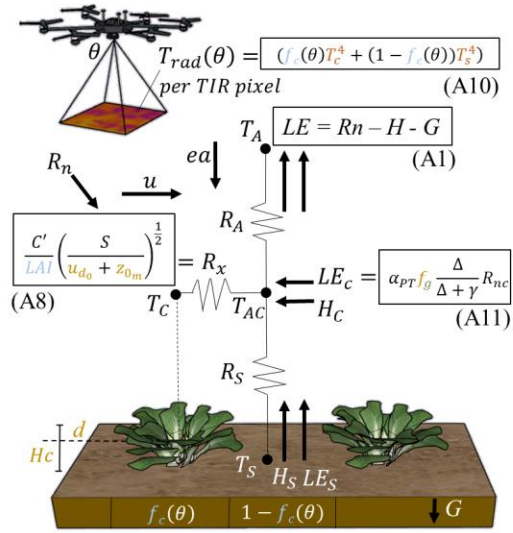
Table 1: UAV derived model inputs, their influences within the model, and equation with which they are used. Equations can be found in the appendix A and illustrated in Figure 4. The implementation in this study uses pyTSEB that uses the LAI input to derive the spetial f_c product internally with the model run linking LAI input directly to internally derived f_c .

UAV Input	Role in Model	Equation(s)
Surface temperature (T_c, T_s)	Drives partitioning and energy balance	A5, A6, A10
Leaf Area Index (LAI)	Canopy resistance and transpiration estimation	A8, A12
Green LAI fraction (f_g)	Controls LE_c in Priestley–Taylor term	A11
Crop height (h_c)	Aerodynamic roughness estimation	A8, A9 (via d_0, z_0)
pyTSEB Derived	Role in Model	Equation(s)
Fractional cover (f_c) (via LAI)	Radiative separation of canopy/soil temps	A10

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 enhances canopy interception of net radiation and reduces soil energy exposure through internally derived fractional cover (f_c), shifting available energy toward canopy latent heat flux (LE_c) and generally increasing ET . The fraction of green LAI (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 structural shading, 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), which control turbulent heat exchange between the surface and atmosphere. Taller canopies enhance aerodynamic coupling and promote

evaporative cooling, whereas shorter canopies increase sensible heat flux and reduce ET. 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 Spatial Inputs for Boundary Layer Conditions

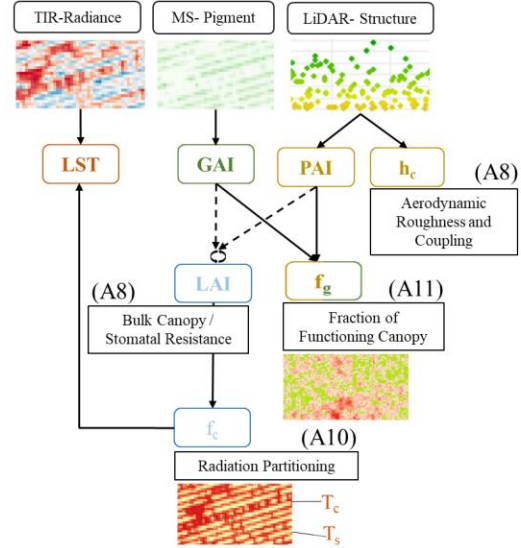


Figure 4: Conceptual schematic and example data illustrating how UAV-derived inputs constrain energy balance partitioning within the TSEB-PT model. The left panel shows the model architecture, highlighting partitioning of net radiation (R_n) into latent (LE), sensible (H), and ground (G) heat fluxes and the pathways through which UAV-derived variables influence these components. Key inputs include land surface temperature (LST), leaf area index (LAI), fraction of green LAI (f_g), fractional cover (f_c ; internally derived from LAI within TSEB), and canopy height (h_c). The right panel presents an example LiDAR point cloud illustrating canopy structure used to derive PAI and h_c together with spatial maps of LST , GAI , and f_g ; the spatial distribution of f_c is shown as computed internally by the model from the supplied LAI . Data are shown for a sugar beet field, illustrating seasonal changes in canopy structure and function and their influence on modeled energy partitioning and evapotranspiration. 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; α_{PT} (-), Priestley-Taylor coefficient modified by f_g .

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

The thermal infrared (TIR) data collected by the UAV consistently underestimated ground surface temperature when compared to in-field reference targets during the 2021 season. The uncorrected TIR data showed a mean RMSE of 4.19 °C relative to thermometer readings but maintained strong agreement in relative temperature patterns across dates ($R^2 = 0.97$). After applying corrections using ground reference targets, the seasonal RMSE improved to 2.78 °C. Sensor offset (RMSE) was most strongly correlated with increased air temperature (0.74), followed by higher wind speed (0.55) and denser humidity (0.34). Based on these relationships, a multiple linear regression model was developed to predict and correct TIR sensor bias. This model was applied to subsequent field seasons, resulting in an average increase of 2.2 °C in the LST orthomosaics to improve temporal consistency across acquisition dates. **These correlations and accuracy shifts are illustrated in Fig. D2 (Appendix). To further quantify the impact of the correction, Fig. 5 shows the field-averaged differences between LST estimates over the growing season.**

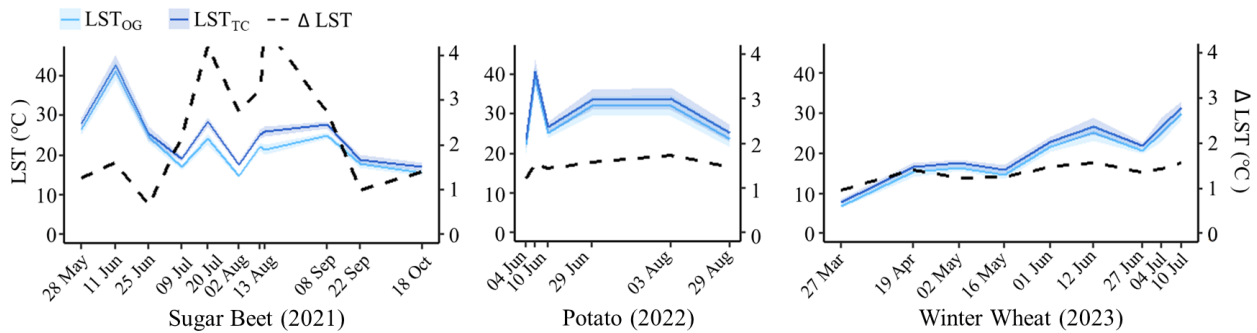


Figure 5: Field-averaged land surface temperature (LST) before (LST_{OG}) and after temperature correction (LST_{TC}). The dashed line represents the temperature difference between the two LST estimates.

For LAI estimation, both multispectral derived green area index (GAI) and LiDAR derived plant area index (PAI) were evaluated against ground based ceptometer LAI measurements. Across all three crops, PAI estimates were consistently more accurate, with lower RMSE values and higher correlation to field observations. Specifically, PAI achieved R^2 values of 0.99 across all three crops with an overall RMSE of $0.27 \text{ m}^2 \text{ m}^{-2}$, whereas GAI showed greater variability, particularly in winter wheat, resulting in an overall RMSE of $1.02 \text{ m}^2 \text{ m}^{-2}$ and R^2 of 0.88, based on a limited number of calibration samples. The discrepancy between GAI and PAI was most evident during senescence, when chlorophyll degradation reduced the spectral signal used in GAI estimation, while LiDAR still captured high canopy structural density. These results highlight the functional–structural divergence between optical and structural measurements of LAI, especially under changing vegetation conditions. A comparison of GAI and PAI estimates against ground LAI measurements at the field scale is shown in Fig. 6.

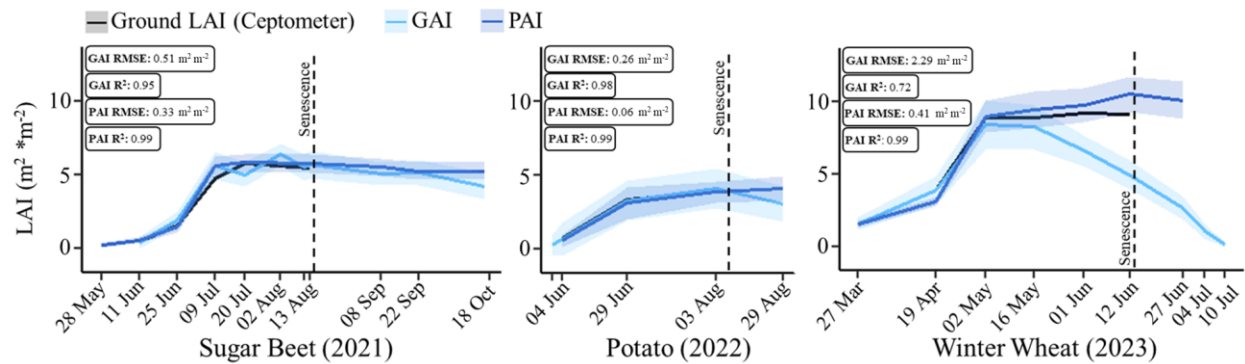


Figure 6: Field averaged UAV derived green area index (GAI) and plant area index (PAI) compared to ground based ceptometer LAI measurements across each campaign for three growing seasons. Ground measurements conclude prior to the onset of senescence, during which divergence between GAI and PAI becomes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

UAV derived canopy height (h_c) showed strong agreement with ground based measuring stick observations across all crops. In the 2023 winter wheat season, where canopy structure was most uniform, h_c estimation achieved excellent accuracy ($\text{RMSE} = 0.01 \text{ m}$, $R^2 = 0.99$). Lower accuracy was observed in potato ($\text{RMSE} = 0.12 \text{ m}$), likely due to the effects of ridge planting and heterogeneous canopy closure within sampled areas. Despite this, the UAV LiDAR system provided reliable height estimates across all crops, with an overall RMSE of 0.06 m and $R^2 = 0.90$. These results support the suitability of UAV based h_c for use in aerodynamic roughness parameterization within the TSEB-PT model. A comparison of UAV derived and ground measured canopy heights is shown in Fig. 7.

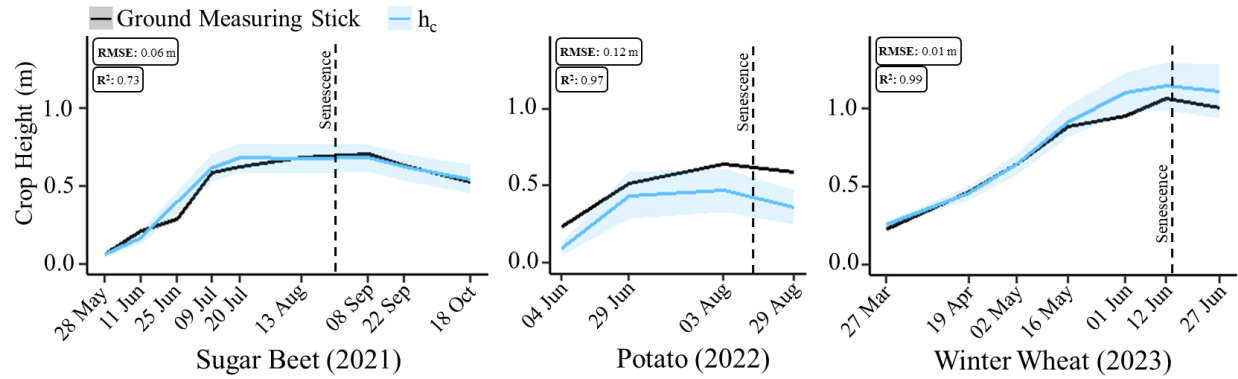


Figure 7: Comparison of UAV LiDAR derived canopy height (h_c) and ground based measuring stick data for each season. UAV derived values represent field wide averages, while ground measurements reflect averages within designated control point (CP) zones.

