

**UNIVERSIDADE FEDERAL DE VIÇOSA**

**Evaluating SAFER energy balance model in Mediterranean citrus crop  
conditions**

Kevin Alain Salamanca Lopez  
*Magister Scientiae*

**VIÇOSA - MINAS GERAIS  
2025**

**KEVIN ALAIN SALAMANCA LOPEZ**

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Dissertation submitted to the Applied  
Meteorology Graduate Program of the  
Universidade Federal de Viçosa in partial  
fulfillment of the requirements for the  
degree of *Magister Scientiae*.

Adviser: Hewlley M. A. Imbuzeiro

Co-adviser: José F. de Oliveira Júnior

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To my family.

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“He who must proclaim much, must be able to remain silent for a long time; he who must throw a lightning bolt must be able to remain a cloud for a long time. A flash of lightning does not come by accident, it is condensed, which takes time.”.

(Friedrich Nietzsche)

## ABSTRACT

LOPEZ, Kevin Alain Salamanca, M.Sc., Universidade Federal de Viçosa, July, 2025. **Evaluating SAFER energy balance model in Mediterranean citrus crop conditions.** Adviser: Hewlley Maria Acioli Imbuzeiro. Co-adviser: José Francisco de Oliveira Júnior.

Accurate estimation of actual crop evapotranspiration ( $ET_a$ ) is crucial for effective irrigation management, especially in regions facing growing water scarcity. This study evaluates the performance of the Simple Algorithm for Evapotranspiration Retrieving (SAFER) in a Mediterranean citrus orchard using remote sensing and Eddy Covariance (EC) data. The model was calibrated using local flux tower data from 2021 to 2022. Results showed strong agreement between observed and modeled  $ET_a$  during the wet season, with excellent statistical metrics ( $R^2 = 0.89$  and  $0.85$ ;  $r = 0.95$  and  $0.92$ ;  $RMSE = 0.95$  mm day<sup>-1</sup> and  $0.91$  mm day<sup>-1</sup>; bias =  $-0.94$  mm day<sup>-1</sup> and  $0.53$  mm day<sup>-1</sup> for 2021 and 2022, respectively), confirming the reliability of SAFER under well-watered conditions. However, the model performance decreased significantly during the dry season,  $R^2 = 0.352$  and  $0.167$ ;  $r = -0.593$  and  $0.408$ ;  $RMSE = 0.86$  mm day<sup>-1</sup> and  $0.68$  mm day<sup>-1</sup>; bias =  $0.01$  mm day<sup>-1</sup> and  $0.38$  mm day<sup>-1</sup> for 2021 and 2022, respectively, likely due to the limited capacity of vegetation indices to detect plant physiological stress under water-deficit conditions. SAFER detected spatial variability in  $ET_a$  across the orchard, highlighting its potential for irrigation zoning. Comparisons with studies in tropical and semi-arid regions demonstrated consistency in mid-season  $ET_a$  estimates, supporting the model's adaptability. Despite reduced accuracy under drought conditions, SAFER remains a cost-effective and reliable tool for  $ET_a$  monitoring during optimal growth periods. Overall, it shows strong potential as a remote sensing-based tool for sustainable crop management, though dry-season applications require additional stress-adjustment factors.

Keywords: Evapotranspiration; Remote sensing; Eddy Covariance; SAFER model; Citrus orchard; Mediterranean climate

## RESUMO

LOPEZ, Kevin Alain Salamanca, M.Sc., Universidade Federal de Viçosa, julho de 2025. **Avaliação do modelo de balanço de energia SAFER em condições de cultivo de citros no Mediterrâneo.** Orientadora: Hewlley Maria Acioli Imbuzeiro. Coorientador: José Francisco de Oliveira Júnior.

