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Keypoints/Highlights:

1. Introduce three innovative procedures (one linear regression-based and two interpolation-based) to accurately determine daily evapotranspiration at high spatial resolution.
2. Generate high spatiotemporal resolution ET_a maps with minimal error using aerial imagery.
3. Enable better understanding of plant and meteorological interactions with detailed ET_a maps.

Impact:

The approach used in this study offers high spatiotemporal resolution ET_a maps using sensor-fusion of aerial imagery and infield observations, aiding researchers in understanding plant health and meteorological interactions to develop optimized irrigation techniques. This in-depth understanding could significantly improve water usage efficiency in drought-prone regions.

Abstract

Spatial estimates of crop water use during the growing season are crucial for precision irrigation management, especially under conditions of water scarcity and climate change. The on-farm trial detailed in this paper focuses on a processing tomato field in the Sacramento Valley of California. Different meteorological parameters, including temperature, precipitation, relative humidity, shortwave radiation, and wind speed, were measured hourly at three specific locations in the field using on-the-ground sensors. Additionally, these sensors captured canopy surface reflectance properties in multiple bands, covering the wavelength range of 420–956 nm. The collected hourly meteorological and crop biophysical data were used to predict reference evapotranspiration (ET_o) and calculate crop

coefficients (K_c), which were then used to derive point-based estimates of canopy evapotranspiration (ET_c). High-resolution multispectral and thermal aerial imagery were collected eight times during the growing season of 2021 (June–August). Several canopy properties, including leaf area index and crop height, were computed from the aerial imagery. The spatial data was combined with meteorological information from nearby weather stations to map actual evapotranspiration (ET_a) with the High-Resolution Mapping of EvapoTranspiration (HRMET) model at 5-m resolution. Next, the eight ET_a maps and the daily sensor-based ET_c estimates for the entire growing season were combined to predict high-resolution ET_a maps for days when aerial imagery was not collected. Three different algorithms for prediction were implemented: Linear Regression, Weighted Piecewise Linear Interpolation, and Forward Interpolation. The performance of these algorithms was evaluated using metrics such as Nash-Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Kling-Gupta Efficiency (KGE). Results indicate that Forward Interpolation is the most suitable algorithm (NSE=0.694; MAE=0.06; RMSE=0.07; KGE=0.894) for gap-filling and approximating daily high-resolution ET_a maps (average hourly estimates for each day) for the entire growing season for our study site. This innovative procedure aims to establish a decision support system for efficient irrigation scheduling, fusing different sources of spatiotemporal information to optimize irrigation in drought-prone areas.

Keywords

Predictive modeling, Spatial estimates, Process based modelling, Evapotranspiration, Data fusion

STATEMENT and DECLARATIONS:

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Abbreviations

Reference Evapotranspiration (ET_o), Actual Evapotranspiration (ET_a), Canopy Evapotranspiration (ET_c), High Resolution Mapping of EvapoTranspiration (HRMET), Crop Coefficient (K_c), Normalized Difference Vegetation Index (NDVI), California Irrigation Management Information System (CIMIS), Linear Regression (LR), Weighted Piecewise Linear Interpolation (WPLI), Forward Interpolation (FI), Nash-Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Kling-Gupta Efficiency (KGE)

1. Introduction

The imperative for sustainability in crop production has grown significantly due to the increasing world population and the escalating impacts of climate change (Granata, 2019). Particularly in the western United States, agricultural irrigation uses substantial quantities of water, averaging 1.8 ML of water per acre in 2018 (Sowby & Dicataldo, 2022; U.S. Department of Agriculture, 2023). California is currently the leading producer and exporter of agricultural produce in the USA—growing over a third of the vegetables and three-quarters of the fruits and nuts consumed in the country (California Department of Food and Agriculture, 2024; Howitt et al., 2014). However, producers in this region, particularly in Central Valley, encounter significant challenges in effectively managing water and energy use (Berger et al., 2016; Escrivá-Bou et al., 2018; Schwabe et al., 2020; U.S. Department of Agriculture, 2023). With the recent advancement of affordable commercial technologies such as public weather stations, satellite imagery, wireless sensor networks, and decision support tools, precision irrigation management is becoming a widely adopted practice across California (Jha et al., 2022). These state-of-the-art technologies are now widely used to facilitate precision micro irrigation, such as deep root irrigation, subsurface drip irrigation, overhead sprinkler irrigation, deficit irrigation, pressure-compensated drip irrigation, automated surface irrigation (Gu et al., 2020; Olsen et al., 2015; Tindula et al., 2013). These irrigation methods require high-resolution spatial data at intervals that are actionable for optimized water management (Chen et al., 2019; Jha et al., 2022; Kisekka et al., 2014; Welle & Mauter, 2017). Actual evapotranspiration (ET_a) (Berti et al., 2014; Jensen & Allen, 2016; Mehdizadeh, 2018; Ravazzani et al., 2012) is a useful indicator in determining the irrigation requirement by understanding the water loss from surface and within the crop matrix (Brenner et al., 2018; Xia et al., 2016).

There are several established energy balance methods to estimate evapotranspiration using meteorological data, canopy characteristics, soil surface properties, etc. (Brenner et al., 2018; Montero et al., 2018). Many of these methods use some version of the Penman-Monteith equation (Monteith, 1965; Penman & Schofield, 1951), which estimates the latent heat flux as a residual term in the energy balance equation (Ahmadi et al., 2022). Reference Evapotranspiration (ET_o) is an empirically-derived value that refers to the ability of the atmosphere to absorb water independently assuming a constant conductance, leaf area index (LAI), and height of a reference crop—either well-watered alfalfa or grass (Gu et al., 2020; Kazemi et al., 2020). The crop specific reference evapotranspiration, denoted as ET_c , is obtained by multiplying meteorological data-driven ET_o with a crop coefficient (K_c) that is a relative representation of the various physical and physiological characteristics (leaf area, crop height, canopy cover percentage, aerodynamic resistance, etc.) specific to the crop (Ghiat et al., 2021; Jensen & Allen, 2016).

One approach for estimating the K_c at either a point or over a field-scale domain is to develop empirical models that use the normalized difference vegetation index (NDVI) (Benedetti & Rossini, 1993) as input (Choudhury et al., 1994; Kamble et al., 2013; Pelta et al., 2022; Tasumi et al., 2006). NDVI is a canopy reflectance property in the red and near-infrared spectrum which shows a strong correlation with LAI and crop height (Rouse et al., 1974; Zipper & Loheide, 2014). Hence, these energy balance models allow on-the-ground, canopy-based sensors to continuously estimate the ET_c of the canopy by sensing parameters such as meteorological variables, NDVI, and soil moisture. In-situ ground sensors are thus capable of providing hourly ET_c data for irrigation management, but they are limited in capturing spatial variability or areas of water stress within an agricultural field (Jha et al., 2022; Nocco et al., 2019).

High-resolution, spatial estimates (<5 m² pixels) of evapotranspiration can complement in-situ ground sensor estimates (Bisquert et al., 2016; Ramirez-Cuesta et al., 2019). Remotely sensed data—collected using satellite, piloted or unoccupied aerial imagery, etc.—can provide estimates of radiometric surface temperature and multispectral indices. Remote-sensing-based ET_a models combine these remotely sensed data, along with the meteorological parameters to solve the energy balance equation and provide estimates of ET_a (Ahmadi et al., 2022; Chen et al., 2022; French et al., 2015; Guzinski et al., 2020).

Some remotely sensed ET_a models include the One-Source Energy Balance (OSEB) (Su, 2002), Two-Source Energy Balance (TSEB) (Norman et al., 1995), Dual Temperature Difference (DTD) (Hoffmann et al., 2016), Deriving

Atmosphere Turbulent Transport Useful To Dummies Using Temperature (DATTUTDUT) (Timmermans et al., 2015; Xia et al., 2016), Surface Energy Balance Algorithm for Land (SEBAL), Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC), and High Resolution Mapping of EvapoTranspiration (HRMET) (Zipper & Loheide, 2014). The OSEB model considers the whole surface as a single uniform layer (does not differentiate soil and canopy) but is less sensitive to the variations of surface temperature (Su, 2002). The SEBAL, METRIC, and DATTUTDUT (a variation of OSEB that only use the surface temperature as input) models require the presence of both hot and cold pixels (Timmermans et al., 2015; Xia et al., 2016; Zipper & Loheide, 2014). The TSEB model does differentiate between soil and canopy components within the same pixel and does not require hot and cold pixels, but is more effective for homogeneous fields and is somewhat sensitive to the temperature difference between the ground and air (Norman et al., 1995). DTD overcomes the temperature bias but requires more aerial missions—making the data collection process more expensive and complicated (Hoffmann et al., 2016). In contrast to the previously mentioned methods, the HRMET model is designed to have simplified inputs (meteorological data from publicly accessible weather stations, thermal and multispectral imagery of the field, soil (relatively unchanging) albedo and emissivity etc.) and also does not require hot and cold pixels (Ebert et al., 2022; Niu et al., 2020). This model has performed well in several crops, with an R^2 of 0.89 fit with on-the-ground measured leaf transpiration of peach orchard (Park, 2018; Park et al., 2021) and an R^2 of 0.943 fit with the Shuttleworth-Wallace model for potato and an R^2 of 0.7 fit for sweet corn (Nocco et al., 2019). Therefore, HRMET was used for generating high resolution maps of ET_a in this study.

Current precision agriculture technologies (soil moisture sensors, NDVI sensors) are extensively employed for monitoring abiotic and biotic stresses in plants. However, these technologies can often be inadequate in terms of space and time for taking necessary actions or preventing crop stress. By the time crops exhibit symptoms, internal losses may have already occurred, leading to decreased production. Such occurrences can be averted, or at least minimized, through the spatiotemporal monitoring of growth variability encompassing both healthy and stressed conditions during the season (Jha et al., 2022; Poirier-Pocovi et al., 2020; Zhang et al., 2020). Thus, sensor fusion, which combines data from on-the-ground sensors with aerial imagery, could provide the most effective resource for monitoring crop water use. Previous research in this area has utilized satellite data with spatial resolutions of 30 m to a few global degrees, and at a temporal resolutions of six to eight days (Cammalleri et al., 2013; Miralles et al., 2011; Mokhtari et al., 2021; Mu et al., 2011; Ryu et al., 2011). Alternatively, by integrating easy-to-implement, powerful geostatistical interpolation tools with remotely-sensed ET_a models, as well as the on-the-ground sensor measurements, it becomes feasible to generate higher-resolution field-level daily ET_a data with a reduced number of aerial missions.

The objective of this study was to develop high-resolution ET_a maps using a sensor data fusion approach to optimize irrigation in drought-prone areas. While previous studies (Mokhtari et al., 2021; Cammalleri et al., 2013) have used interpolation and smoothing techniques to fill temporal gaps in ET_a data, these approaches often fall short in capturing the highly non-linear, day-to-day variability in crop water use driven by environmental fluctuations and physiological responses. To address this limitation, two customized interpolation approaches, Weighted Piecewise Linear Interpolation and Forward Interpolation were developed in this study that are designed to model daily ET_a dynamics more realistically. These methods offer flexibility to reflect sharp transitions and gradual trends without over-smoothing the signal. In addition, a pixel-wise linear regression was modelled to provide a benchmark that accounts for location-specific ET_a patterns based on available observations. This regression approach enables pixel-level calibration that adapts to heterogeneous field conditions. By combining these complementary techniques, the prediction framework presented aims to balance accuracy, interpretability, and operational practicality in generating daily, high-resolution ET_a maps from limited aerial missions.

The average hourly estimates of daily ET_a was achieved in two different segments—first, using HRMET, spatial ET_a maps of a processing tomato field in California from eight different piloted missions during the growing season were generated (June–August) of 2021. Next, three different geostatistical time-series estimation techniques were employed to fuse data from ground sensors with high-resolution ET_a maps to predict ET_a maps for the days in-between the missions. Linear regression and two types of interpolation (Weighted Piecewise Linear Interpolation and Forward Interpolation) were used to predict ET_a maps for the days in-between the missions and evaluated performance using four metrics: Nash-Sutcliffe Efficiency, Mean Absolute Error, Root Mean Squared Error and Kling-Gupta Efficiency.

2. Methodology

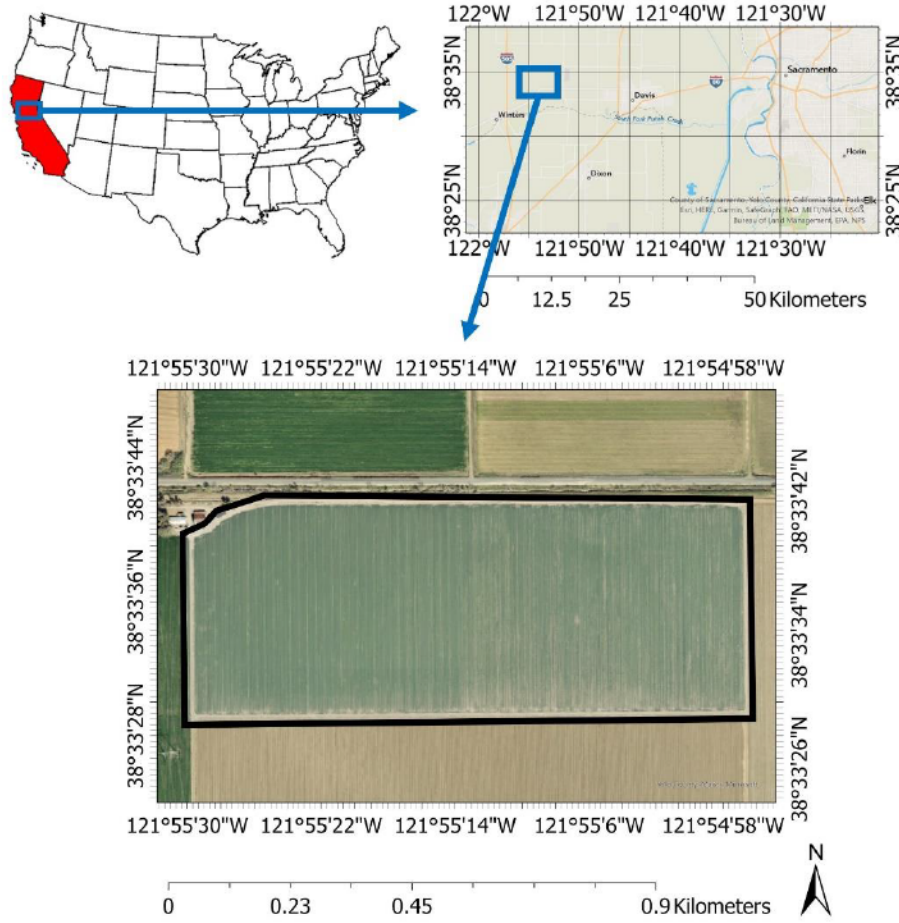


Fig. 1 Geographical location of the processing tomato field in Sacramento Valley of California.