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

To assess the impact of radiometric calibration on ET model performance, we compared TSEB-PT estimates derived from original (LST_{OG}) and target corrected (LST_{TC}) UAV thermal imagery against EC (open and closed energy balance) derived ET values across all three crop seasons as seen in Fig. 8. Across all three crops, applying target-corrected LST (LST_{TC}) generally resulted in slightly lower modeled net radiation (R_n) and latent heat flux (LE), accompanied by increases in sensible heat flux (H). These responses were most evident in sugar beet (2021) and winter wheat (2023), while potato (2022) showed more moderate changes. Soil heat flux (G) exhibited comparatively small responses overall, although winter wheat showed a slightly larger reduction relative to the other crops. Despite these shifts, thermal correction consistently improved agreement with EC observations, with scatterplots showing tighter clustering toward the 1:1 relationship across crops and energy balance assumptions, particularly for LE and H . Improvements were most apparent under closed EC energy balance conditions, where flux alignment strengthened across all seasons.

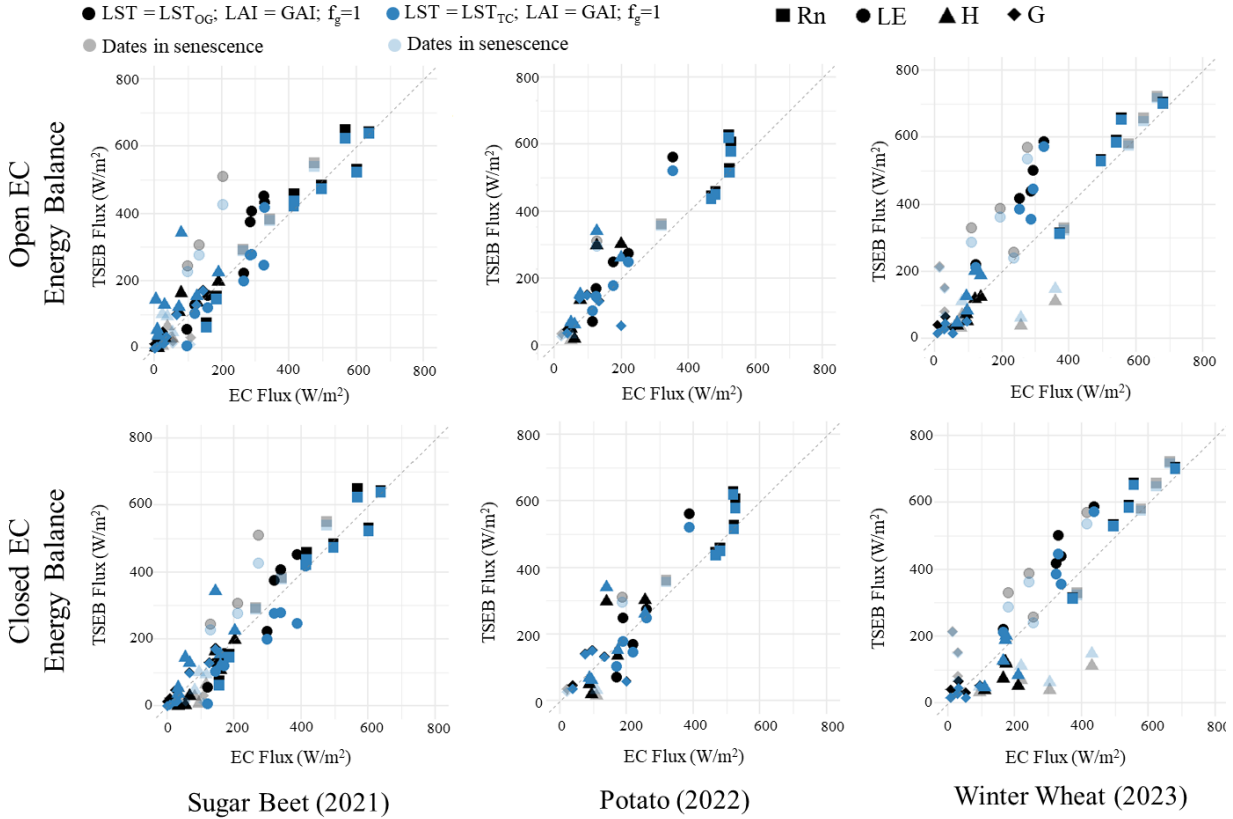


Figure 8. Comparison of modeled TSEB-PT energy fluxes (Rn, LE, H, and G) with eddy covariance (EC) observations across three crop seasons. Upper panels show comparisons using open EC energy balance fluxes, while lower panels show comparisons using closed EC energy-balance fluxes. Colors indicate land surface temperature inputs (original, LST_{0G} ; temperature-corrected, LST_{TC}), symbols indicate flux components, and shaded points represent observations acquired during senescence periods.

These patterns are supported by RMSE and R^2 statistics presented in Table D2 (Appendix), where R^2 reflects the temporal agreement between campaign-scale ET estimates aggregated over the EC footprint. Under open EC energy balance conditions, thermal correction generally reduced LE RMSE across all crops, with the largest improvements observed for winter wheat and sugar beet. In contrast, responses in H were less consistent; RMSE increased for sugar beet and potato but improved for winter wheat when evaluated against closed EC fluxes. Net radiation showed minimal sensitivity overall, while G exhibited mixed but generally small responses across crops. Removing senescence dates produced similar trends but strengthened agreement overall, particularly for LE. Under these conditions, H RMSE often increased slightly with thermal correction under open EC comparisons but improved under closed energy balance conditions, highlighting the influence of EC imbalance on model evaluation. Across all configurations, comparisons using closed EC energy balance data resulted in higher R^2 and lower RMSE relative to open EC comparisons.

Because latent heat flux represents evapotranspiration within the energy balance framework, LE estimates were converted to instantaneous ET (mm h^{-1}) to directly evaluate model performance at UAV acquisition times (Fig. 9).

Consistent with the flux-level results, using temperature-corrected LST (LST_{TC}) generally reduced RMSE across crops relative to LST_{OG} . Under open EC conditions, RMSE decreased 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, with similar but smaller improvements observed under closed EC comparisons. However, thermal correction did not always improve temporal correspondence; for example, during the 2021 sugar beet season, R^2 declined from 0.50 to 0.32 under open EC conditions despite improved RMSE. Excluding senescence dates further strengthened agreement across all crops, with the largest response observed for sugar beet (RMSE reduced from 0.16 to 0.11 mm h⁻¹, R^2 increased from 0.32 to 0.79). Overall, comparisons with closed EC ET produced higher R^2 and slightly lower RMSE across crops, indicating improved consistency when energy balance closure was applied.

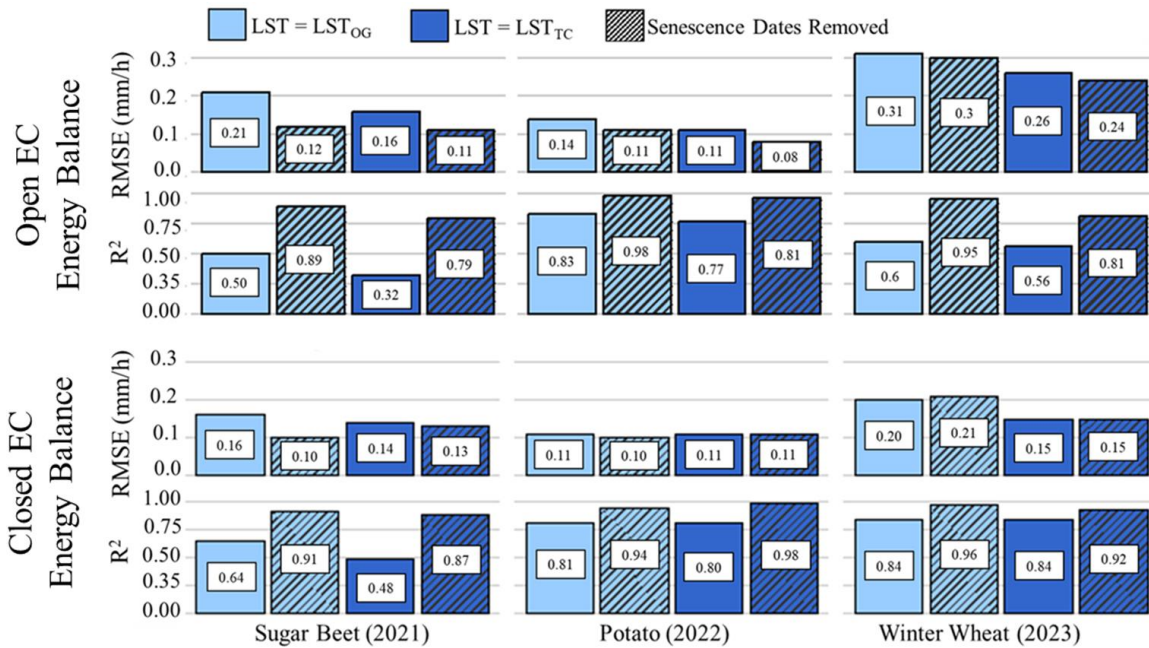


Figure 9. RMSE and R^2 between modeled TSEB-PT ET and EC derived ET, open and closed energy balances, averaged over the EC flux footprint. Two TSEB-PT model runs are compared based on land surface temperature (LST) input: original (OG) and target corrected (TC). Statistical metrics are presented for the entire growing season and excluding senescence periods, highlighting the influence of canopy condition on model performance.

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

Building on the thermal correction analysis, we next evaluated how the choice of LAI input, multispectral-derived GAI versus LiDAR-derived PAI, and the implementation of fractional green LAI ($f_g = GAI/PAI$) influenced TSEB-PT flux estimates (Fig. 10; Table D3). Across crops and seasons, differences between LAI inputs were generally small during early to mid-season conditions when canopies were predominantly green, with all configurations showing similar agreement with EC observations under both open and closed energy balance comparisons.

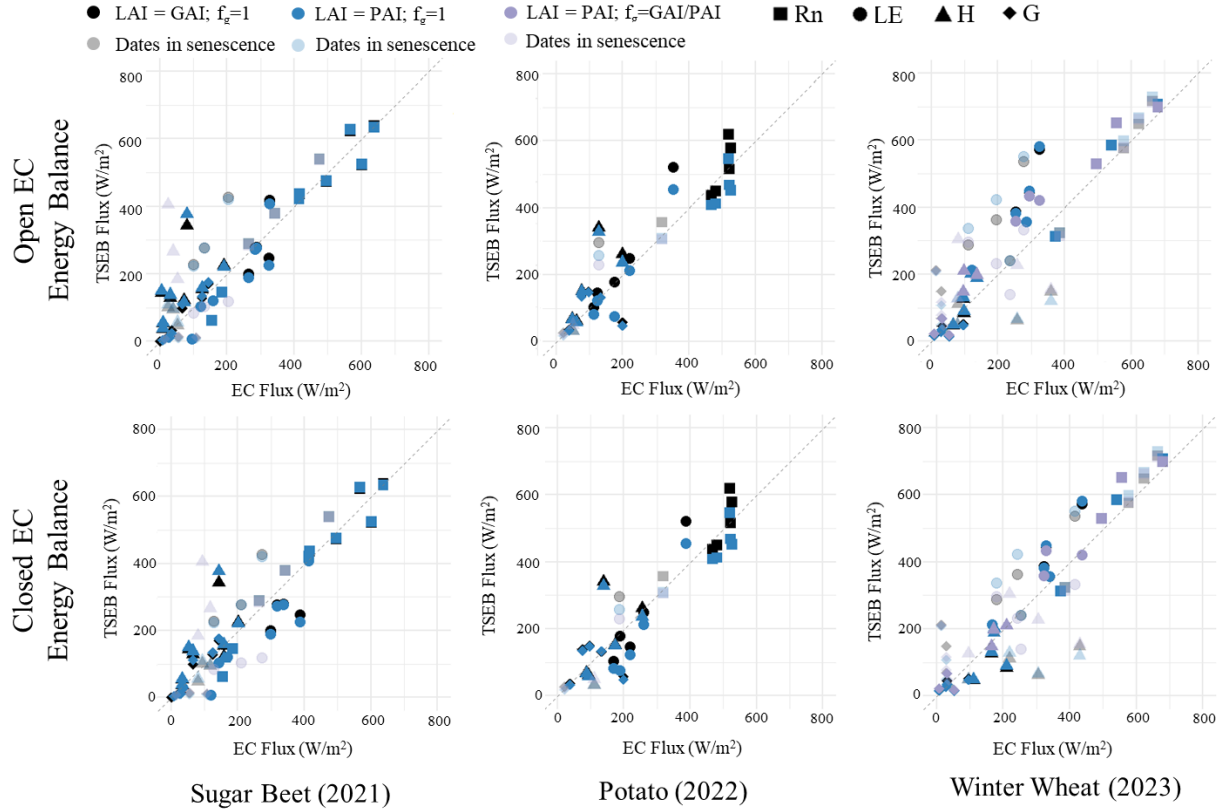


Figure 10. Comparison of modeled TSEB-PT energy fluxes (Rn, LE, H, and G) with eddy covariance (EC) observations across three crop seasons under different LAI parameterizations. Upper panels show comparisons using open EC fluxes, and lower panels show comparisons using energy-balance–closed EC fluxes. Colors indicate LAI/ f_g configurations (GAI; PAI; PAI scaled by $f_g = \text{GAI}/\text{PAI}$), symbols denote flux components, and lighter markers represent senescence-period observations.

Clearer differences emerged during senescence. In winter wheat, using LAI = PAI with $f_g = 1$ resulted in systematic overestimation of fluxes, particularly LE, whereas LAI = GAI improved agreement with EC observations across both energy balance assumptions (Table D3 appendix). Scaling PAI using f_g further reduced this bias and shifted modeled fluxes closer to the 1:1 relationship in the scatterplots. Similar but smaller responses were observed for sugar beet and potato.

Flux-level behavior in the scatterplots is consistent with these patterns. Across crops, replacing GAI with PAI generally resulted in slight reductions in LE and corresponding increases in H, while Rn and G showed comparatively small changes. These effects were most evident during senescence and were reduced when f_g was applied. RMSE statistics support these observations: GAI generally produced lower RMSE for LE in sugar beet and winter wheat, whereas PAI performed slightly better for potato. Differences in Rn and G were small overall, while H showed the greatest sensitivity to LAI configuration. Across crops and configurations, comparisons using energy-balance–closed EC data consistently yielded higher R^2 and lower RMSE relative to open EC comparisons.

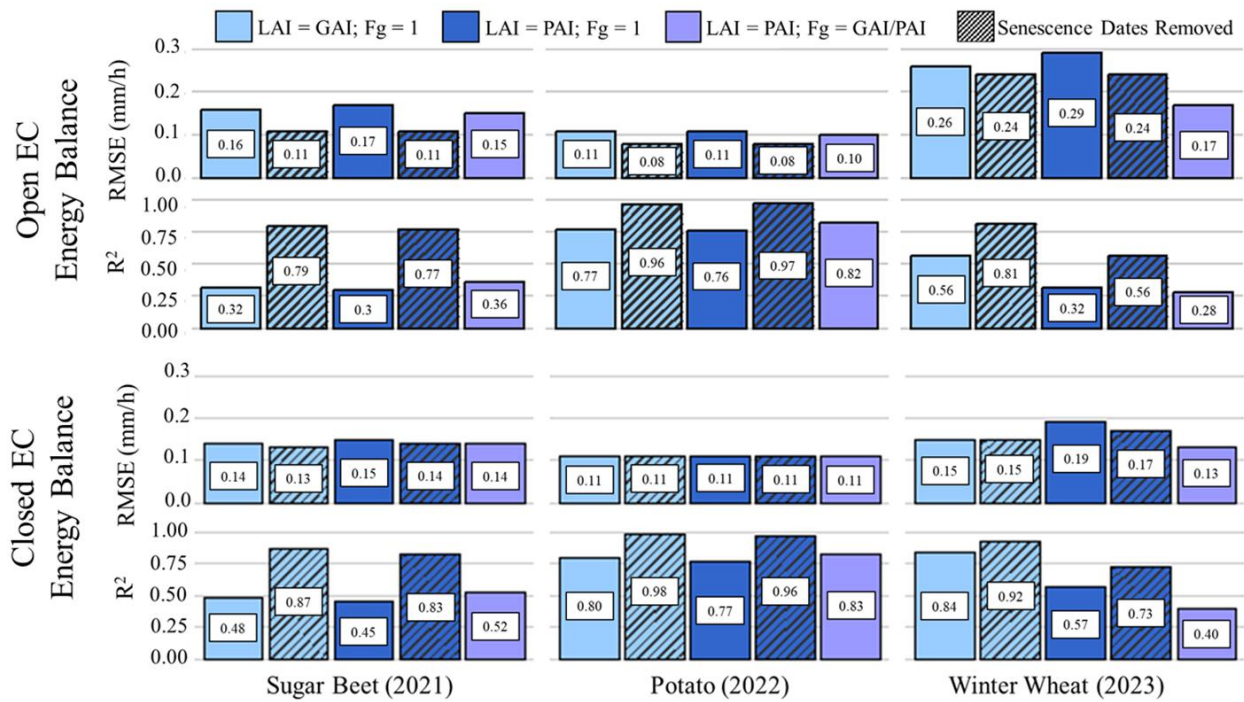


Figure 11. RMSE and R^2 between TSEB-PT modeled ET and EC derived ET, open and closed energy balances, averaged over the EC flux footprint. Two different LAI inputs were evaluated: green area index (GAI) and plant area index (PAI). Statistical metrics are shown for all campaign dates and separately for dates excluding senescence. During senescence periods, a third approach using the fraction of green LAI ($f_g = \text{GAI/PAI}$) was also evaluated to scale transpiration according to functional canopy condition.

Because latent heat flux represents evapotranspiration within the energy balance framework, LE estimates were converted to instantaneous ET (mm h^{-1}) to assess the influence of LAI and f_g parameterization on ET performance (Fig. 11). When all dates were considered, differences among LAI configurations became evident, particularly in winter wheat. Using LAI = PAI resulted in increased ET overestimation ($\text{RMSE} \approx 0.29 \text{ mm h}^{-1}$; $R^2 \approx 0.32$), whereas LAI = GAI improved agreement ($\text{RMSE} \approx 0.26 \text{ mm h}^{-1}$; $R^2 \approx 0.56$). Applying f_g (GAI/PAI) further reduced this bias, lowering RMSE ($\approx 0.17 \text{ mm h}^{-1}$) and improving agreement under both open and energy-balance-closed EC comparisons. Across crops, evaluations against closed EC ET consistently yielded higher R^2 and slightly lower RMSE.

Excluding senescence dates reduced differences among LAI configurations across all crops. Under these conditions, RMSE values were similar ($\approx 0.08\text{--}0.17 \text{ mm h}^{-1}$) and R^2 values were consistently high, particularly for potato (R^2 up to ~ 0.98). Differences between GAI and PAI became minimal, indicating that both structural and spectral LAI representations perform similarly when canopy function and structure are closely aligned.

3.4. Input impacts on resulting magnitude of ET map spatial variability

This study revealed that TSEB-PT derived ET with very-high-resolution data varied with both magnitude and spatial distribution across campaign dates influenced by the choice of UAV derived inputs. Appendix Figures B10 and B11

present field averaged ET values along with their standard deviations, demonstrating how input configurations affect field spatial variability in modeled ET. To explore the sensitivity of ET spatial variability to input differences, we analyzed the changes in the coefficient of variation (CV) of ET in response to modifications in key model inputs. Specifically, Figure 12 shows how ET CV responds to the differences in input CV for LST (TIR_{OG} CV – TIR_{TC} CV), LAI sources (GAI CV – PAI CV), and f_g ($f_g = 1$ CV - GAI/PAI derived f_g CV). These comparisons help establish the connection between input variability and the spatial behavior of ET estimates, providing insight into which inputs most strongly influence the spatial characteristics of TSEB-PT outputs across varying crop and environmental conditions.

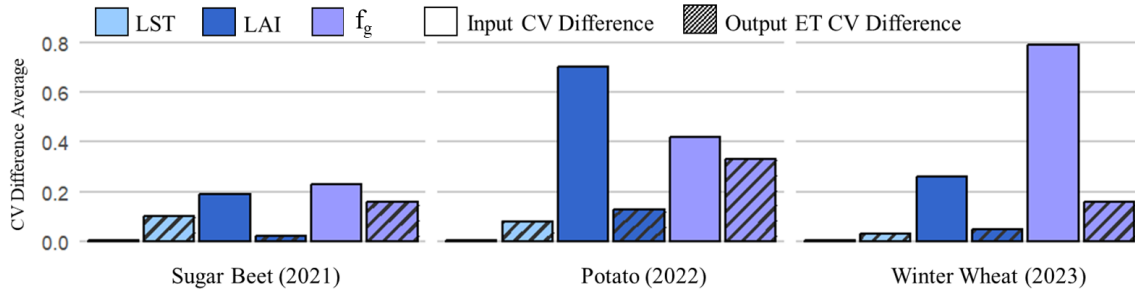


Figure 12: Comparison of average differences in the coefficient of variation (CV) between key TSEB-PT input variables (LST, LAI, f_g) and the resulting ET estimates across three crop types. This highlights how changes in the spatial variability of each input affect the spatial variability of modeled 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.

Notably, with a uniform increase in average LST resulted in significant shifts in the spatial distribution of TSEB-PT ET estimates. In contrast, despite greater coefficient of variation (CV) between MS derived GAI and LiDAR derived PAI inputs, their influence on ET spatial variability was comparatively limited. The incorporation of a dynamic f_g , derived from the fusion of GAI and PAI, substantially altered the spatial representation of ET, underscoring the importance of this parameter.

Given the substantial change in ET spatial variability resulting from an essentially uniform shift in LST inputs, we further examined the corresponding ET maps for potato in early season (low vegetation cover) and late season maps (variability in vegetation state). This was to characterize the different spatial magnitudes of ET change were spatially distributed with uniform shifts in LST. These comparisons are presented in Fig. 13 where the LST_{OG} ET (lower LST and higher resulting ET) results were subtracted from those when LST_{TC} inputs were used.