2.1 Site and Dataset Description

The experimental site was a 3 ha processing tomato field under standard agronomic practices in Winters, CA, located in the Sacramento Valley (Northern Central Valley) of California (as shown in Fig. 1). Prior to transplanting, the field underwent conventional tillage, including disking and bed shaping to prepare the beds for drip irrigation and transplant establishment. Tomatoes were transplanted into raised beds with subsurface drip irrigation. Nutrient inputs were followed using recommended guidelines in processing tomato systems and were managed through pre-plant applications of phosphorus and potassium, with nitrogen supplied in-season. Weed control consisted of pre-emergent herbicide applications and inter-row mechanical cultivation. To manage *Phelipanche ramosa* (broomrape), rimsulfuron was applied as a foliar spray during the early reproductive stage, following established protocols for in-season broomrape suppression in tomato cropping systems. Tomato seedlings were transplanted in mid-April 2021 at a density of approximately 30,000 plants per hectare. Information about data types, all available features, frequency of data availability over the season, and different data sources is provided in Table 1. The soil type in the location was dominantly Caply silty clay (90.2 % of the area) and Tehama loam (9.8% of the area) (U.S. Department of Agriculture, 2019). All data for this study were collected during the growing season of 2021 (June–August). The soil apparent electric conductivity of the field was measured using EM38-MK2 Geonics (Ontario, Canada) before the growing season in March 2021. This equipment measures soil electrical conductivity as a proxy measurement of electromagnetic induction of the soil. Based on the spatial variability, the field was classified into low (86.03–110.86 mS m^{-1}), medium (110.86–118.34 mS m^{-1}), and high (118.34–137.35 mS m^{-1}) apparent electrical conductivity (at 1.50 m depth) areas. Three canopy-based Arable Mark II sensors (California, USA) were installed at three different locations of the field (Rossini et al., 2021). Using plant spectral reflectance, these (Arable Mark II) sensors measure

Table 2 Resolution of the images collected by aerial piloted aircraft throughout the 2021 growing season.

Mission timeline	Image dimensions (Reflectances)	Image dimensions (Thermal)
June 14	1935x4025x4	1493x3093
June 23	1971x4101x4	1527x3164 ^a
June 30	1872x3894x4	1450x3004
July 08	1901x3956x4	1466x3039
July 14	2002x4166x4 ^b	934x1942
July 21	1920x3995x4	1484x3075
July 27	1926x4007x4	1477x3062
August 5	1924x4002x4	1468x3044

^a Thermal image with the largest dimension (~ 0.25 m pixel⁻¹) ^b Reflectance image with the largest dimension (~ 0.19 m pixel⁻¹). All images were resized (pixel size-enhanced) to the largest dimension.

While nearest-neighbor interpolation avoids altering the original reflectance values, it may result in pixel-level discontinuities at image boundaries due to the 14% reduction in pixel size. This tradeoff was considered acceptable for preserving raw reflectance integrity, but it may have minor implications for spatial consistency, especially in heterogeneous areas.

2.2 Framework for spatial ET_a estimation and geostatistical time-series interpolation

Traditional decision-making relies on point estimates that have high temporal resolution. Such measurements could provide robust data for a specific location in a field but do not account for spatial variability. To overcome this limitation, the High-Resolution Mapping of Evapotranspiration (HRMET) model (Zipper & Loheide, 2014) was used in this study, enabling spatial estimates of ET_a every 6-10 days throughout the growing season. However, ET_a values can fluctuate between two consecutive missions based on weather, management, and crop responses. Geostatistical time-series interpolation techniques were used to fill data gaps between missions and build prediction models for spatial ET_a on future dates. These predictive models used the eight HRMET-derived ET_a maps and average hourly ET_c for each day obtained from the in-situ Arable Mark II sensors.

For each pixel in the HRMET-generated images, three different spatiotemporal estimation techniques were used—(i) linear regression, (ii) Weighted Piecewise Linear Interpolation (WPLI) and (iii) Forward Interpolation (FI). These techniques were used to estimate daily spatial ET_a for the growing season. Depending on the method, the estimates were generated for days between mission dates or after the most recent mission. The linear regression fits a line for each pixel in a spatial ET_a map, based on their HRMET-generated values and the corresponding daily sensor ET_c values for the mission days. Then for a new ET_c value, the corresponding ET_a value of that pixel is found as the projection on that line. The WPLI uses two consecutive HRMET-generated maps from two respective missions and predicts the spatial ET_a maps in between these dates, while FI only uses the HRMET-generated maps from the past to predict the spatial ET_a on a future date. Fig. 2 shows the detailed analysis pipeline of the presented algorithms and framework.

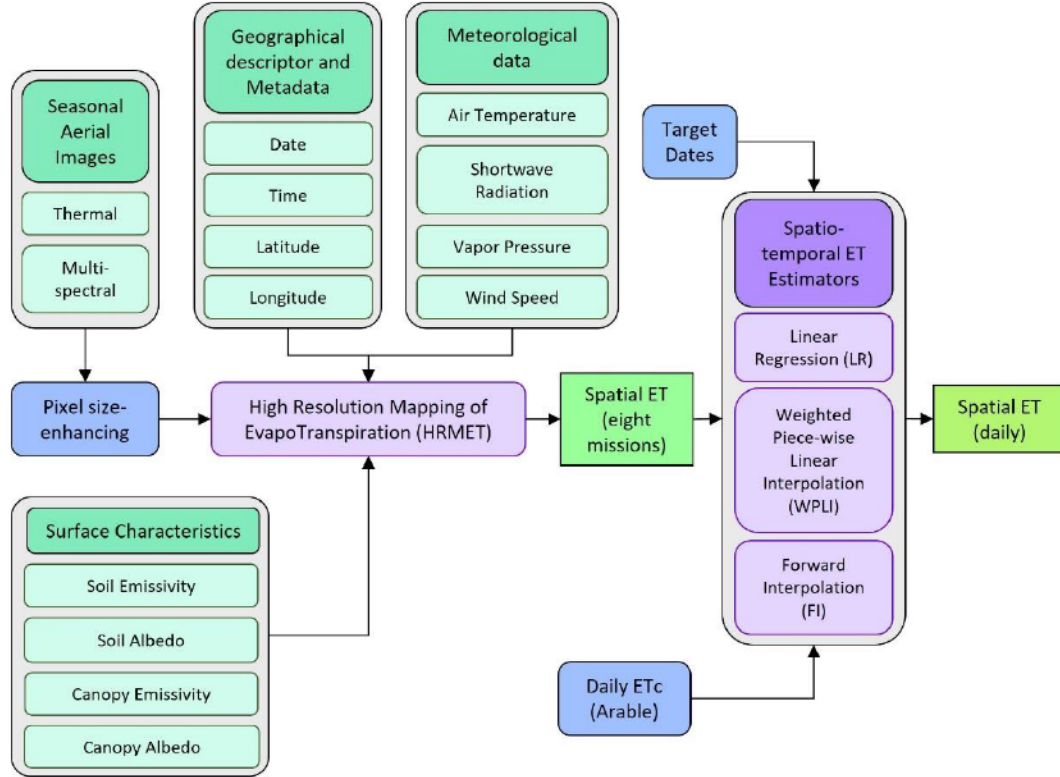


Fig. 2 Detailed analysis pipeline for high spatiotemporal estimation of ET_a using HRMET-generated maps and geostatistical time-series interpolation techniques, including linear regression, Weighted Piecewise Linear Interpolation (WPLI), and Forward Interpolation (FI).

2.2.1 Modeling Spatial Evapotranspiration using HRMET

The High Resolution Mapping of EvapoTranspiration (HRMET) (Zipper & Loheide, 2014), a model-based approach, was used to estimate spatial ET_a using the surface energy balance equation. The available energy (A) at the field surface is defined as the difference between net incoming radiation (R) and the sensible heat flux transmitted in the subsurface (G). The energy balance equation states that A can be partitioned into sensible heat flux (H) and latent heat flux (λET) and is expressed as follows:

$$A = R - G = H + \lambda ET \quad (1)$$

Once λET is calculated from eqn. 1, it can be directly converted to an ET_a rate (mm hr^{-1}).

As shown in Fig. 3, the model requires four types of inputs parameters: site location, meteorological data sourced from the nearest CIMIS weather station, surface characteristics such as emissivity (ϵ) and albedo of crop canopy and soil, and spatially variable biophysical crop characteristics (radiometric surface temperature, LAI, and crop height). In this study, the ϵ values for soil and vegetation were used as 0.94 and 0.95, respectively.

Using the respective ϵ values for these two types of surfaces, the longwave radiation component of R was calculated using Stefan Boltzmann Law for graybody radiation as: $\epsilon \sigma T^4$, where T denotes the surface temperature (K) and σ is the Stefan Boltzmann constant ($\text{W m}^{-2}\text{K}^{-4}$). The shortwave component was calculated using incoming radiation data from CIMIS, LAI, soil and vegetation surface albedos with the help of radiation extinction model (Norman et al., 1995). The same model was also used to estimate G , allowing the computation of A .

Once A was calculated, H was iteratively computed by estimating the diabatic correction factor for momentum and heat flux, friction velocity, aerodynamic resistance and excess resistance to heat transport, with a convergence criterion of 0.1%. The spatial ET_a was then subsequently calculated from the latent heat flux λET , which is the difference between A and H . This calculation was carried out at a 5-meter resolution, allowing for the representation of canopy-scale indices that include both plant and soil components within each pixel (Nocco et al., 2019).

HRMET was implemented in RStudio (Allaire, 2012) using the following packages: *raster*, *rgdal* (to import thermal and multispectral reflectance spatial data), *readxl* (to import meteorological parameters and canopy characteristics), *lubridate* (for datetime processing). The rest of the algorithm was devised, designed and custom-implemented (for further details, see <https://github.com/samzipper/HRMET>).

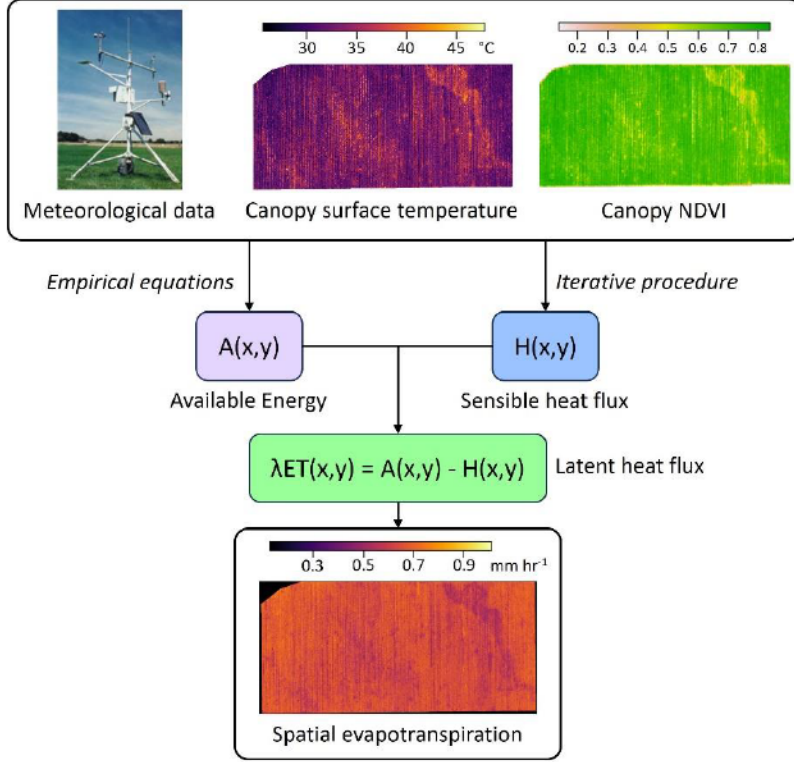


Fig. 3 Pipeline for developing spatial ET_a maps using High-Resolution Mapping of EvapoTranspiration (HRMET) model. The meteorological data picture was obtained from (CIMIS, 2024).

2.2.2 Estimating Temporal Evapotranspiration using Geostatistical Estimation Techniques

Geospatial interpolation techniques were used for function approximation to predict spatiotemporal ET_a estimates in between a set of known discrete spatial ET_a maps (from eight missions). To perform interpolation, it is assumed that the set of known points are sampled without errors from a continuous function (Kress, 1998). Through these known set of points, the target function (ET_a) passes exactly following a specific trend. Traditional interpolation methods, including nearest-neighbor interpolation, linear interpolation, polynomial interpolation, spline interpolation (Kress, 1998; Meijering, 2002), are commonly used in such contexts. However, these methods tend to oversimplify the underlying dynamics of the system, as they do not fully capture the highly non-linear, complex temporal variability of plant behavior over short timescales. To address this limitation, two different geostatistical spatiotemporal interpolations techniques were developed to estimate spatial ET_a in this work—Weighted Piece-wise Linear Interpolation (WPLI), and Forward Interpolation (FI), respectively. These methods not only retain the simplicity of linear transitions but also adapt locally based on daily variations, improving accuracy in representing the temporal variability of ET_a . In addition, two different variations of Linear Regression (LR) were incorporated to compare the outputs against the efficiency of interpolation methods.