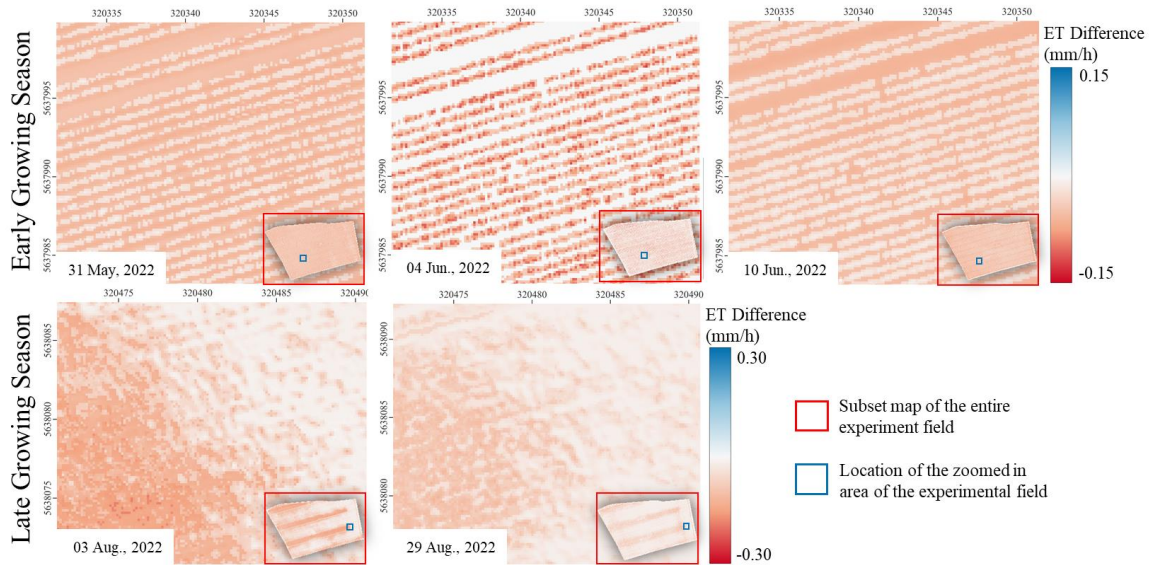


Figure 13: Difference in TSEB-PT ET estimates using original land surface temperature (LST_{OG}) ET minus reference target corrected (LST_{TC} ; $ET_{OG} - ET_{TC}$) ET. The maps illustrate how the magnitude and spatial pattern of ET differences vary with dominant evaporative sources (soil vs. canopy) 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.

Two key characteristics on how increased LST offset changes spatial variability in TSEB-PT ET outputs were observed. First, in early-season conditions with lower f_c , the dominant flux, whether from soil evaporation or canopy transpiration varied across dates and increased the contrast between soil and canopy with the increased temperature from LST_{TC} . Second, later in the growing season, the magnitude of ET change differed significantly depending on presence of stressed vegetation. In these cases, stressed vegetation showed a substantially larger ET reduction after LST correction. This shows thermal correction reshaped the spatial structure of modeled water use, amplifying contrasts between stressed and non-stressed zones.

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. 14 & 15.

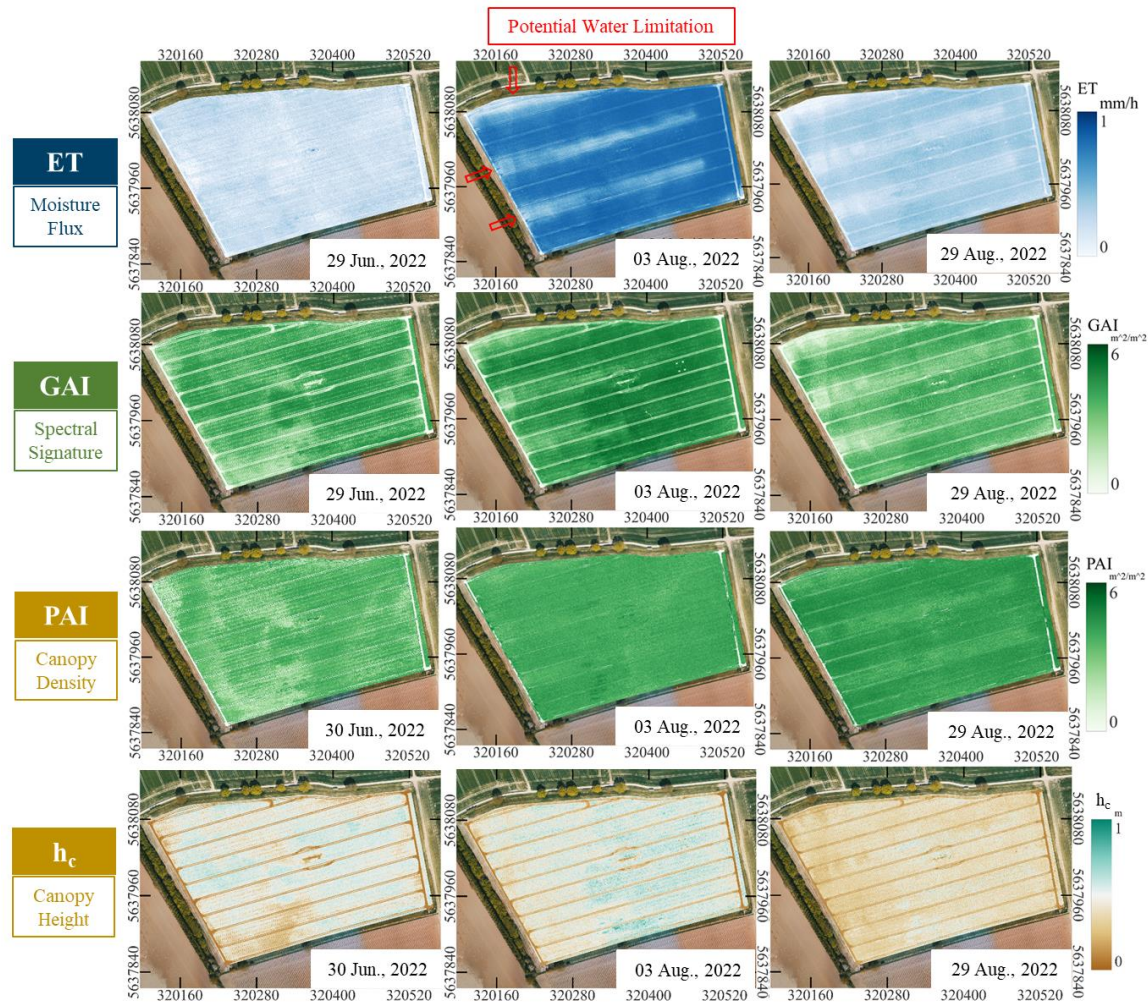


Figure 14: Particular dates in the potato 2022 season of Evapotranspiration (ET), green area index (GAI), plant area index (PAI) comparisons around moments of potential water related stress. ET map shows clear structures within field related to irrigation patterns on the 3rd of August more so than with 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.

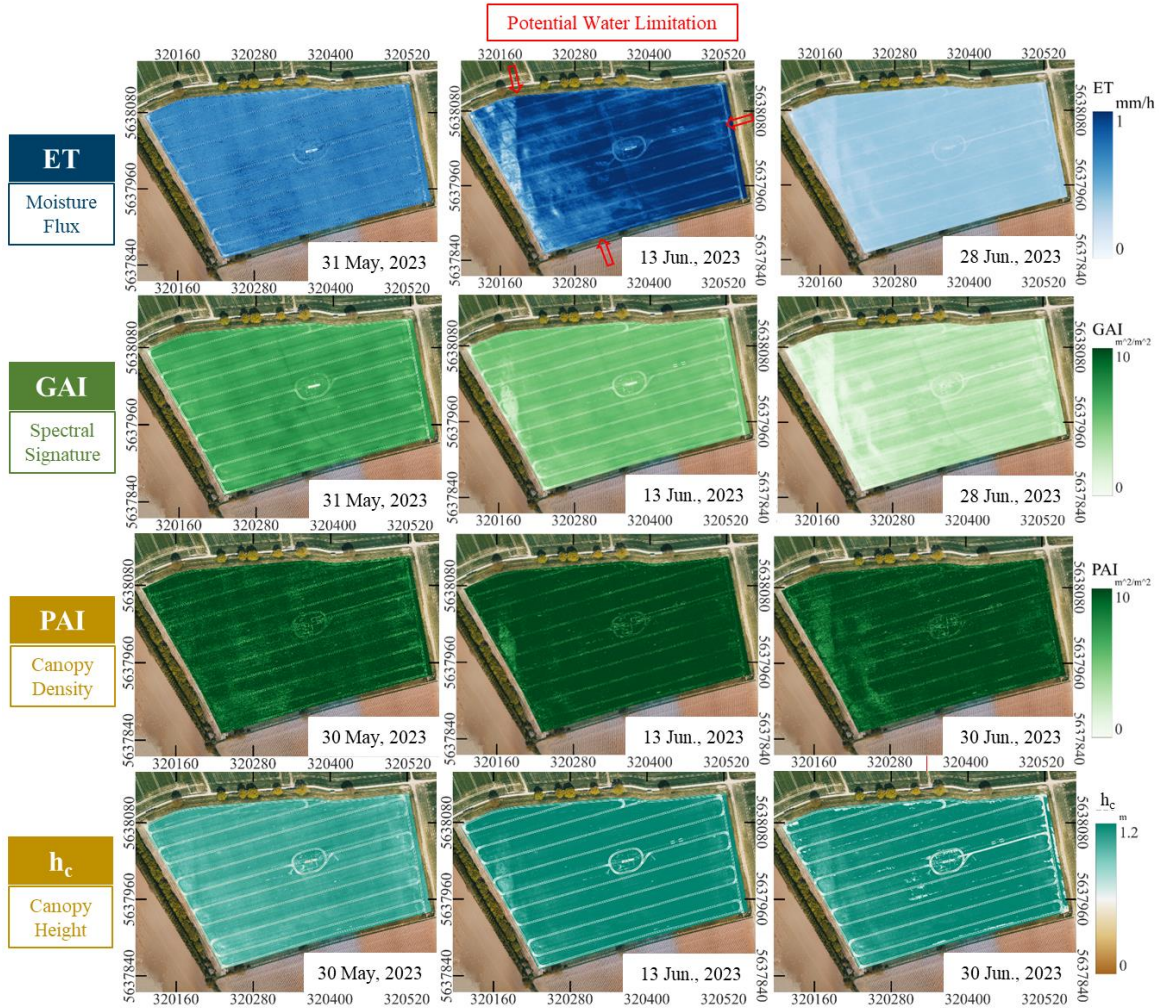


Figure 15: Particular dates in the winter wheat 2023 season of Evapotranspiration (ET), green area index (GAI), plant area index (PAI) comparisons around moments of potential water related stress. ET map shows clear structures within field related to soil layer properties and root depth on the 13th of 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

For integration into farm management and irrigation decision-making, evapotranspiration (ET) estimates must be available at the daily scale to support soil water balance calculations and irrigation scheduling. To evaluate the operational applicability of UAV-derived ET, instantaneous ET rates from individual UAV acquisitions were upscaled to daily values and compared with daily EC ET measurements under both open and energy-balance-corrected conditions, as well as with FAO-56 reference ET (ET_0) (Allen et al., 1998; see C3 in the Appendix).

Upscaling of instantaneous UAV-based ET was performed following the approach of Cammalleri et al. (2014). Using the best-performing UAV TSEB-PT configuration identified in this study, consisting of $LST = LST_{TC}$, $LAI = LiDAR$

(PAI) as the LAI input, $f_g = GAI/PAI$, and $h_c = \text{LiDAR-derived crop height}$, daily ET estimates were generated and evaluated against EC-derived daily ET. A daily crop water stress proxy ($K_s = ET/ET_o$) was also computed, providing further insight into crop water status relative to atmospheric demand, where values below unity indicate reduced evapotranspiration likely associated with water limitation (Allen et al., 1998).

Fig. 16 shows continuous daily ET time series from EC measurements (open and closed energy balance conditions), FAO-56 reference ET, and upscaled UAV-derived daily ET based on field-average, flux-footprint-weighted, and potential water limitation zone (PWLZ - identified in Figs. 14–15) aggregations. Across all crops, UAV-derived daily ET followed the temporal patterns observed in EC-based ET and reference ET. Differences were observed among spatial aggregations, with PWLZ-based estimates frequently deviating from footprint and field averages.

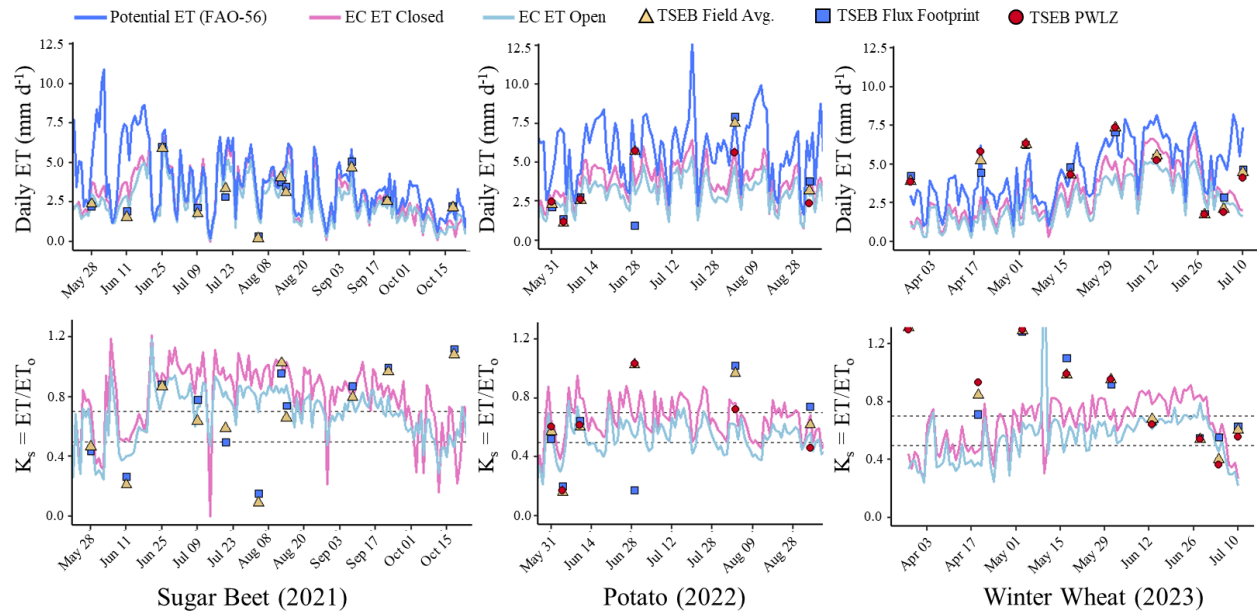


Figure 16. Daily evapotranspiration (ET) time series and daily-scale stress proxy derived from UAV–TSEB and EC measurements. Top panels: interpolated daily ET from UAV acquisition compared against EC daily ET (open and closed energy balances) and FAO-56 reference/potential ET. Bottom panels: corresponding relative ET stress proxy (K_s) computed as the ratio of daily actual ET to FAO-56 reference/potential ET, illustrating seasonal development of water deficit conditions across crops. Horizontal dashed lines represent 0.7 possible water stress and 0.5 likely water stress compared to atmospheric demand. The different shapes depict different spatial domains of pixel averages from the UAV instantaneous UAV ET that is then upscaled to daily it with including TSEB field average, the flux footprint weighted average, and the average within the potential water limitation zones (PWLZ) from Figs. 16 and 17.

Daily K_s values derived from UAV ET showed temporal variability consistent with seasonal development. Periods where K_s declined below 0.7 and 0.5 were observed, particularly within PWLZ areas, indicating reduced ET relative to atmospheric demand. These reductions correspond with relatively lower ET values observed in Figs. 14 and 15 compared to other areas within the field.

For comparability with previous studies, daily UAV-derived TSEB ET performance metrics (RMSE, R^2 , and bias) relative to daily EC ET under open and closed energy balance conditions are summarized in Fig. 17. Daily UAV-derived TSEB ET showed variable agreement with EC measurements across crops and years, with performance influenced by both crop type and EC energy balance treatment. For sugar beet (2021), agreement was moderate, with RMSE ranging from 0.96 to 1.30 mm d^{-1} and R^2 between 0.57 and 0.61. For potato (2022), agreement was strongest, with high R^2 (~ 0.80) and moderate RMSE (1.53–1.61 mm d^{-1}). Winter wheat (2023) showed the weakest agreement, with higher RMSE (1.90–2.30 mm d^{-1}) and low R^2 (0.27–0.30).

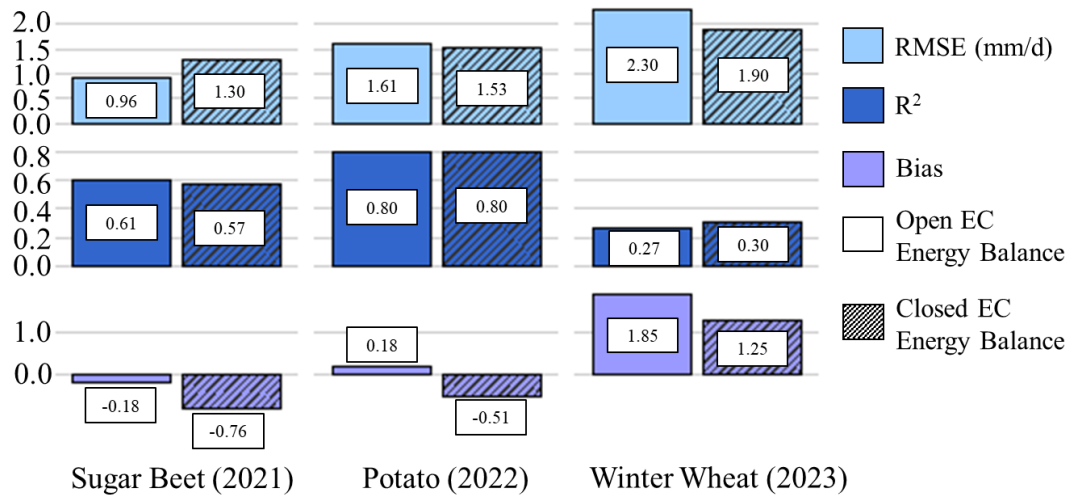


Figure 17. Comparison of daily UAV-derived TSEB evapotranspiration (ET) against eddy covariance (EC) measurements for sugar beet (2021), potato (2022), and winter wheat (2023). Model performance is evaluated using RMSE (mm d^{-1}), coefficient of determination (R^2), and bias (mm d^{-1}) for both opened and closed EC energy balance corrected conditions. Closed EC estimates are shown with hatched bars.

Across all crops, bias analysis revealed clear crop-dependent patterns, with underestimation for sugar beet, near-neutral behavior for potato, and strong overestimation for winter wheat. For sugar beet, bias ranged from -0.18 mm d^{-1} (open) to -0.76 mm d^{-1} (closed). For potato, bias ranged from $+0.18 \text{ mm d}^{-1}$ (open) to -0.51 mm d^{-1} (closed). For winter wheat, bias ranged from $+1.25 \text{ mm d}^{-1}$ (closed) to $+1.85 \text{ mm d}^{-1}$ (open). Differences between open and closed EC comparisons further indicate that the choice of EC energy balance treatment influences both the magnitude and direction of agreement, reinforcing that EC-based ET should be interpreted as a reference with inherent uncertainty rather than an absolute benchmark.

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 are closely aligned, yielding similar ET estimates. This is consistent with a prior one-source energy balance study showing LiDAR derived LAI can perform comparably to MS based LAI for ET estimations (Wei et al., 2023). However, few studies have examined how model performance shifts under stress or senescence, when canopy structure and function diverge.

Under these conditions, PAI remained high due to persistent canopy structure, which appears to contribute to higher ET overestimation. In contrast, GAI, which reflects pigment concentration and photosynthetic activity, captured physiological decline and produced more conservative estimations that better aligned with EC ET. This effect was most pronounced in winter wheat, where structural density persisted even as transpiration decreased. While PAI and

ground based ceptometer LAI showed better agreement in absolute values, especially in dense canopies where GAI saturates, neither completely captures declining physiological function. The results may indicate that GAI (functional LAI) better reflected actual transpiration capacity, which could explain the improved model performance when it was compared to PAI with f_g held constant at 1.

The automatic derivation of f_c from LAI in pyTSEB complicates input selection, as f_c governs radiation partitioning between soil and vegetation and directly influences G . This was reflected in crop-specific responses (see Table D2 in the appendix), where it is possible PAI improved G estimates in winter wheat by better representing structural shading in dense canopies, while GAI performed better for sugar beet and potato, where lower and more open canopies with greater soil exposure are more effectively captured by multispectral inputs. These differences highlight how LAI and f_c interactions become more critical with increasing canopy height and density. GAI may underestimate shading in dense or senescent canopies, reducing f_c and vegetation energy allocation, whereas PAI may overestimate transpiration in structurally intact but functionally declining canopies. While both inputs perform similarly under non-stressed conditions, GAI provides better physiological realism during stress, whereas PAI better represents structural controls. This suggests multispectral inputs may be sufficient for simpler canopies, while LiDAR-derived structure becomes increasingly important for taller, denser crops such as winter wheat. Future implementations could benefit from decoupling f_c and LAI (which are linked in the current model implementation), using PAI to represent structural shading and GAI to represent functional canopy resistance.

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 use of f_g to scale transpiration according to physiological status, improving ET agreement with EC observations, particularly during early stress and senescence.

The f_g input proved effective even before visible signs of senescence (e.g. winter wheat), detecting early transpiration suppression due to stress. Despite its value, f_g is not required in TSEB-PT and is typically omitted. Comparable scaling is also lacking in models like SEBAL and METRIC, which treat vegetation as a single layer, an approach more suited to satellite-scale applications where such structural-functional distinctions are impractical. UAV platforms, however, not only offer the spatial resolution needed, but also provide new sensing capabilities, such as 3D structural mapping from LiDAR, that facilitate the integration of inputs like f_g .

UAV based ET studies that exclude the use of f_g in their TSEB-PT implementation further supports the importance of its inclusion. Gómez-Candón et al. (2021) reported overestimated ET ($RMSE = 0.24 \text{ mm h}^{-1}$) in wheat without using f_g . This overestimation is more apparent in the later season with senescence. Similarly, Tunca et al. (2023a) reported overestimation in stressed sorghum and suggested that manual adjustment of the Priestley–Taylor coefficient (α) may

be a potential solution. Our results further indicate that incorporating f_g can provide a targeted and spatially dynamic means of accounting for such effects. Bozorgi et al. (2024) also identified inaccurate assumptions about green canopy fraction as a source of TSEB bias, reinforcing the importance of function based scaling.