2.2.2.1 Linear Regression

Linear regression was used to model the relationship between explanatory and response variables. In this study, the response variable is the pixel-wise ET_a rate (mm hr^{-1}) obtained from HRMET while the explanatory variables were represented by daily evapotranspiration (mm hr^{-1}) estimated from the canopy sensors. Specifically, $X = \{X_1, \dots, X_n\}$ be the set of n explanatory variables and $Y^{i,j}$ be the ET_a rates at the $(i, j)^{\text{th}}$ pixel as calculated with HRMET. To predict spatial ET_a maps (mm hr^{-1}) for all days without aerial missions based on sensor variables, a LR function was developed with the following form:

$$f^{i,j}(X) = \theta_0^{i,j} + \theta_1^{i,j}X_1 + \theta_2^{i,j}X_2 + \dots + \theta_n^{i,j}X_n \quad (2)$$

where $\theta^{i,j}$ are parameters learned by minimizing the residual sum of errors between predicted and observed ET_a values at pixel (i, j) . Note that $f^{i,j}$ was defined distinctly for each pixel (i, j) to predict spatial ET_a maps from non-spatial explanatory variables. The underlying assumption of this approach is that the evapotranspiration of each pixel correlates with variables measured by Arable Mark II sensors, and that this correlation is specific to each pixel.

Among the two variations of LR implemented in this study, the first variation fills the gaps between missions. In this method, the true function was estimated using both past and future missions. The second variation finds the best-fit line using past mission data only.

In this study, only one explanatory variable (daily ET_c from Arable) is used to model pixel-specific ET_a . Meaning, for an explanatory variable X_1 that represents the Arable sensor-based ET_c for the aerial mission days, the corresponding response variable Y is the HRMET-derived ET_a for each (i, j) pixel on those same days. In this regard, eqn. 2 is modified to the following equation:

$$Y^{i,j} = \theta_0^{i,j} + \theta_1^{i,j}X_1 \quad (3)$$

where $Y^{i,j}$ is the HRMET-generated ET_a rates at pixel (i, j) and X_1 is the average daily ET_c of the three Arable Mark II sensors. $\theta_0^{i,j}$ and $\theta_1^{i,j}$ are regression coefficients learned independently for each pixel by minimizing the residual sum of squares between the predicted and observed ET_a values. Both variations of LR were implemented using the *LinearRegression* class in the Scikit-learn library, a Python package (Pedregosa et al., 2011).

Filling-the-gaps: Leave-one-out cross-validation was performed to evaluate the ability of LR to predict ET_a maps between missions. Specifically, all ET_a maps were used except the k^{th} mission to fit the LR model and evaluate its prediction for the k^{th} mission. This process was repeated for all missions $k \in [1, 8]$. This linear regression approach was denoted as LR^{all} .

Forecasting: In the forecasting setup, only previous ET_a maps from HRMET were used to fit the above-mentioned LR model and evaluate the prediction of the following ET_a map. Since LR needs at least one ET_a map before making predictions, the first forecast starts from the second mission. In this scenario, linear regression approach was denoted as LR^{t-1} .

2.2.2.2 Weighted Piece-wise Linear Interpolation

Linear interpolation assumes the target function to be a straight line between any two consecutive points. Mathematically, in a two-dimensional plane, if two points (x_1, y_1) and (x_2, y_2) are given, then any points located in the interval $[x_1, x_2]$ lies in the straight line connecting (x_1, y_1) and (x_2, y_2) . The value of such a point (x_3, y_3) where, $\{x_3: x_1 < x_3 < x_2\}$ can be found using the following equation:

$$y_3 = y_1 + (x_3 - x_1) \times \frac{y_2 - y_1}{x_2 - x_1} \quad (4)$$

In this study, each x_n represents a mission conducted between June 14, 2021, to August 8, 2021. y_{x_n} is a spatial ET_a value of $(i, j)^{th}$ pixel for the corresponding date. Using the daily ET_c readings from the in-situ canopy sensors, a trend can be extracted from those values instead of assuming a straight line between two consecutive missions. This trend offers more accurate ET_a maps for each day, revealing fluctuations in ET_a values corresponding to changes in meteorological parameters. To accommodate this trend, the linear interpolation technique was modified, introducing a novel method that we termed *Weighted Piece-wise Linear Interpolation (WPLI)*. Based on our literature search, this method or a similar method has not been implemented before. WPLI observes the daily sensor-based ET_c trends as a piece-wise linear segments, modeling daily pixel-specific ET_a proportionally based on both preceding and succeeding aerial missions. The significance of each mission is weighted according to the difference between their operating dates and the target date of estimation. Further details on this weighing mechanism as per the day difference are provided in Online Resource 1.

WPLI was mathematically formulated as follows. At first, the 3 Arable sensors measurements were averaged to find the reference trend—denoted by $ET_{c_{x_n}}$. Then, for each $(i, j)^{th}$ pixel in the map, the following procedures are followed:

- For two consecutive missions, f_k and f_{k+1} , the ratios $C_{f_k}^{i,j}$ and $C_{f_{k+1}}^{i,j}$ of the ET_a values in the map and the Arable sensor were calculated.

$$C_{f_n}^{i,j} = \frac{y_{f_n}^{i,j}}{ETc_{f_n}} \quad (5)$$

where $f_n \in \{f_k, f_{k+1}\}$

- Forward trend $F_{x_n}^{i,j}$, using $C_{f_k}^{i,j}$ were calculated.

$$F_{x_n}^{i,j} = C_{f_k}^{i,j} \times ETc_{x_n} \quad (6)$$

where $x_n \in [f_k, f_{k+1}]$

- Backward trend $B_{x_n}^{i,j}$, using $C_{f_{k+1}}^{i,j}$ were calculated.

$$B_{x_n}^{i,j} = C_{f_{k+1}}^{i,j} \times ETc_{x_n} \quad (7)$$

where $x_n \in [f_k, f_{k+1}]$

- For each day $x_n \in [f_k, f_{k+1}]$, the ET_a values from $F_{x_n}^{i,j}$ and $B_{x_n}^{i,j}$ using the following equations were approximated.

$$w = \frac{1}{(f_{k+1} - f_k) - 1} \quad (8)$$

$$y_{x_n}^{i,j} = F_{x_n}^{i,j} \{1 - w(x_n - 1)\} + B_{x_n}^{i,j} w(x_n - 1) \quad (9)$$

Eqn. 9 uses the concept of Inverse distance weighting (IDW) on time scale (Lu & Wong, 2008). In IDW, the value of an unknown point is calculated based on its distance from two or more known points (Júnior et al., 2019). A weight factor is added on each known point such that the factor decreases with the increase in distance (Lu & Wong, 2008). The same weighting approach was adopted in this study for time series data. For a non-mission day x_n : $x_n - f_k < f_{k+1} - x_n$, the weight of $F_{x_n}^{i,j}$ would be proportionally greater than the weight of $B_{x_n}^{i,j}$ in calculating $y_{x_n}^{i,j}$. Iterating using this approach in between the consecutive missions f_k and f_{k+1} , the resultant $y_{x_n}^{i,j}$ vector was a piece-wise linear graph.

The ET_c values measured by the point-based Arable Mark II sensors on the dates of different missions are shown as ET_c in Table 3 and were used to calculate $C_{f_n}^{i,j}$ ratios in eqn. 5. In practical application, out of eight missions, each two consecutive missions (mission k and $(k + 1)$, $k \in [1,7]$) should be used to generate the spatial ET_a for the intermediate dates, along with their corresponding ET_c. However, to assess the performance of WPLI, alternate missions (mission k and $(k + 2)$, $k \in [1,6]$) were used instead of the consecutive missions to generate the spatial ET_a for the intermediate dates, including the one for mission $(k + 1)$. Then, the original HRMET-generated ET_a for that date was compared with the reconstructed images. WPLI was implemented in MATLAB (The MathWorks Inc., 2023d) with the help of the following functions: *readgeoraster* from Mapping Toolbox (The MathWorks Inc., 2023c) (for importing HRMET-generated ET_a maps), *daysact* from Financial Toolbox (The MathWorks Inc., 2023a) (for calculating the difference between target dates and the mission dates), default functions such as, *readtable*, *strrep*, *linspace* for certain operations between different data-types. The rest of the algorithm was devised, designed and custom-implemented.

2.2.2.3 Forward Interpolation

Forward Interpolation (FI) uses a similar concept to WPLI. However, in this method, the value of any pixel in the spatial ET_a image is estimated from the previous mission(s) only. The goal of this method is to predict the ET_a based on ET_a -ET_c ratios ($C_{f_n}^{i,j}$ s from eqn. 5) from the previous mission(s) and the ET_c on the target day. In other words, past trends are projected into the future and this trend is used to predict spatial ET_a for each individual pixel using the concepts of geostatistical linear interpolation. In doing this, the equations of IDW (Lu & Wong, 2008) are modified to be unidirectional in the time-series scale. That means, in the time scale, all the known data points are in the past (in

one direction only) compared to the unknown data. The procedures for this method to approximate each $(i, j)^{\text{th}}$ pixel are as follows:

- $C_{f_n}^{i,j}$ for each $f_n \in \{f_1, \dots, f_k\}$ (the mission on date f_k and all its previous missions of the season) were calculated using eqn. 5. For example, to find the spatial ET_a for July 9, 2021 (a date with no mission), f_n included the missions on June 14, 2021, June 23, 2021, June 30, 2021, and July 8, 2021, respectively (here, f_1 refers to June 14, 2021, and f_k refers to July 8, 2021).
- Separate forward trends $F_{x_n}^{i,j}$ using each obtained $C_{f_n}^{i,j}$ were estimated using eqn. 6 in the interval $(f_k, f_{k+1}]$ (similar notation as eqn. 6). In practice, f_{k+1} can be any day in the future, but in this study, f_{k+1} denoted the next scheduled mission for evaluation purposes (see more details in the results section).
- For each day $x_n \in (f_k, f_{k+1}]$, the corresponding weight factor of each mission were calculated using the following equations.

$$\delta_{x_n, f_k} = x_n - f_k \quad (10)$$

$$w_{x_n, f_k} = \frac{\frac{1}{\delta_{x_n, f_k}}}{\sum_{f_k} \frac{1}{\delta_{x_n, f_k}}} \quad (11)$$

As depicted in equations 10 and 11, the weight factor for each previous mission, for a given day, is inversely proportional to the difference between that day and the corresponding mission (similar to the approach described in the case of WPLI, with the condition that the difference in days must be at least 1. Therefore, an open interval is used at the beginning). The obtained weights are then normalized in the following way.

$$\sum_{f_k} w_{x_n, f_k} = 1 \quad (12)$$

The ET_a value was approximated using all forward trends ($F_{x_n}^{i,j}$) and their corresponding weight factors (w_{x_n, f_k}) using the following equation.

$$y_{x_n}^{i,j} = \sum_{f_k} F_{x_n}^{i,j} w_{x_n, f_k} \quad (13)$$

Eqns. 10–13 show that the closer the missions from the target date, the more weights are assigned to the corresponding mission data.

Three variations of FI method were implemented, named FI-1, FI-2, and FI- ∞ , respectively. Forward Interpolation-1 (FI-1) considers only one previous mission, Forward Interpolation-2 (FI-2) considers the previous two missions and Forward Interpolation combined (FI- ∞) considers all the previous missions of the season while approximating the ET_a for any non-mission day. In a similar fashion, any variations of the FI method can be modeled (for example, FI- k , where $k = 1, 2, 3, 4, \dots$). The reason for adapting these variations was to see whether the value of ET_a for a specific date depends on the most recent field conditions, or all the past days since the beginning of the season.

The ET_c values measured by the point-based Arable Mark II sensors on the dates of different missions are shown as ET_c in Table 3 and were used to calculate $C_{f_n}^{i,j}$ ratios in eqn. 5. For performance evaluation, for each day of the season after the first mission (June 14, 2021), the previously available missions were used respectively. For example, for FI- ∞ , missions $(1 \dots k)$, $k \in [1, 7]$ were used to generate the spatial ET_a for mission $(k + 1)$. Then, the original HRMET-generated ET_a for the $(k + 1)$ mission was compared with the reconstructed image for that day. All variations of FI were implemented in MATLAB (The MathWorks Inc., 2023d) with the help of the following functions: *readgeoraster* from Mapping Toolbox (The MathWorks Inc., 2023c) (for importing HRMET-generated ET_a maps), *daysact* from Financial Toolbox (The MathWorks Inc., 2023a) (for calculating the difference between target dates and the mission dates), default functions such as, *readtable*, *strrep*, *linspace* for certain operations between different data-types. The rest of the algorithms were devised, designed and custom-implemented.

2.3 Model Efficiency and Evaluation Metrics

The effectiveness of the algorithms used in this study was tested using the following four error metrics—Mean Absolute Error (MAE) (Willmott & Matsuura, 2005), Root Mean Squared Error (RMSE) (Willmott, 1984), Nash-Sutcliffe model efficiency coefficient (NSE) (Nash & Sutcliffe, 1970), and Kling-Gupta Efficiency (KGE) (Gupta et al., 2009; Kling et al., 2012). The mathematical definitions of these metrics are provided in Online Resource 2.

2.4 Data Preprocessing

The multispectral and thermal images had different dimensions for each mission as shown in Table 2. Therefore, thermal images were resized (pixel size-enhanced) to 1527×3164 , and multispectral images to 2002×4166 for all the 4 channels using nearest-neighbor interpolation (Meijering, 2002). This step was implemented in MATLAB (The MathWorks Inc., 2023d) using the *imresize* function from the Image Processing Toolbox (The MathWorks Inc., 2023b). First, the daily ET_c trend was obtained by averaging the ET_c data from the three in-situ canopy sensors, expressed in $mm\ d^{-1}$ (shown in Fig. 4 and Table 3). This value was then converted to $mm\ hr^{-1}$ by dividing it by 24 hr.

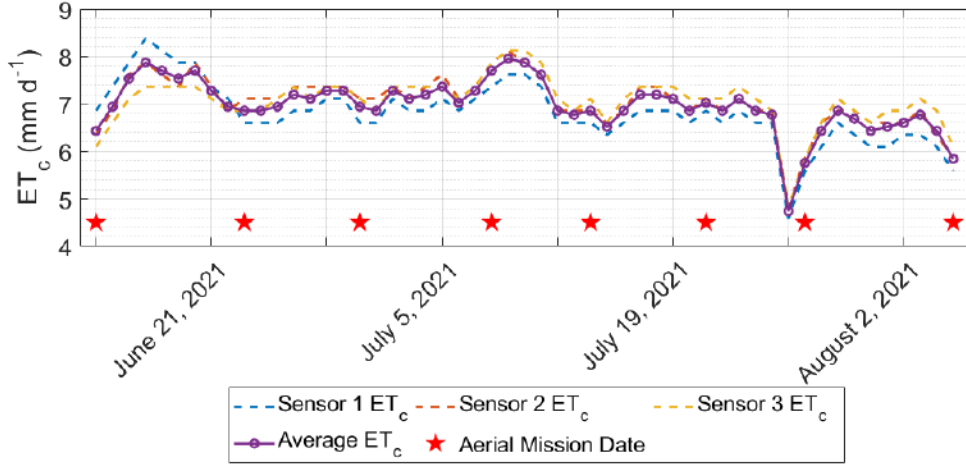


Fig. 4 Daily ET_c trends of the three Arable Mark II sensors located at the field along with their average values. The figure also shows the dates of aerial missions.