As shown in Figure 12, f_g influenced spatial ET variability more strongly than LAI type alone, highlighting its importance for accurate measurement. In winter wheat, this influence was limited, likely due to LAI saturation (>6), where additional canopy does not meaningfully alter radiation interception through f_c . In contrast, sugar beet and potato, with lower canopy density, showed greater f_g sensitivity. Given the strong link between f_c and f_g , improving f_c parameterization beyond the fixed extinction coefficient of the Beer–Lambert law used within the model could be valuable.

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 volume. 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 assessments, instantaneous evapotranspiration (ET) estimates derived from UAV-based TSEB-PT were upscaled to daily totals. Unlike some remote sensing approaches that directly estimate daily ET, TSEB provides instantaneous fluxes at the time of acquisition. In this study, daily ET was derived using a ETrF approach (Section 3.6; Eq. C2), based on the best-performing instantaneous configuration ($LST = LST_{TC}$, $LAI = PAI$, $f_g = GAI/PAI$). Although relatively simple, this approach enabled direct comparison with EC-derived daily ET and facilitated comparison with previously reported studies.

The resulting daily ET estimates showed good agreement with EC observations across all crops, although winter wheat proved the most challenging. While relatively few studies report daily ET performance for TSEB at field scale, available results for winter wheat indicate RMSE values on the order of $\sim 1.5\text{--}2.0\text{ mm day}^{-1}$ (Hazdour et al., 2025). Comparable performance has been reported for single-source energy balance models such as SEBAL and SEBS, with daily ET RMSE values of approximately 2.15 mm day^{-1} and 1.53 mm day^{-1} , respectively (Zoratipour et al., 2023). For sugar beet and potato, fewer studies report daily ET performance; however, reported hourly estimates from satellite-based approaches ($\approx 0.09\text{--}0.21\text{ mm h}^{-1}$) (Acharya & Sharma, 2021; Ebert et al., 2022) are consistent with, and in some cases higher than, those observed in this study. These comparisons suggest that UAV-based TSEB-PT provides comparable or improved ET accuracy while offering clear advantages in spatial resolution and acquisition flexibility. This is consistent with Mokhtari et al. (2021), who showed that while spatial resolution has limited impact on field-averaged ET accuracy, higher-resolution UAV data improves the detection of spatial variability and localized stress conditions. While field-averaged ET estimates may be similar between UAV and satellite approaches, the added

spatial detail from UAV observations enables more precise assessment of crop water status and supports targeted irrigation management. However, direct comparisons between studies should be interpreted cautiously due to differences in spatial resolution, temporal aggregation, crop conditions, and EC processing methods.

Crop-specific behavior further supports these findings. Winter wheat showed a tendency toward ET overestimation, consistent with previous studies reporting positive bias under dense canopy conditions (Hazdour et al., 2025; Zoratipour et al., 2023), 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. Increased soil contribution can elevate LST and shift energy partitioning toward sensible heat, leading to reduced modeled ET (Norman et al., 1995; Kustas & Norman, 1999; Hoffmann et al., 2016). 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). These contrasting behaviors highlight the importance of canopy structure, canopy function, and soil fraction in controlling model performance across crop types.

Future improvements in daily ET estimation could be achieved through both alternative upscaling formulations and improved temporal sampling strategies. Methods such as evaporative fraction (EF), radiation-based (Rs) scaling, and other empirical approaches have shown varying performance depending on crop phenology and time of day (Nassar et al., 2021). Recent developments include refined EF-based methods (Wei et al., 2025) and emerging machine learning approaches for instantaneous-to-daily ET scaling (Tunca et al., 2026), which may better capture diurnal variability under heterogeneous canopy and meteorological conditions. In addition, Nassar et al. (2021) demonstrated improved performance when UAV acquisitions were conducted near midday compared to later afternoon periods. This is particularly relevant for UAV systems, which can be deployed flexibly to target optimal acquisition windows or repeated flights. Together, these findings suggest that improving daily ET estimation will require a combination of optimized upscaling methods, appropriate flight timing, and, where feasible, multi-temporal UAV observations to better represent the diurnal ET cycle.

4.5. Future considerations with UAV TSEB model implementation

Satellite-based ET models have traditionally operated at coarse spatial scales, assuming simplified canopy structure and uniform land cover. In nearly all TSEB-PT applications, the LAI input is based on green LAI or GAI (Chirouze et al., 2014). Because f_c is often derived from LAI via the Beer–Lambert law in TSEB-PT (e.g. current pyTSEB), this can bias flux estimates in stressed or senescent crops by excluding nonfunctioning foliage that still shades the soil, leading to overestimation of soil heat flux (G) and soil-related flux components (Chirouze et al., 2014). While some studies have used plant area index (PAI) for f_c (Guzinski et al., 2014; Guzinski et al., 2020), these are rarely derived from purely structural metrics. As noted by Chirouze et al. (2014), f_c should reflect total canopy structure, whereas LAI should represent only the photosynthetically active portion. UAV observations provide the opportunity to characterize both canopy structure and function at high spatial resolution. Leveraging structural LiDAR-derived PAI

for f_c (radiation partitioning) and MS-derived GAI for LAI (canopy resistance) may improve the physiological realism of LE_c and H_c partitioning, and merits further investigation.

Further sensor innovations could enhance the parameterization of ET models. For example, more detailed structural information from the entire canopy could be used to derive multi-layer GF profiles (Bates et al., 2022), supporting improved estimates of structural LAI. Additionally, LiDAR intensity, typically operating in the NIR range (Kim et al., 2009), has shown physiological associations with crop LAI (Hütt et al., 2022) and biomass (Montzka et al., 2023), offering potential as a dual-use input that integrates both structural and functional canopy traits into LAI and f_g estimates. UAV LiDAR can also contribute to guiding the parameterization of surface roughness as adjustments made to soil resistance coefficients has shown to be important (Li et al., 2019). Moreover, UAV-mounted radar systems, including synthetic aperture radar (SAR) and ground-penetrating radar (GPR), may provide additional pathways for assessing canopy and surface moisture conditions (Wu & Lambot et al., 2022), which are important for accurate energy flux partitioning. This may be particularly relevant during senescence, when separating canopy cooling associated with transpiration from structural or non-transpirational effects becomes more challenging. In this context, additional moisture information could help better constrain these components. Recent work has also shown that coupling TSEB with surface soil moisture data can improve the estimation of transpiration (Song et al., 2022), highlighting the potential of integrating UAV-based radar observations. Furthermore, hyperspectral UAV sensors can further constrain canopy function, with sun-induced solar chlorophyll fluorescence (SIF) improving ET estimation and photochemical response index (PRI) providing additional insight into light-use efficiency and stress responses (Derardja et al., 2024; Jonard et al., 2020; Wang et al., 2022;). By leveraging the spatial precision and 3D reconstruction capabilities of UAV platforms, future research may further refine ET model inputs and improve accuracy across structurally complex and heterogeneous crop environments.

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 artificially increase modeled ET (Mokhtari et al., 2021). Additional work has demonstrated that shadowing can significantly affect vegetation indices, f_c , and LAI estimation, thereby influencing TSEB flux partitioning (Lu et al., 2022; Gao et al., 2023). These effects are most pronounced in discontinuous canopies or systems with higher soil fractions, where mixed soil, shadow, and vegetation signals are more prevalent (Duran-Gomez et al., 2026). However, recent findings suggest that shadow pixels should not be removed, as they contribute to the composite radiometric signal and can improve agreement with EC observations when retained in TSEB modeling (Duran-Gomez et al., 2026). Instead, shadow compensation approaches may be more appropriate, as they have been shown to improve flux estimation compared to shadow removal methods (Aboutaleb et al., 2019). This highlights an additional advantage of LiDAR-based inputs, which are independent of illumination conditions and largely unaffected by shadowing or reflectance variability. Although shadow effects were likely limited in this study due to predominantly well-developed canopies and UAV acquisitions near solar noon, future work should consider shadow compensation strategies, particularly for MS-based LAI estimation and for LST retrieval under conditions of higher soil exposure.

The interaction between shadowing, acquisition timing, and ET estimation also emphasizes the importance of temporal sampling. UAV systems, with their flexible deployment, allow acquisitions at optimal times (e.g., near solar noon) and enable repeated observations throughout the day to better capture diurnal variability, including the movement and influence of shadows. This capability also supports integration with satellite observations, where UAV data can be used to validate and sharpen spatial resolution (Jaafar et al., 2022) and to gap-fill or improve temporal interpolation of ET between satellite overpasses (Hazard et al., 2025). Together, these approaches highlight the complementary role of UAV and satellite systems in improving both spatial detail and temporal continuity of ET estimates.

Finally, further improvements in TSEB implementation may be achieved through testing alternative resistance formulations and refining G parameterization. Previous studies have explored modified resistance schemes (Li et al., 2019; Lun et al., 2026) and highlighted limitations of simplified G representations such as fixed fractional approaches (Hoffmann et al., 2016). In this study, G showed generally good agreement but remained sensitive to LAI input type, with GAI improving estimates in sparser canopies (sugar beet and potato) and PAI performing better in dense canopies (winter wheat), emphasizing the importance of input selection alongside model parameterization. Additionally, model choice may be adapted to canopy conditions: TSEB-2T was used in the 2021 sugar beet campaign (data not shown) and improved performance early season under low vegetation cover, but TSEB-PT was more robust for dense canopies. This suggests that adaptive or hybrid use of TSEB variants based on canopy structure and phenological stage could further improve ET estimation across crop systems.

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

Moving toward practical applications in farm management, physically based models such as TSEB-PT offer key advantages over machine learning approaches by explicitly representing land–atmosphere energy exchange without requiring extensive training data. In this study, TSEB-PT achieved accurate ET estimates across three crop seasons using minimal ground inputs, limited to a small number of control plots for LAI and canopy height calibration and early-season thermal reference targets. This highlights the operational potential of combining the robustness of TSEB-PT with UAV platforms, where model performance can be enhanced through improved environmental characterization from high-quality sensor inputs. The results further demonstrate that the type of UAV-derived sensor data play a critical role in improving model performance and supporting more informed management.

The high spatial resolution of UAV ET mapping enables detection of sub-field variability that is not observable with conventional scouting or coarse-resolution satellite data. In this study, TIR-derived ET identified early signs of crop stress prior to changes detected by multispectral reflectance (GAI) or LiDAR-derived structural metrics (PAI and h_c). For example, in the potato field, ET maps revealed under-irrigated zones shortly after irrigation events (see Fig. 14), while in winter wheat, persistently low ET aligned with shallow gravel layers, indicating naturally water-limited zones that experienced early senescence (see Fig. 15). Such spatially explicit information is critical for improving irrigation efficiency and yield optimization.

A daily water stress proxy ($K_s = ET/ET_0$), based on atmospheric demand (FAO-56), further supported the identification of water-limited conditions by capturing the interaction between atmospheric demand and soil water availability, consistent with approaches used in previous studies (Giardina et al., 2019). The use of high-resolution UAV data improved delineation of stress zones and preserved the magnitude of stress signals that would otherwise be averaged out at coarser scales. As shown in Fig. 8, comparisons across spatial scales (field average, EC footprint, and delineated stress zones) highlight how aggregation can mask localized stress and reduce interpretability, particularly in the potato field during the 3–29 August period, when spatial variability was most pronounced.

Further studies support the use of energy balance approaches for stress detection and irrigation response. For example, Nieto et al. (2022) showed that TSEB-derived variables, particularly transpiration and stomatal conductance, provide robust indicators of crop water stress, outperforming temperature-based indices alone. Similarly, integrating ET-based metrics with CWSI formulations has been shown to improve detection of irrigation treatments and water deficits in UAV applications (Sánchez-Virosta et al., 2025). In practical applications, UAV-derived ET maps can be integrated with rainfall and irrigation data to estimate crop water deficits or surpluses, supporting more precise irrigation scheduling. High-resolution ET data has been identified as a critical requirement for improving water management and reducing inefficiencies in agricultural systems (Wanniarachchi and Sarukkalige, 2022). Furthermore, combining ET with additional metrics such as gross primary productivity (GPP) and water use efficiency (WUE) can provide valuable insights for decision-making at local scales (Elfarkh et al., 2023). Similarly, UAV-based ET mapping has been shown to improve irrigation management and crop yield through spatially targeted interventions (Ankela et al., 2026).

Despite these advantages, practical implementation requires consideration of spatial scaling. The very-high-resolution outputs used in this study (15 cm GSD), and similar UAV-based datasets, exceed the resolution typically required for operational irrigation management, where decisions are made at coarser management-unit scales (e.g., irrigation sectors or management zones) (von Hebel et al., 2021). In practice, these zones are typically defined at meter- to tens-of-meter scales or aggregated into a limited number of homogeneous units based on soil properties, yield, and evapotranspiration patterns (e.g., Serrano et al., 2020; Flint et al., 2023). While UAV data resolves variability at much finer scales, its primary value lies in diagnosing within-field heterogeneity in crop water use and stress. These high-resolution ET maps can then be aggregated to match operational management units, supporting a multi-scale framework in which fine-resolution data informs model parameterization and stress detection, while coarser representations are used for irrigation planning and decision-making.

5. Conclusion

This study demonstrates the effectiveness of integrating very-high-resolution UAV multi-sensor data with the TSEB-PT model for accurate, field-scale evapotranspiration (ET) estimation across sugar beet, potato, and winter wheat over full growing seasons. With minimal ground calibration of UAV inputs, the model showed robust performance across crops and strong agreement with eddy covariance (EC) measurements at both instantaneous flux and ET scales. **This**

agreement was largely preserved when upscaling to daily ET using a reference ET fraction (ET_{rF}) approach, supporting the reliability of UAV-based TSEB estimates for water balance applications.

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 derived at different spatial scales (field average, EC footprint, and delineated stress zones) highlighted the importance of scale in interpreting crop water status, with fine-resolution data improving detection and characterization of stress severity that could otherwise be masked in aggregated measurements.

Among UAV-derived inputs, TIR data was both the most influential and the most error-prone, with uncooled sensors systematically underestimating LST under high-temperature and high-VPD conditions, leading to ET overestimation. Applying ground-based thermal correction improved ET magnitude and spatial contrast, emphasizing the strong sensitivity of TSEB to LST accuracy. Vegetation inputs were also critical and revealed clear crop-dependent behavior. While LiDAR-derived PAI and multispectral-derived GAI performed similarly during peak growth, GAI better captured functional decline under stress and senescence, whereas PAI remained high due to persistent canopy structure. This divergence was most important in winter wheat, where the tall, dense canopy increased the chance that cooling associated with canopy structure rather than transpiration would be over interpreted as active water use. By integrating structural (LiDAR) and functional (multispectral) information through a dynamic f_g (GAI/PAI), transpiration was constrained to more realistic levels, producing the greatest improvement in ET accuracy and spatial representation.

Overall, this study demonstrates that UAV-based TSEB-PT provides a powerful framework for monitoring crop water use and stress at actionable scales. UAV platforms offer key advantages over satellite systems by enabling fine-scale reconstruction of canopy structure using 3D LiDAR, alongside thermal and spectral sensing for improved characterization of surface–atmosphere interactions. In addition, the on-demand flexibility of UAV systems allows data acquisition at optimal times of day and under conditions that may limit satellite observations (e.g., cloud cover), improving the temporal representation of ET dynamics. The combination of high-resolution UAV data with a physically based modeling framework that is applicable across multiple crops with minimal ground calibration enables accurate ET estimation and early detection of water limitations at precise spatial scales.

Key contributions of this study include:

- Demonstrating the robustness of TSEB-PT with UAV inputs and minimal ground calibration.
- Underscoring the importance of accurate TIR calibration, especially during heat stress.
- Clarifying divergence between structural (PAI) and functional (GAI) LAI inputs under stress.
- Shows LiDAR performs comparably to MS methods for LAI at peak canopy.
- Proposing a LiDAR-MS fusion approach to estimate f_g for dynamic transpiration scaling.
- Demonstrating the value of f_g to improve ET accuracy across varying physiological states.

- Identifying crop-specific modeling challenges, especially in dense canopies like winter wheat.
- Showing the potential of UAV TIR based ET mapping to detect early stress to guide targeted irrigation.

Future improvements are expected through advances in dynamic emissivity correction, enhanced LiDAR-based canopy reconstruction, and improved representation of canopy structure–function interactions (e.g., LAI, f_c , f_g). In addition, integration with satellite data through gap-filling and fusion-based spatial sharpening approaches could further improve the temporal continuity, spatial detail, and coverage of ET estimates. Coupled with increased UAV spatial resolution and temporal sampling, these developments are poised to enhance ET estimation, stress detection, and irrigation management.

889 **Appendix A: Description of the TSEB-PT model implementation**

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

895 **A1. Energy balance equations**

$$896 \quad R_n = LE + H + G \quad (A1)$$

897 Fluxes are partitioned into canopy and soil components:

$$898 \quad R_{nc} = H_c + LE_c \quad (A2)$$

$$899 \quad R_{ns} = H_s + LE_s + G \quad (A3)$$

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

$$901 \quad G = c_g R_{ns} \quad (A4)$$

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

903 **A2. Sensible heat partitioning and air temperature**

904 The total sensible heat flux H is calculated as:

$$905 \quad H = H_c + H_s = \rho C_p \left[\frac{T_{ac}-T_c}{R_a} \right] = \rho C_p \left[\frac{T_c-T_{ac}}{R_x} + \frac{T_s-T_{ac}}{R_s} \right] \quad (A5)$$

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

909 The in-canopy air temperature is:

$$910 \quad T_{AC} = \frac{\frac{T_A}{R_a} + \frac{T_c}{R_x} + \frac{T_s}{R_s}}{\frac{1}{R_a} + \frac{1}{R_x} + \frac{1}{R_s}} \quad (A6)$$

911 **A3. Resistance parameterizations**

912 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).

924 **A4. Radiometric temperature decomposition**

The observed directional radiometric temperature T_{RAD} is decomposed as:

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

Where $f_c(\theta)$ = vegetation fractional from the viewing angle (θ) calculated from UAV based multispectral.

928 **A5. Priestley-Taylor approach to canopy transpiration**

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

$$LE_c = \alpha_{PT} f_g \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (A11)$$

Where $\alpha_{PT} = 1.26$ (iteratively reduced if needed to achieve plausible solution $LE_s > 0$; see W. Kustas & Anderson (2009)); f_g = fraction of green LAI derived from UAV based hybrid combination of multispectral and LiDAR data; Δ = slope of saturation vapor pressure curve ($kPa K^{-1}$); γ = psychrometric constant ($kPa K^{-1}$).

$$f_c(\theta) = 1 - \exp[-k_{be}(\theta)LAI] \quad (A12)$$

with k_{be} being the extension coefficient of canopy with a leaf angle distribution defined by the Campbell (1990) parameter.

$$k_{be} = \frac{\sqrt{\chi^2 + \tan^2 \theta}}{\chi + 1.774 (\chi + 1.182)^{-0.733}} \quad (A13)$$

938

939 **Appendix B: Sensor derived metrics**

940 **B1. Green area index (multispectral)**

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

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

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

945 $k(\theta)$ = extinction coefficient, parametrized using SunScan ceptometer LAI measurements. k was adjusted once
946 between early and mid-late season and then held constant through senescence.

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

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

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

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

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

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

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

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

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

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

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

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

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

964 C2. FAO 56 reference ET (Potential ET)

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

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

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

970 C3. TSEB upscaling to Daily ET using reference ET fraction (ET_rF)

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

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

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

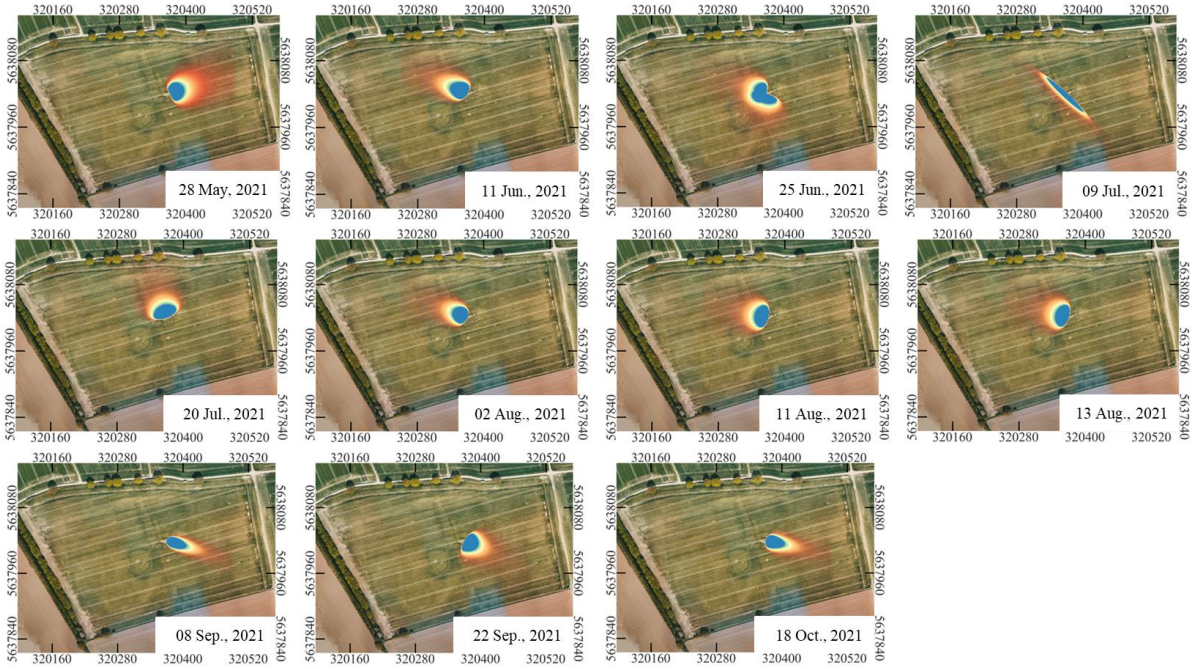
976 Here, $ET_r F$ differs from the evaporative fraction ($EF = LE/(R_n - G)$) and is used for temporal upscaling following
 977 Cammalleri et al. (2014).