Table 3 Daily readings of some meteorological parameters on the missions—an average of the three field-installed Arable Mark II sensors in the growing season of 2021 (June–August)

Date (of 2021 season)	NDVI	Avg Air Temp (°C)	Max Air Temp (°C)	ET_c ($mm\ hr^{-1}$)	Min RH (%)	RH at Max Temp (%)	VPD (kPa)
June 14	0.77	21.93	29.26	0.25	0.32	0.43	11.7
June 23	0.83	21.67	30.07	0.27	0.33	0.35	12.0
June 30	0.86	22.33	30.74	0.27	0.51	0.53	9.7
July 08	0.87	22.91	35.13	0.30	0.32	0.34	13.7
July 14	0.85	20.85	29.78	0.27	0.38	0.42	11.0
July 21	0.83	21.91	32.39	0.28	0.29	0.30	13.0
July 27	0.80	23.67	31.22	0.23	0.30	0.32	16.0
August 5	0.76	21.29	29.46	0.23	0.38	0.46	11.0

The HRMET model estimates ET_a in units of $mm\ hr^{-1}$, using meteorological variables at hourly resolution. These instantaneous rates typically peak around solar noon due to maximum net radiation and incoming shortwave radiation, which enhance surface heating and vapor pressure gradients—key drivers of evapotranspiration (Zipper & Loheide, 2014).

Since the available spatial ET_a data was limited to instantaneous (hourly) estimates collected at varying times of day across different aerial mission dates, in order to approximate the daily total ET_a , the mean hourly ET_a for each day was calculated. These instantaneous values were typically recorded close to solar noon, when net radiation and vapor pressure gradients are strongest, leading to peak ET_a rates. While this approximation provides a daily-scale estimate, it does not capture the typical diurnal peak in ET_a that occurs around midday, a potential limitation of this approach.

2.5 Correlation Analysis and Feature Selection

Table 4 shows Pearson's Correlation Coefficients between the average of all pixel values in the HRMET-generated ET_a map (denoted as Mean ET_a) and different meteorological parameters on the missions. In practice, the coefficients with absolute values greater than 0.9 are considered very highly correlated, and those in the range of 0.7–0.9 are considered highly correlated (Calkins, 2005). From the table, the mean ET_a does not have a remarkably high correlation (greater than 0.9) with any of the meteorological parameters, but it has a high correlation (both positive and negative) with 9 parameters. The highest correlation (0.764) is with ET_c (canopy evapotranspiration). While considering the input variables of the spatiotemporal estimators, the interdependency of the canopy parameters was also considered. According to the interdependency of the predictors, if some predictor is itself derived using other predictors, using all the predictors as model input might negatively affect the model performance (Schneider et al., 2010). As the ET_c parameter in Arable Mark II sensors is calculated from other parameters such as temperature, humidity, radiation, wind speed, crop coefficient, NDVI, and field evapotranspiration, ET_c has an interdependency with all of the above parameters (Arable, 2021). Therefore, in this study, ET_c is the only parameter that was used to find the temporal variation of daily spatial ET. In other words, the effect of the other parameters was accounted for through ET_c .

Table 4 Pearson's Correlation Coefficients for the mean value of HRMET generated ET_a maps (Mean ET_a) with different meteorological parameters measured by the on-ground sensors (Arable) on the missions (Arable, 2021).

Parameter(s)	Correlation coefficients with Mean ET_a
Chlorophyll Index (cl)	0.556
Field Evapotranspiration (ET)	0.720
Canopy Evapotranspiration (ET_c)	0.764
Normalized Difference Vegetation Index (NDVI)	0.571
Minimum Relative Humidity (min rh)	0.067
Relative Humidity at Maximum Temperature (rh at max temp)	-0.110
Relative Humidity at Minimum Temperature (rh at min temp)	0.646
Heat stress hours (swdw)	0.702
Maximum Temperature of the day (max temp)	0.489
Average Temperature of the day (mean temp)	-0.342
Minimum Temperature of the day (min temp)	-0.702
Maximum Temperature at Dew Point (max temp dew)	0.523
Daily Precipitation Amount (precip)	0.586
Daily Precipitation Duration (precip hours)	0.586
Cumulative Precipitation Amount (cumulative precip)	0.058
Sea Level Pressure	-0.736
Vapor Pressure Deficit (vpd)	-0.315
Crop coefficient (K_c)	0.557
Leaf Wetness	0.721
Temperature at Dew Point (dew temp)	0.481
Crop Water Demand	-0.721
Sunshine Duration	0.737
Wind Speed	0.275

Wind Direction in Degrees	-0.753
Maximum Wind Speed (wind speed max)	-0.215
Minimum Wind Speed (wind speed min)	-0.125

3 Results

3.1 Timeseries Comparison between different interpolation methods:

To compare the effectiveness of the presented interpolation techniques (WPLI and FI) over standard baseline interpolation methods, including nearest-neighbor interpolation, linear interpolation, and spline interpolation (Meijering, 2002). In this regard, the comparison was performed during the first three aerial missions period (June 14–30, 2021), Sensor 1 ET_c daily measurements for this duration were used as a reference to model the temporal variation of ET_c . Meanwhile, Sensor 2 was treated as a test case, where only its daily ET_c measurements on the aerial mission days (June 14, 23 and 30, 2021) were used to reconstruct the full daily time series via interpolation.

The accuracy of each method was accessed by comparing the interpolated values to the actual daily ET_c measurements from Sensor-2. Among the baseline methods, spline interpolation performed best with an RMSE of 0.42 mm d^{-1} , followed by linear (0.58 mm d^{-1}) and nearest-neighbor (0.63 mm d^{-1}). In contrast, the proposed WPLI and FI methods achieved substantially lower RMSEs of 0.29 mm d^{-1} and 0.24 mm d^{-1} , respectively. The errors represent a 31% (WPLI) and 43% (FI) improvement over spline, and more than 60% improvement over nearest-neighbor interpolation. During this period, the actual daily ET_c from Sensor-2 had a mean of 7.27 mm d^{-1} and a standard deviation of 0.38 mm d^{-1} , highlighting the ability of the proposed methods to capture subtle, day-to-day variations with greater reliability.

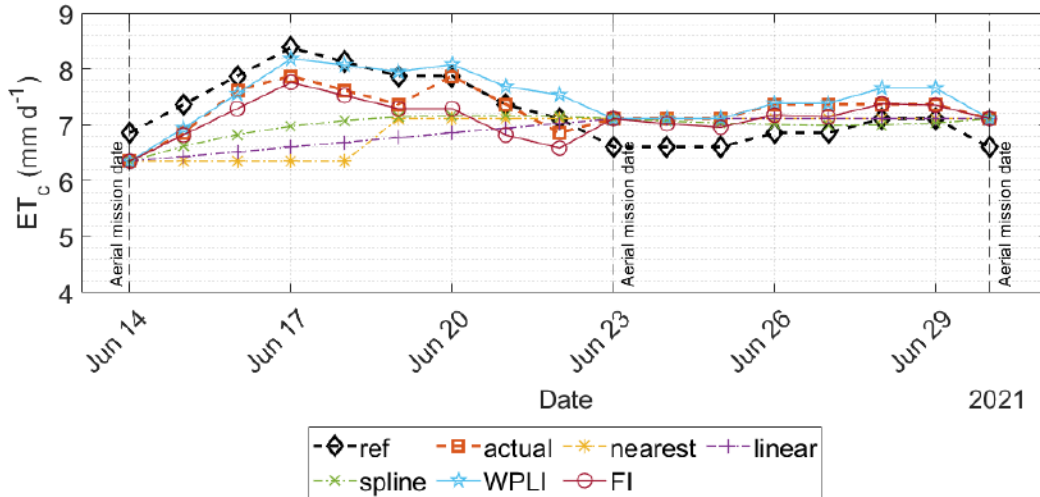


Fig. 5 Comparison between different baseline interpolation techniques (nearest-neighbor interpolation, linear interpolation, spline interpolation) and the novel interpolation techniques (WPLI and FI) presented in this paper. The figure also shows the daily ET_c measurements of Sensor 1 (marked as 'ref') and Sensor 2 (marked as 'actual') for the first three aerial missions in June 14, 23 and 30, 2021, respectively (Marked in dashed line).

3.2 Linear Regression (LR)

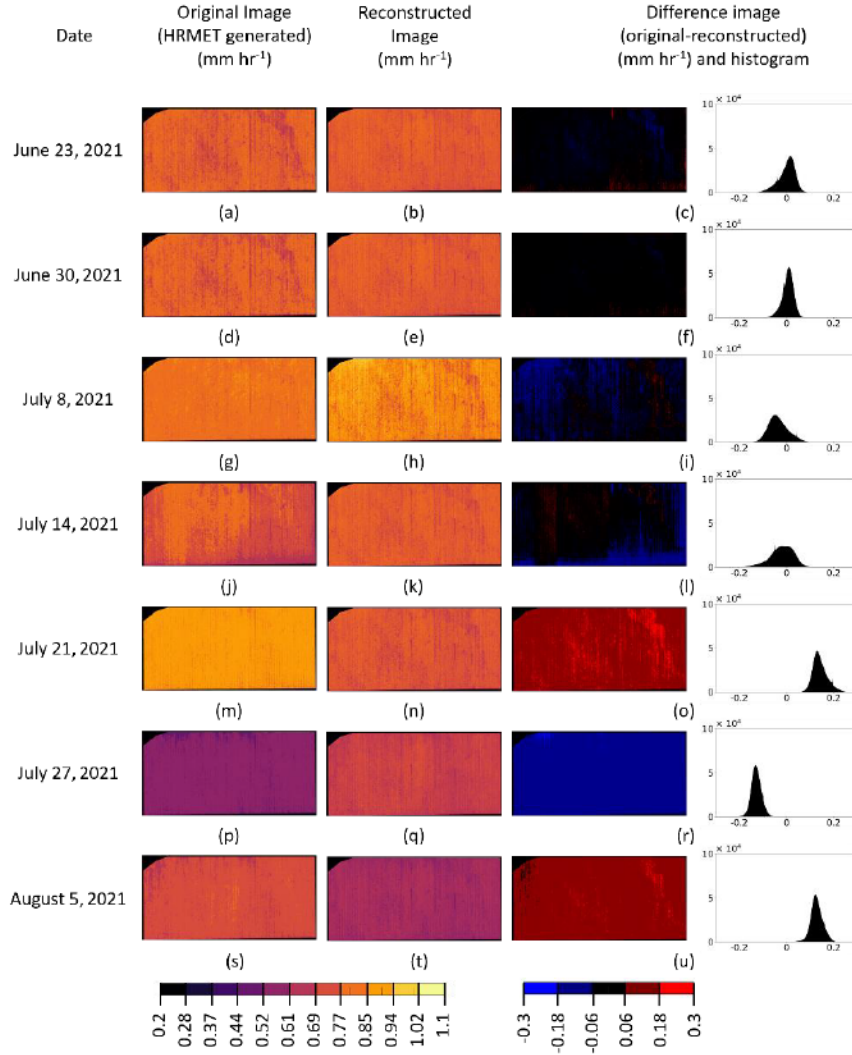


Fig. 6 (From left) Original (HRMET-generated) images, reconstructed images using LR^{all} , images showing the pixel-wise spatial difference in reconstruction and the histogram of the spatial difference for missions 2-8.

Fig. 6 shows the reconstructed images using LR^{all} , with the original HRMET-generated ones, the spatial differences (*original – reconstructed*) between the two images, and the histogram of the differences. Both original and reconstructed images were discretely scaled in the range of 0.2–1.1 mm hr⁻¹, whereas the difference images were scaled in a discrete progression in between -0.3–0.3 mm hr⁻¹. In the difference maps, when the original pixels have higher ET_a values than the reconstructed one, the respective areas are red (0–0.3 mm hr⁻¹ for positive errors) and in the opposite cases, the areas are blue (-0.3–0 mm hr⁻¹ for negative errors).

For missions 2 and 3 (June 23 and June 30, 2021), LR^{all} had high predictive efficiency, as shown by the difference maps that are mostly black, indicating errors in a range -0.06–0.06. The corresponding histograms of differences are mostly centered around zero, the means were 0.002 mm hr⁻¹ and 0.007 mm hr⁻¹ whereas, the standard deviations were 0.04 mm hr⁻¹, and 0.03 mm hr⁻¹, respectively.

During mission 4 (July 8, 2021), the spatial ET_a values generated by HRMET were slightly higher than before, which is reflected by an ET_c of 0.3 mm hr⁻¹ measured by in-field sensors (Table 3). Being the day that had the highest daily ET_c of the season, LR^{all} consequently produced a globally higher ET_a map. In this case, approximately 75% of pixels had ET_a values that are overestimated by LR^{all} compared to HRMET, with errors in a range of -0.18–0.07 mm hr⁻¹.

In the case of mission 5 (July 14, 2021), the HRMET-generated ET_a map shows a vertical band of higher ET_a rates (in between 0.8–0.9 mm hr⁻¹), whereas the bottom right corner has lower ET_a rates (in between 0.5–0.6 mm hr⁻¹). As can be seen by the difference map, LR^{all} missed this spatial variability estimated by HRMET. Instead, LR^{all} generated an ET_a map that is more spatially uniform, with ET_a values between 0.7–0.9 mm hr⁻¹. The center of the field is reasonably approximated by LR^{all} , with 75% pixels that are black in the difference map (errors in the range of -0.06–0.06 mm hr⁻¹).

For mission 6 (July 21, 2021) and mission 7 (July 27, 2021), the HRMET-generated ET_a maps exhibit differences in value, showing the highest and lowest ET_a rates of the season, respectively. However, these extremes were not clearly reflected in the daily ET_c measured by in-field Arable Mark II sensors. For instance, despite showing significantly higher ET_a rates than during the previous mission, July 21 had a daily ET_c of 0.28 mm hr⁻¹, which is only 0.01 mm hr⁻¹ higher than during July 14 (Table 3). For this reason, LR^{all} strongly underpredicted ET_a for this day. On the other hand, July 27th showed significantly lower ET_a rates while LR^{all} overpredicted it, despite producing a map that has globally lower ET_a than for previous missions.

Finally, the HRMET-generated map from mission 8 (August 5, 2021) has values that are closer to those observed during the early period of the season (e.g., June 23 and 30). However, the daily ET_c measured by in-field sensors was especially low (0.23 mm hr⁻¹, see Table 3). Consequently, LR^{all} produced an ET_a map that underpredicted the values of the HRMET-generated map.

3.3 Weighted Piece-wise Linear Interpolation (WPLI)

The spatial ET_a maps for the missions obtained using HRMET were used to predict the daily ET_a maps between the missions with the help of WPLI. For performance evaluation, each of missions 2–7 was used for testing. To generate spatial ET_a for each of these mission dates, the previous mission and the next mission were used, along with their corresponding ET_c from Table 3. For example, missions 1 and 3 were used to generate the spatial ET_a for the days in between, which included the date for mission 2. During the time of image prediction, the algorithm did not have any knowledge about mission 2—it considered that day as any other days. After interpolating the image for the same day as mission 2, the predicted (reconstructed) image was compared against the original HRMET generated image. Similarly, missions 6 and 8 were used to reconstruct the spatial ET_a for mission 7 and compared against the HRMET generated image (original) for the same day.

Fig. 7 shows the original HRMET generated images, reconstructed images using WPLI, and the spatial differences (*original – reconstructed*) between the two images. The scaling in this figure and the notation of the scales are the same as Fig. 6.

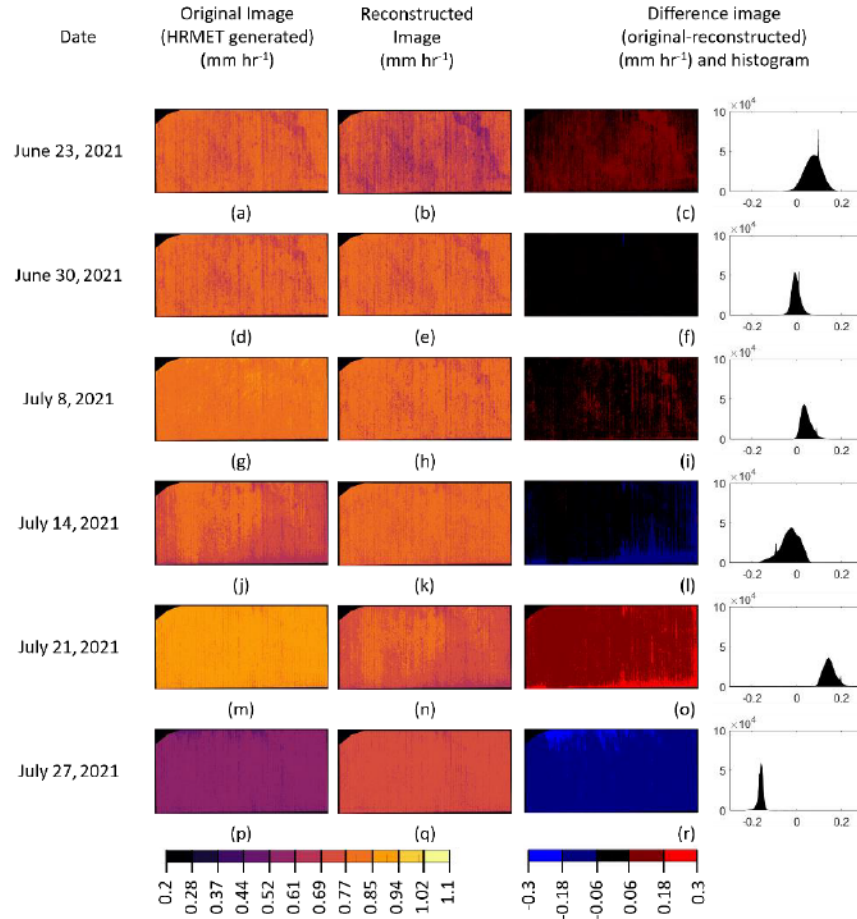


Fig. 7 (From left Original (HRMET-generated) images, reconstructed images using WPLI, images showing the pixel-wise spatial difference in reconstruction and the histogram of the spatial difference for missions 2–7.

Original images (Fig. 7) are specific for the date and time of the mission, whereas the reconstructed images show the average hourly ET_a map for the day. For the reconstruction of the ET_a map on the same date as mission 2 (June 23, 2021), the original maps from mission 1 (June 14, 2021) and 3 (June 30, 2021) were used. In the case of mission 1, there were a significant number of pixels (noticeable at the top right portion of the image, covering around 10% of the total area) showed relatively lower ET_a values (in between 0.3–0.4 mm hr⁻¹) compared to the rest of the field (that falls in the range of 0.5–0.7 mm hr⁻¹). These lower ET_a pixels indicate that the canopy cover in those areas were comparatively less, with significant reflectance captured from soils, resulting in a lower ET_a value from crops. However, for mission 3, most of those pixels' ET_a increased a significant portion (raising to at least 0.5 mm hr⁻¹). But as the reconstructed image was interpolated between the very low (in between 0.3–0.4 mm hr⁻¹) and a higher ET_a value (in between 0.5–0.6 mm hr⁻¹), for those pixels, the error (*original* – *reconstruction*) value was much higher (in the range of 0.07–0.18 mm hr⁻¹). This explains the spike in the corresponding histogram of the error (at about 0.1 mm hr⁻¹ in the x-axis).

The reconstructed image for mission 3 (June 30, 2021), the spatial canopy coverage looks very similar to that of mission 2 (June 23, 2021) based on the ET_a range (in between 0.4–0.7 mm hr⁻¹) and spatial variability. Therefore, the corresponding reconstruction error was smaller (less than ± 0.06 mm hr⁻¹). The smaller spike in the error histogram (magnitude 25% less than that of mission 2 and location at about 0.01 mm hr⁻¹) was plausibly due to the similar reason discussed above.

At mission 4 (July 8, 2021) the canopy almost completely covered the ground (reducing the visible distinction between the brighter pixels and the darker pixels), and the original image had higher ET_a values than those for all the previous missions (in the range of 0.7–0.9 mm hr⁻¹). At the same time, the corresponding ET_c measurement was higher (0.3 mm hr⁻¹) than the previous mission dates (0.25, 0.27 and 0.27 mm hr⁻¹, respectively) as shown in Fig. 4 and Table 3.

Therefore, except for the specific pixels showing high temporal variability (an increase in ET_a by about 0.3 mm hr^{-1}), the rest of the reconstruction was moderately accurate (with a mean of 0.04 mm hr^{-1} and a standard deviation of 0.03 mm hr^{-1}). The error distribution in the histogram was less than 0.1 mm hr^{-1} for the most part, with a short spike of 1×10^4 pixels located at approximately 0.075 mm hr^{-1} .

At mission 5 (July 14, 2021), the original ET_a map indicated higher spatial variability in a band in the top left and mid-left section (covering around 40% of the total area on) showing relatively higher ET_a (in the range of $0.6\text{--}0.7 \text{ mm hr}^{-1}$) than the bottom right corner, that covers about 5% of the total area, ET_a values being around 0.4 mm hr^{-1} . But because the ET_c for the day was relatively lower (0.27 mm hr^{-1} whereas that of mission 4 was 0.30 mm hr^{-1}), the reconstruction followed that trend with the lower value. At the same time, WPLI used the data from mission 6 (July 21, 2021), which was unusually high itself (in the range of $0.9\text{--}1.0 \text{ mm hr}^{-1}$). Hence, the reconstruction for mission 5 date was relatively on the higher end (around $0.7\text{--}0.8 \text{ mm hr}^{-1}$), resulting in a negative error around the bottom right corner (about 10% of the area that shows relatively lower ET_a value (around 0.4 mm hr^{-1}) in the original image).

This variability (at mission 5) can be accounted on the reconstructed image of mission 6 (July 21, 2021) image. However, the spatial ET_a for that day was significantly higher (around $0.9\text{--}1.0 \text{ mm hr}^{-1}$) compared to the ET_c (Fig. 4) point measurement on that day (0.28 mm hr^{-1}). At the same time, the reconstruction image used data from mission 7 (July 27, 2021) that consists of relatively lower spatial ET_a pixels than all other missions (in the range of $0.3\text{--}0.4 \text{ mm hr}^{-1}$). Which is why the reconstruction of July 21, 2021, showed comparatively lower values (around 0.6 mm hr^{-1} , with some patches in the left side covering around 40% of the total area with ET_a values around 0.7 mm hr^{-1}). At the same time, the lower ET_a values (around $0.4\text{--}0.5 \text{ mm hr}^{-1}$) in the bottom right corner (about 10% of the area that shows relatively higher reconstruction error value, around $-0.18\text{--}0.07 \text{ mm hr}^{-1}$) obtained from mission 5 image was reflected on the reconstruction of mission 6. That is why, on the corresponding reconstruction difference image, the same pixels had higher reconstruction errors (in the range of $0.19\text{--}0.3 \text{ mm hr}^{-1}$).

Even though the similar error was expected in the reconstruction image for mission 7 (July 27, 2021) as it uses the high ET_a data (in the range of $0.9\text{--}1.0 \text{ mm hr}^{-1}$) from HRMET generated mission 6 (July 21, 2021) image, the corresponding ET_c for July 27, 2021, showed a relatively lower value (0.23 mm hr^{-1}). This resulted in a negative error, in the range of $-0.18\text{--}0.07 \text{ mm hr}^{-1}$, with the top left corner (about 5% of the total area) showing bright blue spots (reconstruction error in the range of $-0.3\text{--}0.19 \text{ mm hr}^{-1}$). The corresponding mean error was -0.16 mm hr^{-1} , with a standard deviation of 0.01 mm hr^{-1} . The corresponding error histogram is thus skewed left, centered at -0.18 mm hr^{-1} . The variation is not as high as the reconstructed image of July 21, 2021.

3.4 Forward Interpolation (FI)

Similar to WPLI, the ET_a (HRMET) maps on the missions were used as inputs to generate the intermediate maps with the help of FI_{∞} . The ET_c from Table 3 was used to calculate the ratios of the previous missions. For the performance assessment, for each of the missions between 2–8, the previous mission images have been used and compared with the original HRMET images on the respective missions.

Fig. 8 shows the original images from HRMET, reconstructed images using FI_{∞} , and the spatial differences (*original* – *reconstructed*) between the two images. The scaling in this figure and the notation of the scales are same as Figs. 6 and 7.

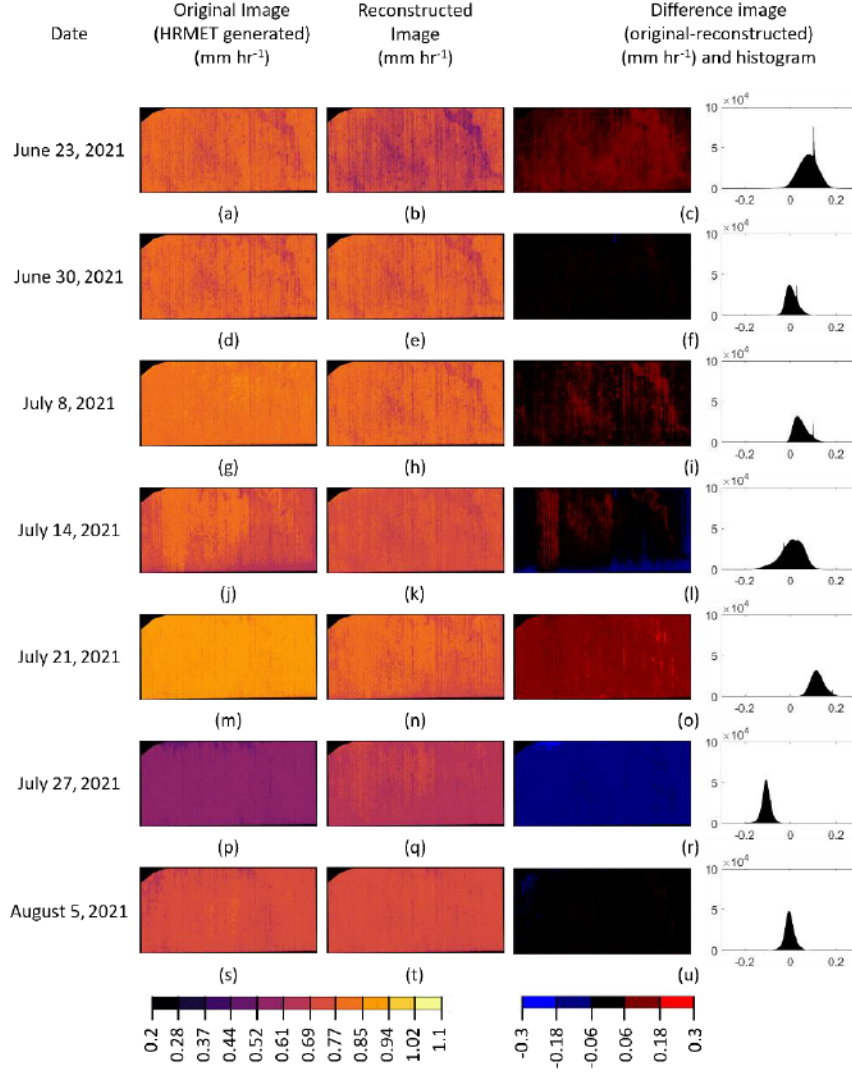


Fig. 8 (From left) Original (HRMET-generated) images, reconstructed images using FI- ∞ , images showing the pixel-wise spatial difference in reconstruction and the histogram of the spatial difference for missions 2–8.