978 C4. Water stress coefficient

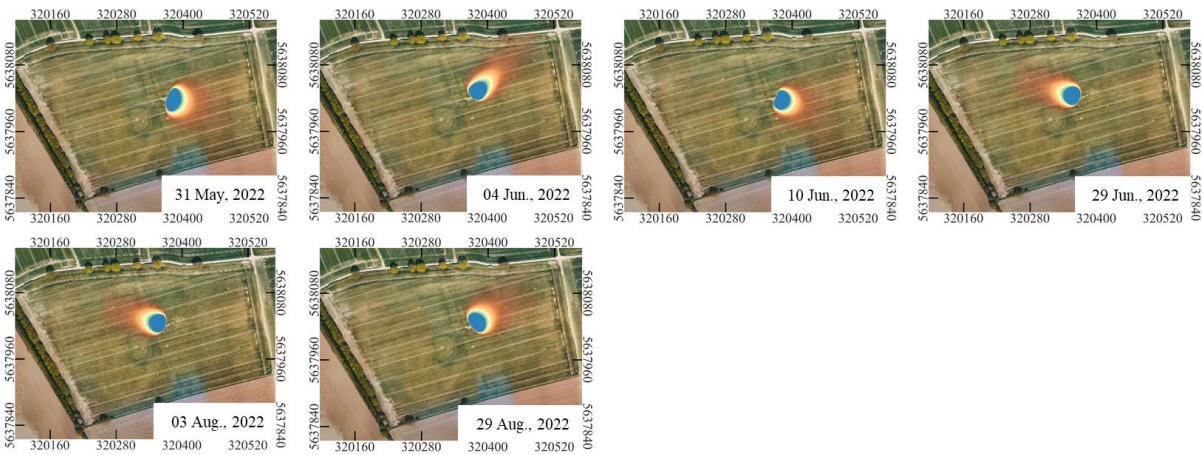
979 ET estimations from UAV TSEB and EC were compared relative to atmospheric demand (reference ET) introduced
 980 from Allen et al. (1998) as follows:

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

982 Appendix D: Supplemental material



983



984

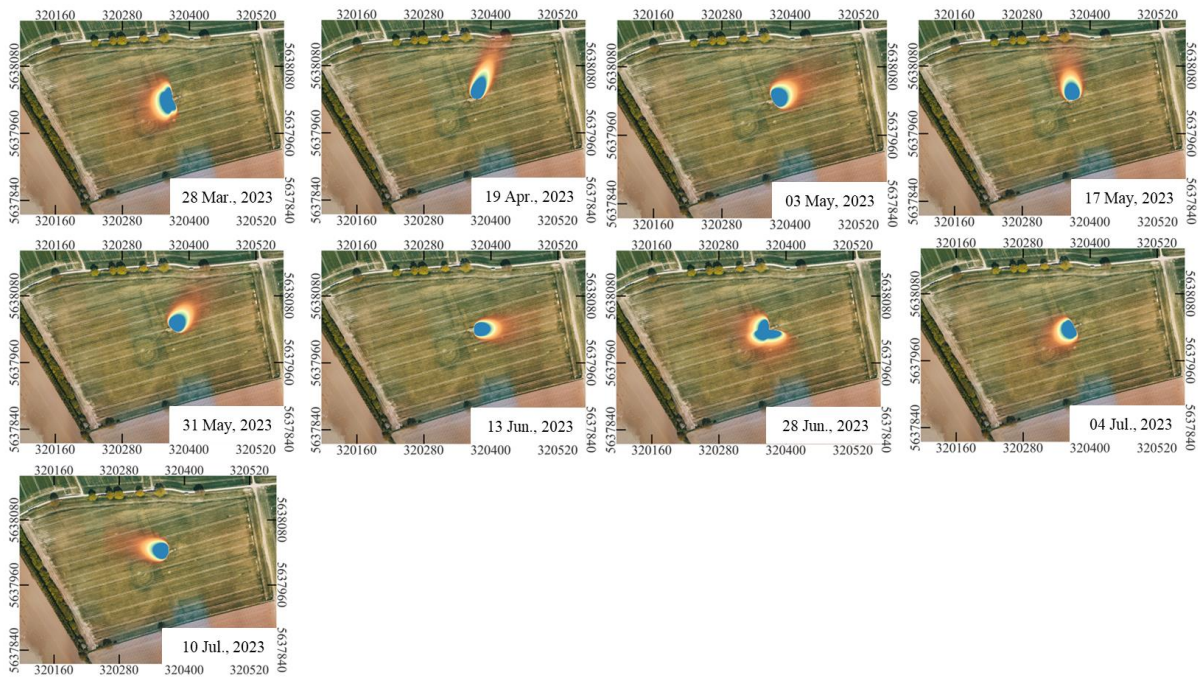


Figure D1: The estimated EC footprints for each TIR campaign flight time interval to be used to compare the TSEB-PT ET values within this spatial extent to the EC ET estimations.

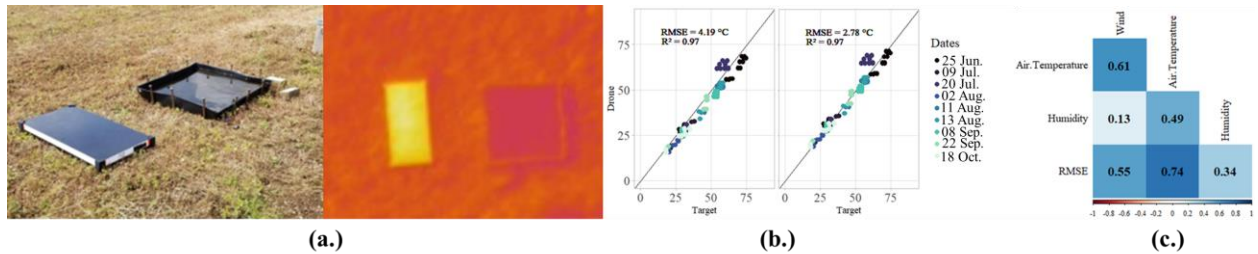


Figure D2 (a.) ground photo and aerial TIR view of the hot and cold temperature ground reference targets (b.) pre-correction and post-correction graphed RMSE of TIR images in the 2021 season (c.) correlation of weather factors with RMSE.

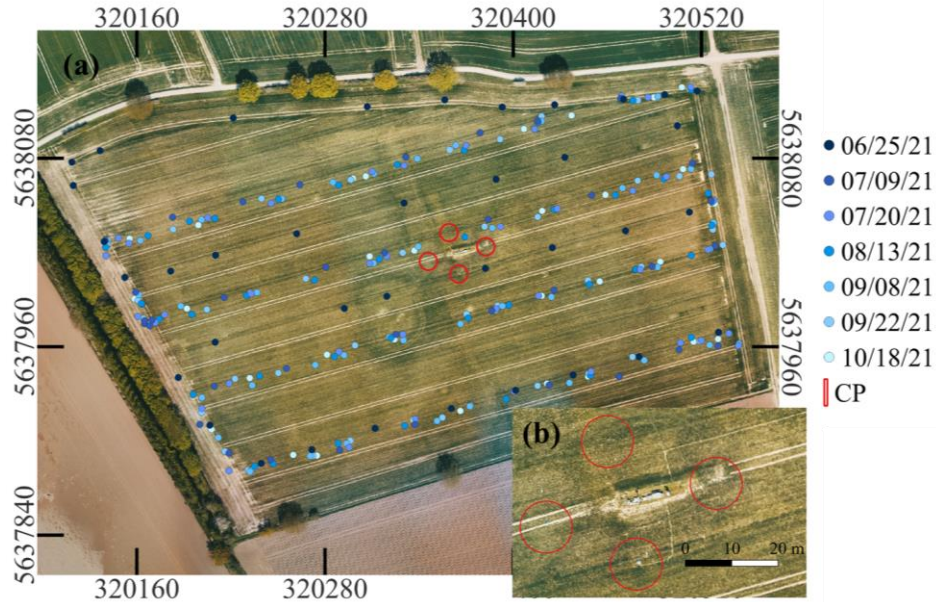


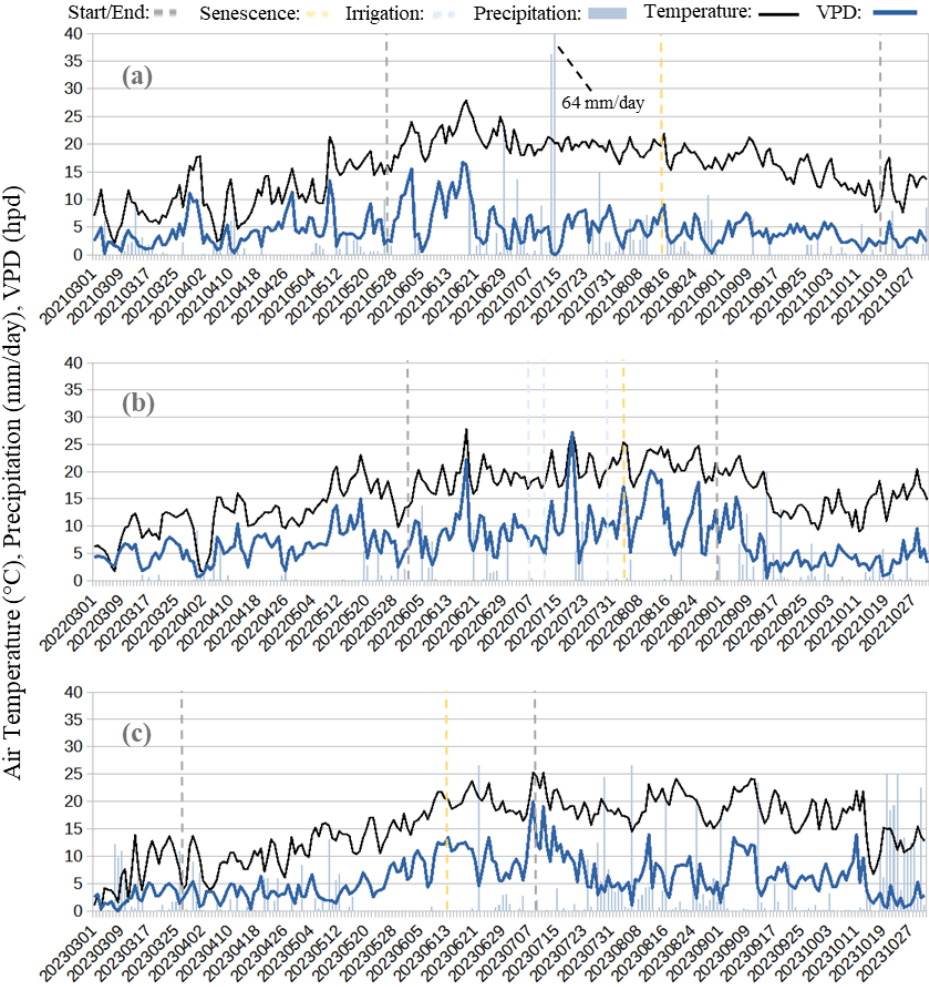
Figure D3: (Left) Location of continuous measurement plots (CP) around climate station in the middle of the experiment field site. (Right) Crop height measuring locations for the listed 2021 campaigns by color.

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

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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; $f_g = \text{GAI/PAI}$				LAI =PAI; $f_g = \text{GAI/PAI}$				LAI =PAI; $f_g = \text{GAI/PAI}$			
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; $f_g = \text{GAI/PAI}$				LAI =PAI; $f_g = \text{GAI/PAI}$				LAI =PAI; $f_g = \text{GAI/PAI}$			

		RMSE	R ²			RMSE	R ²			RMSE	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		

Code availability

Data will be available upon request.

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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