While HRMET is mission date/time specific, both the interpolation methods (WPLI and FI- ∞) provide an hourly ET_a estimate for each day near solar noon. Nevertheless, the FI- ∞ reconstructed images show different values than WPLI reconstructed images because FI- ∞ only uses the data from the previous missions, whereas WPLI uses both a past and a future mission. To reconstruct the image on mission 2 (June 23, 2021), FI- ∞ only used the data from mission 1 (June 14, 2021). Therefore, in the FI- ∞ reconstructed image for that date, the pixels which had relatively lower ET_a value (in between 0.3–0.5 mm hr $^{-1}$) on mission 1 (meaning that those pixels were not covered by canopy yet) also showed to have low ET_a value (in between 0.3–0.5 mm hr $^{-1}$), while those pixels in the original image for that day was in the range of 0.5–0.6 mm hr $^{-1}$. This explains the spike in the corresponding histogram of the error (at about 0.1 mm hr $^{-1}$ in the x-axis). Similarly, the error histogram in case of mission 3 (June 30th, 2021) has a spike. Although for this image, the magnitude of the spike is relatively smaller (about half of the previous magnitude for mission 2 reconstruction error) because some of the canopy growth (and hence the relevant pixels showing a higher ET in the range of [0.5,0.6] mm hr $^{-1}$) were already observed in mission 2 (June 23, 2021) image. In other word, the reconstruction image for mission 3 could not capture the canopy full coverage based on the missions 1 and 2 image, resulting in some positive errors (with a mean of 0.007 mm hr $^{-1}$ and a standard deviation of 0.03 mm hr $^{-1}$).

Despite the higher ET_c observed on July 8, 2021, in mission 4, FI- ∞ utilized HRMET-generated images from prior missions with comparatively lower ET_a (in the range of 0.4–0.6 mm hr $^{-1}$). Therefore, for those pixels, the error was

much higher compared to the rest of the pixels (in the range of 0.07–0.18 mm hr⁻¹, with a mean of 0.05 mm hr⁻¹ and a standard deviation of 0.04 mm hr⁻¹). This error is also observed as a spike around 0.1 mm hr⁻¹ in the histogram.

Similar to WPLI, for mission 5 reconstructed images (July 14, 2021), the spatial variability of the ET_a on that day was not captured due to a point ET_c reading and lack of similar variability in the images from the previous missions (as mentioned in the description of Fig. 7). For that reason, the comparatively higher ET_a pixels in the top left section and mid-left (covering around 40% of the total area) caused positive error in the difference image (around 15% of the total area, error in the range of 0.07–0.18 mm hr⁻¹). Similarly, the lower ET_a pixels in the bottom right corner (about 5% of the total area) caused negative errors in the difference image (in the range of -0.18–0.07 mm hr⁻¹). The corresponding error was, therefore, more spread (also observed in the histogram), with a mean of 0.006 mm hr⁻¹ and a standard deviation of 0.05 mm hr⁻¹.

An interesting reconstruction is observed during mission 6 (July 21, 2021). Even though the ET_c did not reflect the high spatial ET_a values (as mentioned in the description of Fig. 7), unlike WPLI, FI-∞ does not use the lower ET_a map from mission 7 (July 27, 2021). Hence, the reconstruction error was smaller (mostly in the range of 0.07–0.18 mm hr⁻¹, with a few bright red spots across the image indicating the corresponding error was in the range of 0.19–0.3 mm hr⁻¹) compared to the LR and WPLI images. However, until this date, the reconstructed image had comparatively higher error in the top right lower ET_a section (about 10% of the total area, more visible at the beginning of the season, ET_a values in the range of 0.4–0.6 mm hr⁻¹). Both mission 6 (July 21, 2021) and 7 (July 27, 2021) reconstructed images still had some spatial variability from that of mission 5 (July 14, 2021)—the former showing it more prominently than the latter (because of the proportional difference of the days). In case of mission 7 (July 27, 2021), despite the daily ET_c being lower (0.23 mm hr⁻¹ as opposed to 0.27–0.3 mm hr⁻¹), the most importance was given on the unusually higher spatial ET_a from mission 6 (July 21, 2021). This caused an overall negative reconstruction error (in the range of -0.18–0.07 mm hr⁻¹, with a mean of -0.11 mm hr⁻¹, a standard deviation of 0.03 mm hr⁻¹ and left skewed error histogram (centered around -0.15 mm hr⁻¹).

Finally, during the last mission (August 5, 2021), the previous two images used in the reconstruction showed higher and lower ET_a values compared to all other HRMET-generated images. But as the daily ET_c and spatial ET_a ratio were proportionate with most of the missions in the season, the reconstruction had very low errors (in the range of ±0.05 mm hr⁻¹). Most of the errors for this date were due to the lower ET_a values near the top left section (about 5% of the total area) of the ET_a map on this date.

3.5 Performance Evaluation

Table 5 evaluates the performance of the three different techniques used in this paper (LR, WPLI, FI) using four model efficiency metrics (NSE, MAE, RMSE, KGE) and shows their average performance for the mission dates (missions-specific efficiency are provided in Online Resource 3). The table quantifies the reconstruction errors, as shown in column 3 of Figs. 6, 7 and 8, with the help of these error metrics. The performance of LR^{all} was comparable to WPLI and FI to predict in-between days (in terms of MAE, RMSE and KGE scores). The results also show that LR^{t-1} was less efficient to predict future ET_a maps based on previous observations. This is most likely due to the lack of sufficient temporal data points per pixel and existence of non-linear parameters responsible for plant growth (Paine et al., 2012). As LR tried to fit a line through very few data points, it was strongly sensible to noise or random variations. WPLI showed better NSE and KGE scores than LR^{all} as instead of fitting a line through all data points, WPLI used a piecewise linear model, therefore it captured the temporal variability more efficiently, resulting in a lower error variance. However, WPLI only used one past mission, whereas FI used all available past missions, leading to obtaining the best scores for all four metrics.

Table 5 Average efficiency of LR^{all} , LR^{t-1} , WPLI, FI with four different error metrics (NSE, MAE, RMSE, KGE) for the growing season of 2021 (June–August). Pixel-wise errors were first calculated for each aerial mission, then averaged across the field, and finally averaged across all test days. MAE and RMSE are reported in units of mm hr⁻¹.

Evaluation Metric	LR^{all}	LR^{t-1}	WPLI	FI
NSE	-6.88	-6.084	0.57	0.694
MAE	0.077	0.159	0.078	0.06
RMSE	0.084	0.177	0.087	0.07
KGE	0.503	-0.104	0.855	0.894

Here to be noted that RMSE and MAE values reported in Table 5 were calculated on a pixel-by-pixel basis for each aerial mission day, with the missions-specific values provided in Online Resource 3. Specifically, for each pixel, the difference between interpolated ET_a and actual HRMET-generated ET_a values for that date. These pixel-level errors were then averaged across the entire map to obtain a single MAE and RMSE value for that mission. Finally, the summary values reported in Table 5 are the averages of these map-level errors across all aerial missions in the 2021 growing season.

To provide a clearer interpretation of the interpolation errors, we also computed normalized RMSE (nRMSE) and normalized MAE (nMAE) by dividing each metric by the corresponding actual ET_a value for each aerial mission date, then averaging across all valid dates. For the FI method, the nRMSE and nMAE were 9.36% and 8.21%, respectively. For WPLI, the nRMSE and nMAE were 12.10% and 11.05%, respectively. These values complement the absolute error metrics in Table 5 by offering a relative assessment of model performance across the growing season, which is particularly helpful given the variability of ET_a magnitudes across dates and locations.

Table 6 compares the efficiency of the three different types of forward interpolation (FI-1, FI-2, FI- ∞) with the help of the four error metrics and shows their average performance for the mission dates. Results show that FI-2 obtained the best NSE score, FI- ∞ obtained the best MAE and KGE scores. Best RMSE score was combinedly achieved by both FI-2 as well as FI- ∞ .

Table 6 Average efficiency of 3 different types of forward interpolation (FI-1, FI-2, FI- ∞) with different error metrics (NSE, MAE, RMSE, KGE) for the growing season of 2021 (June– August). Pixel-wise errors were first calculated for each aerial mission, then averaged across the field, and finally averaged across all test days. MAE and RMSE are reported in units of mm hr^{-1} .

Evaluation Metric	FI-1	FI-2	FI- ∞
NSE	0.611	0.723	0.694
MAE	0.073	0.061	0.06
RMSE	0.08	0.07	0.07
KGE	0.86	0.889	0.894

4 Discussions

4.1 Spatiotemporal ET_a estimation approach:

This study introduces two piecewise linear interpolation methods (WPLI and FI) for estimating daily ET_a on a high-resolution spatial scale in agricultural fields. The process involves combining daily infield biophysical measurements with model-based spatial ET_a estimation, collected on different days through aerial missions. In this regard, two variations of LR are used to model the relationship between daily ET_c and the corresponding ET_a for each pixel, assuming a linear relationship. Despite previous research endeavors into spatiotemporal estimation of plant evapotranspiration (Cammalleri et al., 2013; Semmens et al., 2016; Yang et al., 2017), the approach presented in this study may offer some significant advancements. Previous studies have used techniques like linear interpolation (Mokhtari et al., 2021), spline interpolation and smoothing filters (Cammalleri et al., 2013) for the temporal gap-filling and approximation. While these approaches have worked well for function generalization, they may not be capturing the day-to-day temporal variability. In this study, the day-to-day temporal variability was particularly emphasized and has been modeled exactly as it is (with a piecewise linear representation assuming no error in the sensors) in contrast to a temporal linear or polynomial progression. Therefore, this innovative technique effectively captures the actual temporal variability, with an RMSE range of 0.02–0.16 mm hr^{-1} for the test days (detailed efficiency are provided in Online Resource 3).

Data-driven methods like LR, WPLI and FI are independent of the image size and resolution – hence can be applied to very high-resolution spatial images. They also work very fast (with only polynomial time complexity) and are deterministic in nature (for a specific set of input values, the corresponding output always converges to the same number). These methods, being empirical, are also interpretable and easy-to-implement. Moreover, these spatiotemporal estimators can be implemented with any high-resolution spatial generation ET_a models such as, OSEB (Su, 2002), TSEB (Norman et al., 1995), DTD (Hoffmann et al., 2016), DATTUTDUT (Timmermans et al., 2015), SEBAL (Xia et al., 2016) instead of HRMET (Zipper & Loheide, 2014). Thus, the data-driven method presented in this study offers flexibility of selection of spatial generation models.

Additionally, the use of infield sensors as inputs made the fusion approach used in this study both site and crop specific. The sensors capture crop phenology through biophysical measurements being in the same location as the crops. Finally, much of the existing research has focused on gap-filling between two past dates, while this work developed approaches for predicting the spatial ET_a for a future date. One of the spatiotemporal estimators presented in this study, the FI method, has the ability to predict daily spatial ET_a for a future date in combination with an external daily ET_c predictor.

Although the final ET_a estimates are reported as average hourly estimates per day, they are retained at a 5 m spatial resolution, matching the output resolution of the HRMET model and enabling detailed field-scale analysis. This high spatial granularity is essential for capturing within-field variability in crop water use, which would otherwise be lost in coarser-resolution products. Maintaining such spatial detail is especially beneficial for precision irrigation, as it supports zone-specific water management decisions, particularly in fields with heterogeneous soil or canopy conditions. Recent studies (Ebert et al., 2022; Gao et al., 2023; Bambach et al., 2024) also emphasize the utility of very high-resolution ET data for monitoring crop water demand and optimizing irrigation. Furthermore, the interpolation framework developed in this study is resolution-agnostic and can flexibly accommodate input from any high-resolution ET_a model, not just HRMET. Thus, although the temporal resolution is limited to daily aggregates due to sensor constraints, the spatial richness of the ET_a estimates remains fully leveraged in both analysis and practical application.

4.2 Importance of ET_a prediction in precision irrigation management:

Accurate ET_a estimation is crucial for irrigation scheduling, ensuring that crops receive adequate water without excessive irrigation, which can lead to water wastage and environmental degradation (Ghiat et al., 2021; Zhang et al., 2024). In this study, the presented spatiotemporal estimation techniques (LR, WPLI and FI) can accurately estimate ET_a under favorable conditions (where both on-the-ground sensor measurements and the aerial imagery show similar values), aiding farmers in effective irrigation scheduling. However, the results also highlight challenges in capturing spatial variability in ET_a in some cases. For example, in mission 5, the predictors fail to capture the vertical band of higher ET_a rates observed in the HRMET-generated map, resulting in a more spatially uniform ET_a map. This limitation can have implications for precision irrigation management, as accurate knowledge of spatial variability in ET_a is essential for targeted water application to areas with higher water demand (Niu et al., 2020).

4.3 Limitations and future work:

The three approaches for temporal ET_a prediction in this study (LR, WPLI, and FI) either directly (LR) or indirectly (WPLI and FI) use the daily sensor calculated ET_c to approximate the spatial ET_a . LR maps a linear relationship between the ET_c and the spatial ET_a individually for each pixel. Whereas WPLI and FI extract a piecewise linear time-series trend from the daily ET_c and use that trend to temporally gap-fill for each pixel between two mission dates. Both the approaches require a high correlation between the spatial ET_a and the ET_c . However, from Table 4, the Pearson correlation between mean spatial ET_a for each mission and the corresponding ET_c is 0.764, which falls in the 'highly correlated' region (Calkins, 2005). In addition, HRMET provides an hourly estimate of spatial ET_a specific to the mission date and time. Most of the HRMET-generated values range between 0.46–1.03 mm hr⁻¹ with a median of 0.75 mm hr⁻¹ whereas, the hourly sensor calculated ET_c values range between 0.1–0.9 mm hr⁻¹ with a median of 0.2 mm hr⁻¹ (the average daily trend shown in Fig. 4). Hence, the data obtained from two different sources (HRMET-generated and infield sensors calculated) follow different probability distributions. Especially, for some dates, such as mission 6 date (July 21, 2021), the range of spatial ET_a values and the corresponding ET_c show very different values, as described in the results section. This difference in the data obtained from different sources limits the accuracy of the statistical ET_a estimators.

However, solar radiation also had a strong effect on the ET_a predictions. During the mission of July 27, 2021, the solar radiation measured by CIMIS sensors showed an abrupt increase from a relatively low value (451 Wm⁻² at 11 am) to a higher value (815 Wm⁻² at 12 pm), respectively, while the mission was at 11:25 am. For comparison, solar radiation was typically around 800–900 Wm⁻² in the case of other missions. For instance, solar radiation ranged from 889–959 Wm⁻² on July 14 between 11 am and 1 pm, while the mission was at 12:15 pm. Since HRMET outputs highly depend on solar radiation (Zipper & Loheide, 2014), it is likely that the generated ET_a map has consequently lower rates for this period of the day on July 27, 2021. As the spatiotemporal estimators used the spatial ET_a and sensor ET_c on July 27, 2021, to reconstruct the map of other missions, the reconstructions were affected by this unusually low solar radiation. This abrupt change in solar radiation may have been due to temporary cloud cover, which highlights a

broader limitation of the interpolation approach: on cloudy or overcast days, the underlying assumption of smooth temporal transitions may break down, making the interpolation less meaningful unless such atmospheric disturbances are explicitly accounted for.

For prediction purposes, the daily ET_c (converted to mm hr^{-1}) was used from the sensors, but the HRMET-generated ET_a maps only represent a specific hour of the day (close to the solar noon flight time). This limitation can be addressed by collecting more data during different hours of the day and from different fields of the same crop type, allowing the regression algorithm to more effectively generalize to different data collection protocols. In addition, a multi-input nonlinear model can be explored for mapping the relationship between spatial ET_a and meteorological parameters such as solar radiation. With proper formulation, the model would be able to detect any sudden data fluctuation (for example, cloud coverage on a particular location in the field) and adjust the corresponding ET_a values accordingly.

In this work, an important assumption was that the ET_c maintains a linear relation with the spatial ET_a , and the changes in the ET_c values are piecewise linear with time. These data were based upon one agricultural field and specific crop type. However, the algorithms can be further explored for other crops and in other agro-ecological regions. The investigation conducted in this study show that weather parameters like solar radiation strongly affects the HRMET-generated maps, that can be further investigated (Ahmadi et al., 2022; Andresen & Pollyea, 2012). Other publicly available open resources (e.g., satellite imagery data from Sentinel 2, Landsat 8 and PlanetScope satellites) can be included to establish the model. Due to the variability of these parameters—often presented as time series—there is opportunity to explore the fields of sequential decision-making and modular learning.

Additionally, the use of nearest-neighbor interpolation for resizing reflectance images (Table 2), although chosen to preserve raw pixel values, may lead to spatial misalignments or artifacts, particularly along field boundaries or in regions with sharp reflectance gradients. Future work can evaluate alternative resampling methods such as bilinear or spline interpolation, quantifying their effect on ET_a prediction accuracy to enhance spatial robustness.

The temporal inconsistency between daily and hourly values poses a limitation in our analysis, as the hourly ET_a measurements do not fully reflect the diurnal variation in evapotranspiration, particularly the midday peak. While the daily ET_a can be approximated from the mean of hourly estimates, this simplification may lead to some inaccuracies in capturing peak ET_a values. Future studies will seek to integrate spatial ET_a sources that provide complete daily totals, which would address this issue and offer more accurate diurnal representations.

5 Conclusion

Due to the high-water demand and electricity usage, optimization of irrigation is one of the biggest challenges faced by the farmers and producers in the drought-prone areas. Various precision irrigation technology such as remote sensing, aerial imaging, on-the-ground monitoring, and control can help fight this water scarcity with efficient irrigation planning.

In this regard, this paper presents three different procedures (LR/WPLI/FI) to determine the daily field-scale evapotranspiration (ET_a) in a field on a spatial scale combining daily biophysical measurements and spatial ET_a data on a different day. The pipeline for the daily spatial ET_a generation process involves collecting aerial imagery (reflectance and thermal) on certain dates, resizing the images (pixel size enhanced), using HRMET to obtain spatial ET_a for those dates with the help of meteorological data from the nearest weather station, soil and canopy emissivity and albedo. These HRMET-generated ET_a maps are then used as an input for the approximation algorithms, along with the target date range and the daily ET_c obtained from Arable sensors, both on the missions and the target dates. The output of the pipeline is the daily ET_a maps for the field. Results show that the three specific variations of spatiotemporal estimation techniques (LR^{all} , WPLI, FI- ∞) are able to create daily ET_a maps for the whole season within an error range of 0.02–0.16 mm hr^{-1} for MAE and 0.02–0.16 mm hr^{-1} for RMSE.

The performance of the three approaches (LR/WPLI/FI), along with their variations, was evaluated using four efficiency metrics calculated using the reconstructed images and the original HRMET images from the respective missions. Results show that in between the two interpolation techniques, WPLI is useful for filling in the gaps between two dates. However, FI can create an ET_a map for a future date based on the past images and the ET_c value for that day. Nonetheless, even on some days when some of the readings show more deviated values than usual (July 21 and July 27), the FI can create the ET_a maps for those days within an RMSE range of 0.11–0.12 mm hr^{-1} .

While the model output is a single daily average ET_a value per pixel, this study offers a rare combination of consistent daily estimates at very high spatial resolution (5 m)—a scale often constrained by the limited frequency of aerial missions. Compared to monthly ET products or those derived only from sparse aerial imagery, our method provides a more regular temporal resolution that aligns with field-level irrigation needs. This framework can enhance the understanding of how meteorological and plant health parameters influence ET_a , enable data-driven methods for identifying the important features that affect the ET_a on a plant scale, and inform practitioners of irrigation optimization techniques based on the day-ahead to week-ahead predictions of spatial ET.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability Statement

The data supporting the findings of this study are available within the article and its supplementary materials. Additional data may be provided by the corresponding author upon reasonable request.

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References

- Ahmadi, A., Daccache, A., Snyder, R. L., & Suvočarev, K. (2022). Meteorological driving forces of reference Evapotranspiration and their trends in California. *Science of The Total Environment*, 849, 157823.
- Andresen, J., & Pollyea, A. (2012, July 25). *What is evapotranspiration and why it matters*. Michigan State University Extension. Retrieved August 7, 2023, from [https://www.canr.msu.edu/news/what_is_evapotranspiration_and_why_it_matters#:~:text=Three%20of%20the%20factors%20\(solar,atmosphere%2C%20the%20less%20that%20can](https://www.canr.msu.edu/news/what_is_evapotranspiration_and_why_it_matters#:~:text=Three%20of%20the%20factors%20(solar,atmosphere%2C%20the%20less%20that%20can)
- Arable. (2021, May). *ARABLE MARK 2 MEASUREMENTS*. Arable Labs, Inc. Retrieved August 16, 2024, from https://www.arable.com/wp-content/uploads/2021/10/Arable-Mark-2-Measurements-21_05.pdf
- Bambach, N., N., Knipper, K., McElrone, A. J., Nocco, M., Torres-Rua, A., Kustas, W., Anderson, M., Castro, S., Edwards, E., Duran-Gomez, M., Gal, A., Tolentino, P., Wright, I., Roby, M., Gao, F., Alfieri, J., Prueger, J., Hipps, L., & Saa, S. (2024): The Tree-Crop Remote Sensing of Evapotranspiration Experiment (T-REX): A Science-Based Path for Sustainable Water Management and Climate Resilience. *Bulletin of the American Meteorological Society*, 105(1), E257–E284, <https://doi.org/10.1175/BAMS-D-22-0118.1>.
- Benedetti, R., & Rossini, P. (1993). On the use of NDVI profiles as a tool for agricultural statistics: The case study of wheat yield estimate and forecast in Emilia Romagna. *Remote Sensing of Environment*, 45(3), 311–326. [https://doi.org/10.1016/0034-4257\(93\)90113-C](https://doi.org/10.1016/0034-4257(93)90113-C)
- Berger, M. A., Hans, L., Piscopo, K., & Sohn, M. D. (2016). Exploring the Energy Benefits of Advanced Water Metering. *Energy Analysis and Environmental Impacts Division Energy Technologies Area*, 1–53.

- Berti, A., Tardivo, G., Chiaudani, A., Rech, F., & Borin, M. (2014). Assessing reference Evapotranspiration by the Hargreaves method in north-eastern Italy. *Agricultural Water Management*, 140, 20–25.
- Bisquert, M., Sánchez, J. M., López-Urrea, R., & Caselles, V. (2016). Estimating high resolution evapotranspiration from disaggregated thermal images. *Remote Sensing of Environment*, 187, 423–433.
<https://doi.org/10.1016/j.rse.2016.10.049>
- Brenner, C., Zeeman, M., Bernhardt, M., & Schulz, K. (2018). Estimation of evapotranspiration of temperate grassland based on high-resolution thermal and visible range imagery from unmanned aerial systems. *International Journal of Remote Sensing*, 39(15–16), 5141–5174.
<https://doi.org/10.1080/01431161.2018.1471550>
- Calkins, K. G. (2005, July 18). *Correlation Coefficients*. Retrieved August 16, 2024, from <https://www.andrews.edu/~calkins/math/edrm611/edrm05.htm>
- Cammalleri, C., Anderson, M. C., Gao, F., Hain, C. R., & Kustas, W. P. (2013). A data fusion approach for mapping daily evapotranspiration at field scale. *Water Resources Research*, 49(8), 4672–4686.
<https://doi.org/10.1002/wrcr.20349>
- California Department of Food and Agriculture (2024, February 13). *California Agricultural Production Statistics*. CDFA. Retrieved August 16, 2024, from <https://www.cdffa.ca.gov/Statistics/>
- Chen, A., Orlov-Levin, V., & Meron, M. (2019). Applying high-resolution visible-channel aerial imaging of crop canopy to precision irrigation management. *Agricultural Water Management*, 216, 196–205.
<https://doi.org/10.1016/j.agwat.2019.02.017>
- Chen, H., Jiang, A. Z., Huang, J. J., Li, H., McBean, E., Singh, V. P., Zhang, J., Lan, Z., Gao, J., & Zhou, Z. (2022). An enhanced shuttleworth-wallace model for simulation of Evapotranspiration and its components. *Agricultural and Forest Meteorology*, 313, 108769.
- Choudhury, B., Ahmed, N., Idso, S., Reginato, R., & Daughtry, C. (1994). Relations between evaporation coefficients and vegetation indices studied by model simulations. *Remote Sensing of Environment*, 50(1), 1–17. [https://doi.org/10.1016/0034-4257\(94\)90090-6](https://doi.org/10.1016/0034-4257(94)90090-6)
- CIMIS (2024). *The California Irrigation Management Information System (CIMIS)*. California Department of Water Resources. Retrieved August 16, 2024, from <https://cimis.water.ca.gov/>

- Davis, S. L., & Dukes, M. D. (2010). Irrigation scheduling performance by evapotranspiration-based controllers. *Agricultural Water Management*, 98(1), 19–28. <https://doi.org/10.1016/j.agwat.2010.07.006>
- Ebert, L. A., Talib, A., Zipper, S. C., Desai, A. R., Paw U, K. T., Chisholm, A. J., Prater, J., & Nocco, M. A. (2022). How High to Fly? Mapping Evapotranspiration from Remotely Piloted Aircrafts at Different Elevations. *Remote Sensing*, 14(7), 1660. <https://doi.org/10.3390/rs14071660>
- Escriba-Bou, A., Lund, J. R., & Pulido-Velazquez, M. (2018). Saving Energy From Urban Water Demand Management. *Water Resources Research*, 54(7), 4265–4276.
- French, A. N., Hunsaker, D. J., & Thorp, K. R. (2015). Remote sensing of evapotranspiration over cotton using the TSEB and METRIC energy balance models. *Remote Sensing of Environment*, 158, 281–294. <https://doi.org/10.1016/j.rse.2014.11.003>
- Gadhwal, M., & Sharda, A. (2023). Feasibility and accuracy assessment of UAV, aircraft, and satellite-based remote sensing for irrigation management using canopy temperature and NDVI. In C. Bauer & J. A. Thomasson (Eds.), *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping VIII* (p. 13). SPIE. <https://doi.org/10.1117/12.2664334>
- Gao, R., Torres-Rua, A. F., Nieto, H., Zahn, E., Hipps, L., Kustas, W. P., Alsina, M. M., Bambach, N., Castro, S. J., Prueger, J. H., Alfieri, J., McKee, L. G., White, W. A., Gao, F., McElrone, A. J., Anderson, M., Knipper, K., Coopmans, C., Gowing, I., ... Dokoozlian, N. (2023). ET Partitioning Assessment Using the TSEB Model and sUAS Information across California Central Valley Vineyards. *Remote Sensing*, 15(3), 756. <https://doi.org/10.3390/rs15030756>
- Ghiat, I., Mackey, H. R., & Al-Ansari, T. (2021). A Review of Evapotranspiration Measurement Models, Techniques and Methods for Open and Closed Agricultural Field Applications. *Water*, 13(18), 2523. <https://doi.org/10.3390/w13182523>
- Granata, F. (2019). Evapotranspiration evaluation models based on machine learning algorithms—A comparative study. *Agricultural Water Management*, 217, 303–315.
- Gu, Z., Qi, Z., Burghate, R., Yuan, S., Jiao, X., & Xu, J. (2020). Irrigation Scheduling Approaches and Applications: A Review. *Journal of Irrigation and Drainage Engineering*, 146, 04020007-1 15.
- Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, 377(1), 80–91.

- Guzinski, R., Nieto, H., Sandholt, I., & Karamitilios, G. (2020). Modelling High-Resolution Actual Evapotranspiration through Sentinel-2 and Sentinel-3 Data Fusion. *Remote Sensing*, 12(9), 1433.
- Hoffmann, H., Nieto, H., Jensen, R., Guzinski, R., Zarco-Tejada, P., & Friborg, T. (2016). Estimating evaporation with thermal UAV data and two-source energy balance models. *Hydrology and Earth System Sciences*, 20(2), 697–713. <https://doi.org/10.5194/hess-20-697-2016>
- Howitt, R., Medellín-Azuara, J., MacEwan, D., Lund, J. R., & Sumner, D. (2014). Economic Analysis of the 2014 Drought for California Agriculture. *University of California, Davis*.
- Jensen, M. E., & Allen, R. G. (2016). *Evaporation, Evapotranspiration, and Irrigation Water Requirements*. American Society of Civil Engineers.
- Jha, G., Nicolas, F., Schmidt, R., Suvočarev, K., Diaz, D., Kisekka, I., Scow, K., & Nocco, M. A. (2022). Irrigation Decision Support Systems (IDSS) for California’s Water–Nutrient–Energy Nexus. *Agronomy*, 12(8), 1962. <https://doi.org/10.3390/agronomy12081962>
- Júnior, J. C. da S., Medeiros, V., Garrozi, C., Montenegro, A., & Gonçalves, G. E. (2019). Random forest techniques for spatial interpolation of Evapotranspiration data from Brazilian’s Northeast. *Computers and Electronics in Agriculture*, 166, 105017.
- Kamble, B., Kilic, A., & Hubbard, K. (2013). Estimating Crop Coefficients Using Remote Sensing-Based Vegetation Index. *Remote Sensing*, 5(4), 1588–1602. <https://doi.org/10.3390/rs5041588>
- Kazemi, M. H., Shiri, J., Marti, P., & Majnooni-Heris, A. (2020). Assessing temporal data partitioning scenarios for estimating reference Evapotranspiration with machine learning techniques in arid regions. *Journal of Hydrology*, 590, 125252.
- Kisekka, I., Aguilar, J., Lamm, F., & Rogers, D. (2014). Using Soil Water and Canopy Temperature to Improve Irrigation Scheduling for Corn. *In Proceedings of the 2014 Irrigation Association Conference, Phoenix, AZ, USA*.
- Kling, H., Fuchs, M., & Paulin, M. (2012). Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. *Journal of Hydrology*, 424–425, 264–277.
- Kress, R. (1998). *Numerical Analysis* (Vol. 181). Springer New York. <https://doi.org/10.1007/978-1-4612-0599-9>
- Lu, G. Y., & Wong, D. W. (2008). An adaptive inverse-distance weighting spatial interpolation technique. *Computers & Geosciences*, 34(9), 1044–1055.

- Maes, W. H. (2025). Practical Guidelines for Performing UAV Mapping Flights with Snapshot Sensors. *Remote Sensing*, 17(4), 606. <https://doi.org/10.3390/rs17040606>
- Mehdizadeh, S. (2018). Estimation of daily reference Evapotranspiration (ET_o) using artificial intelligence methods: Offering a new approach for lagged ET_o data-based modeling. *Journal of Hydrology*, 559, 794–812.
- Meijering, E. (2002). A chronology of interpolation: From ancient astronomy to modern signal and image processing. *Proceedings of the IEEE*, 90(3), 319–342.
- Miralles, D. G., De Jeu, R. A. M., Gash, J. H., Holmes, T. R. H., & Dolman, A. J. (2011). Magnitude and variability of land evaporation and its components at the global scale. *Hydrology and Earth System Sciences*, 15(3), 967–981. <https://doi.org/10.5194/hess-15-967-2011>
- Mokhtari, A., Ahmadi, A., Daccache, A., & Drechsler, K. (2021). Actual Evapotranspiration from UAV Images: A Multi-Sensor Data Fusion Approach. *Remote Sensing*, 13(12), 2315. <https://doi.org/10.3390/rs13122315>
- Monteith, J. L. (1965). Evaporation and Environment. *Symposia of the Society for Experimental Biology*, 19, 205–234.
- Montero, D., Echeverry, F., & Hernández, F. (2018). Combination of satellite imagery with meteorological data for estimating reference evapotranspiration. *Revista de Teledetección*, 51, 75. <https://doi.org/10.4995/raet.2018.7688>
- Mu, Q., Zhao, M., & Running, S. W. (2011). Improvements to a MODIS global terrestrial evapotranspiration algorithm. *Remote Sensing of Environment*, 115(8), 1781–1800. <https://doi.org/10.1016/j.rse.2011.02.019>
- Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, 10(3), 282–290.
- Niu, H., Hollenbeck, D., Zhao, T., Wang, D., & Chen, Y. (2020). Evapotranspiration Estimation with Small UAVs in Precision Agriculture. *Sensors*, 20(22), 6427. <https://doi.org/10.3390/s20226427>
- Nocco, M. A., Zipper, S. C., Booth, E. G., Cummings, C. R., Loheide, S. P., & Kucharik, C. J. (2019). Combining Evapotranspiration and Soil Apparent Electrical Conductivity Mapping to Identify Potential Precision Irrigation Benefits. *Remote Sensing*, 11(21), 2460. <https://doi.org/10.3390/rs11212460>
- Norman, J. M., Kustas, W. P., & Humes, K. S. (1995). Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature. *Agricultural and Forest Meteorology*, 77(3–4), 263–293. [https://doi.org/10.1016/0168-1923\(95\)02265-Y](https://doi.org/10.1016/0168-1923(95)02265-Y)

- Olsen, D., Aghajanzadeh, A., & McKane, A. (2015, August). *Opportunities for Automated Demand Response in California Agricultural Irrigation*. Energy Technologies Area. Retrieved August 16, 2024, from <https://eta.lbl.gov/publications/opportunities-automated-demand-0>
- Paine, C. E. T., Marthews, T. R., Vogt, D. R., Purves, D., Rees, M., Hector, A., & Turnbull, L. A. (2012). How to fit nonlinear plant growth models and calculate growth rates: An update for ecologists: *Nonlinear plant growth models*. *Methods in Ecology and Evolution*, 3(2), 245–256. <https://doi.org/10.1111/j.2041-210X.2011.00155.x>
- Park, S. (2018). Estimating plant water stress and evapotranspiration using very-high-resolution (VHR) UAV imagery. *Ph. D. Thesis*.
- Park, S., Ryu, D., Fuentes, S., Chung, H., O'Connell, M., & Kim, J. (2021). Mapping Very-High-Resolution Evapotranspiration from Unmanned Aerial Vehicle (UAV) Imagery. *ISPRS International Journal of Geo-Information*, 10(4), 211. <https://doi.org/10.3390/ijgi10040211>
- Peddinti, S. R., & Kisekka, I. (2022). Estimation of turbulent fluxes over almond orchards using high-resolution aerial imagery with one and two-source energy balance models. *Agricultural Water Management*, 269, 107671. <https://doi.org/10.1016/j.agwat.2022.107671>
- Pelta, R., Beeri, O., Tarshish, R., & Shilo, T. (2022). Forecasting seasonal plot-specific crop coefficient (Kc) protocol for processing tomato using remote sensing, meteorology, and artificial intelligence. *Precision Agriculture*, 23(6), 1983–2000. <https://doi.org/10.1007/s11119-022-09910-6>
- Penman, H. L., & Schofield, R. K. (1951). Some Physical Aspects of Assimilation and Transpiration. *Symposia of the Society for Experimental Biology*, 5, 115–129.
- Poirier-Pocovi, M., Volder, A., & Bailey, B. N. (2020). Modeling of reference temperatures for calculating crop water stress indices from infrared thermography. *Agricultural Water Management*, 233, 106070. <https://doi.org/10.1016/j.agwat.2020.106070>
- Ramírez-Cuesta, J. M., Allen, R. G., Zarco-Tejada, P. J., Kilic, A., Santos, C., & Lorite, I. J. (2019). Impact of the spatial resolution on the energy balance components on an open-canopy olive orchard. *International Journal of Applied Earth Observation and Geoinformation*, 74, 88–102. <https://doi.org/10.1016/j.jag.2018.09.001>

- Ravazzani, G., Corbari, C., Morella, S., Gianoli, P., & Mancini, M. (2012). Modified Hargreaves-Samani Equation for the Assessment of Reference Evapotranspiration in Alpine River Basins. *Journal of Irrigation and Drainage Engineering*, 138(7), 592–599.
- Rossini, P. R., Ciampitti, I. A., Hefley, T., & Patrignani, A. (2021). A soil moisture-based framework for guiding the number and location of soil moisture sensors in agricultural fields. *Vadose Zone Journal*, 20(6).
<https://doi.org/10.1002/vzj2.20159>
- Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring Vegetation Systems in the Great Plains with ERTS. *NASA Special Publication*, 351, 309.
- Allaire, J. (2012). RStudio: integrated development environment for R. *Boston, MA*, 770(394), 165-171.
- Ryu, Y., Baldocchi, D. D., Kobayashi, H., Van Ingen, C., Li, J., Black, T. A., Beringer, J., Van Gorsel, E., Knohl, A., Law, B. E., & Roupsard, O. (2011). Integration of MODIS land and atmosphere products with a coupled-process model to estimate gross primary productivity and evapotranspiration from 1 km to global scales: GLOBAL GPP AND ET. *Global Biogeochemical Cycles*, 25(4), n/a-n/a.
<https://doi.org/10.1029/2011GB004053>
- Schneider, A., Hommel, G., & Blettner, M. (2010). Linear regression analysis: Part 14 of a series on evaluation of scientific publications. *Dtsch Arztebl Int.*, 107(44), 776–782.
- Schowengerdt, R. A. (2007). *Remote Sensing: Models and Methods for Image Processing (3rd ed.)*. Academic Press.
<https://doi.org/10.1016/B978-0-12-369407-2.X5000-1>
- Schwabe, K., Nemati, M., Landry, C., & Zimmerman, G. (2020). Water Markets in the Western United States: Trends and Opportunities. *Water*, 12(1).
- Semmens, K. A., Anderson, M. C., Kustas, W. P., Gao, F., Alfieri, J. G., McKee, L., Prueger, J. H., Hain, C. R., Cammalleri, C., Yang, Y., Xia, T., Sanchez, L., Mar Alsina, M., & Vélez, M. (2016). Monitoring daily evapotranspiration over two California vineyards using Landsat 8 in a multi-sensor data fusion approach. *Remote Sensing of Environment*, 185, 155–170. <https://doi.org/10.1016/j.rse.2015.10.025>
- Sowby, R. B., & Dicataldo, E. (2022). The energy footprint of U.S. irrigation: A first estimate from open data. *Energy Nexus*, 6, 100066.
- Su, Z. (2002). The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes. *Hydrology and Earth System Sciences*, 6(1), 85–100.

- Tasumi, M., Allen, R. G., & Trezza, R. (2006). *Calibrating Satellite-Based Vegetation Indices to Estimate Evapotranspiration and Crop Coefficients*.
- The MathWorks Inc. (2023a). *Financial Toolbox version: 6.5 (R2023a)*, Natick, Massachusetts: The MathWorks Inc. Retrieved August 16, 2024, from <https://www.mathworks.com/help/finance/daysact.html>
- The MathWorks Inc. (2023b). *Image Processing Toolbox version: 11.7 (R2023a)*, Natick, Massachusetts: The MathWorks Inc. Retrieved August 16, 2024, from <https://www.mathworks.com/help/images/resize-an-image.html>
- The MathWorks Inc. (2023c). *Mapping Toolbox version: 5.5 (R2023a)*, Natick, Massachusetts: The MathWorks Inc. Retrieved August 16, 2024, from <https://www.mathworks.com/help/map/ref/readgeoraster.html>
- The MathWorks Inc. (2023d). *MATLAB version: 9.14.0 (R2023a)*, Natick, Massachusetts: The MathWorks Inc. Retrieved August 16, 2024, from <https://www.mathworks.com>
- Timmermans, W. J., Kustas, W. P., & Andreu, A. (2015). Utility of an Automated Thermal-Based Approach for Monitoring Evapotranspiration. *Acta Geophysica*, 63(6), 1571–1608. <https://doi.org/10.1515/acgeo-2015-0016>
- Tindula, G. N., Orang, M. N., & Snyder, R. L. (2013). Survey of Irrigation Methods in California in 2010. *Journal of Irrigation and Drainage Engineering*, 139(3), 233–238. [https://doi.org/10.1061/\(ASCE\)IR.1943-4774.0000538](https://doi.org/10.1061/(ASCE)IR.1943-4774.0000538)
- U.S. Department of Agriculture (2019, July 31). *Web Soil Survey*. Natural Resources Conservation Service. Retrieved August 16, 2024, from <https://websoilsurvey.nrcs.usda.gov/app/>
- U.S. Department of Agriculture (2023, September 08). *Irrigation & Water Use*. Economic Research Service. Retrieved August 16, 2024, from <https://www.ers.usda.gov/topics/farm-practices-management/irrigation-water-use/>
- Welle, P. D., & Mauter, M. S. (2017). High-resolution model for estimating the economic and policy implications of agricultural soil salinization in California. *Environmental Research Letters*, 12(9), 094010.
- Willmott, C. J. (1984). On the Evaluation of Model Performance in Physical Geography. In Gaile, G.L., Willmott, C.J. (Eds.), *Spatial Statistics and Models* (pp. 443–460). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-3048-8_23

- Willmott, C. J., & Matsuura, K. (2005). Advantages of the Mean Absolute Error (MAE) over the Root Mean Square Error (RMSE) in Assessing Average Model Performance. *Climate Research*, 30(1), 79-82.
<https://www.jstor.org/stable/24869236>
- Xia, T., Kustas, W. P., Anderson, M. C., Alfieri, J. G., Gao, F., McKee, L., Prueger, J. H., Geli, H. M. E., Neale, C. M. U., Sanchez, L., Alsina, M. M., & Wang, Z. (2016). Mapping evapotranspiration with high-resolution aircraft imagery over vineyards using one- and two-source modeling schemes. *Hydrology and Earth System Sciences*, 20(4), 1523–1545. <https://doi.org/10.5194/hess-20-1523-2016>
- Yang, Y., Anderson, M. C., Gao, F., Hain, C. R., Semmens, K. A., Kustas, W. P., Noormets, A., Wynne, R. H., Thomas, V. A., & Sun, G. (2017). Daily Landsat-scale evapotranspiration estimation over a forested landscape in North Carolina, USA, using multi-satellite data fusion. *Hydrology and Earth System Sciences*, 21(2), 1017–1037. <https://doi.org/10.5194/hess-21-1017-2017>
- Zhang, B., Huang, J., Dai, T., Jing, S., Hua, Y., Zhang, Q., Liu, H., Wu, Y., Zhang, Z., & Chen, J. (2024). Assessing accuracy of crop water stress inversion of soil water content all day long. *Precision Agriculture*, 25, 1894–1914. <https://doi.org/10.1007/s11119-024-10143-y>
- Zhang, F., Geng, M., Wu, Q., & Liang, Y. (2020). Study on the spatial-temporal variation in Evapotranspiration in China from 1948 to 2018. *Scientific Reports*, 10(1), 17139.
- Zipper, S. C., & Loheide, S. P. (2014). Using Evapotranspiration to assess drought sensitivity on a subfield scale with HRMET, a high-resolution surface energy balance model. *Agricultural and Forest Meteorology*, 197, 91–102.