A estimação precisa da evapotranspiração real da cultura (ETa) é crucial para o manejo eficiente da irrigação, especialmente em regiões que enfrentam escassez hídrica crescente. Este estudo avalia o desempenho do Simple Algorithm for Evapotranspiration Retrieving (SAFER - Algoritmo Simples para Recuperação de Evapotranspiração) em um pomar de citros mediterrâneo usando dados de sensoriamento remoto e de covariância dos vórtices turbulentos (eddy covariance). O modelo foi calibrado usando dados locais de torre de fluxo de 2021 a 2022. Os resultados mostraram uma forte concordância entre a ETa observada e a modelada durante a estação chuvosa, com excelentes métricas estatísticas ( $R^2 = 0,89$  e  $0,85$ ;  $r = 0,95$  e  $0,92$ ; RMSE =  $0,95 \text{ mm dia}^{-1}$  e  $0,91 \text{ mm dia}^{-1}$ ; viés =  $-0,94 \text{ mm dia}^{-1}$  e  $0,53 \text{ mm dia}^{-1}$  para 2021 e 2022, respectivamente), confirmando a confiabilidade do SAFER em condições de boa disponibilidade hídrica. No entanto, o desempenho do modelo diminuiu significativamente durante a estação seca ( $R^2 = 0,352$  e  $0,167$ ;  $r = -0,593$  e  $0,408$ ; RMSE =  $0,86 \text{ mm dia}^{-1}$  e  $0,68 \text{ mm dia}^{-1}$ ; viés =  $0,01 \text{ mm dia}^{-1}$  e  $0,38 \text{ mm dia}^{-1}$  para 2021 e 2022, respectivamente), provavelmente devido à capacidade limitada dos índices de vegetação para detectar o estresse fisiológico das plantas sob condições de déficit hídrico. O SAFER detectou a variabilidade espacial da ETa throughout pomar, destacando seu potencial para o zoneamento de irrigação. Comparações com estudos em regiões tropicais e semiáridas demonstraram consistência nas estimativas de ETa de meia-safra, apoiando a adaptabilidade do modelo. Apesar da precisão reduzida sob condições de seca, o SAFER permanece uma ferramenta confiável e de baixo custo para o monitoramento da ETa durante os períodos de crescimento ideal. No geral, ele mostra um forte potencial como uma ferramenta baseada em sensoriamento remoto para o manejo sustentável de culturas, embora as aplicações na estação seca requeiram fatores de ajuste adicionais para o estresse.

Palavras-chave: Evapotranspiração; Sensoriamento Remoto; Covariância dos Vórtices Turbulentos; Modelo SAFER; Pomar de Citros; Clima Mediterrâneo

## SUMMARY

Article: Evaluating SAFER energy balance model in Mediterranean citrus crop conditions

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## Article

# Evaluating a Simple Algorithm for an Evapotranspiration Retrieval Energy Balance Model in Mediterranean Citrus Orchards

Academic Editor: **Kevin Alain Salamanca Lopez<sup>1,\*</sup>, Gila Abílio João<sup>1</sup>, Hewlley Maria Acioli Imbuzeiro<sup>1</sup>, Daniela Vanella<sup>2</sup>, Simona Consoli<sup>2</sup>, Giuseppe Longo Minnolo<sup>2</sup>, Gabrielle Ferreira Pires<sup>1</sup> and José Francisco de Oliveira Júnior<sup>3</sup>**

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**Abstract**  
Accurate estimation of actual crop evapotranspiration ( $ET_a$ ) is crucial for effective irrigation management, especially in regions facing growing water scarcity. This study evaluates the performance of the Simple Algorithm for Evapotranspiration Retrieving (SAFER) in a Mediterranean citrus orchard using remote sensing and Eddy Covariance (EC) data. The model was calibrated using local flux tower data from 2021 to 2022. The results show strong agreement between observed and modeled  $ET_a$  during the wet season, with excellent statistical metrics ( $R^2 = 0.89$  and  $0.85$ ;  $r = 0.95$  and  $0.92$ ;  $RMSE = 0.95$  mm day<sup>-1</sup> and  $0.91$  mm day<sup>-1</sup>;  $bias = -0.94$  mm day<sup>-1</sup> and  $0.53$  mm day<sup>-1</sup> for 2021 and 2022, respectively), confirming the reliability of SAFER under well-watered conditions. However, the model performance decreased significantly during the dry season,  $R^2 = 0.352$  and  $0.167$ ;  $r = -0.593$  and  $0.408$ ;  $RMSE = 0.86$  mm day<sup>-1</sup> and  $0.68$  mm day<sup>-1</sup>;  $bias = 0.01$  mm day<sup>-1</sup> and  $0.38$  mm day<sup>-1</sup> for 2021 and 2022, respectively, likely due to the limited capacity of vegetation indices to detect plant physiological stress under water deficit conditions. SAFER detected spatial variability in  $ET_a$  across the orchard, highlighting its potential for irrigation zoning. Comparisons with studies in tropical and semi-arid regions demonstrated consistency in mid-season  $ET_a$  estimates, supporting the model's

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adaptability. Despite reduced accuracy under drought conditions, SAFER remains a cost-effective and reliable tool for  $ET_a$  monitoring during optimal growth periods. Overall, it shows strong potential as a remote sensing-based tool for sustainable crop management, though dry-season applications require additional stress-adjustment factors.

**Keywords:** evapotranspiration; remote sensing; eddy covariance; SAFER model; citrus orchard; Mediterranean climate

## 1. Introduction

Net radiation at the Earth's surface is primarily partitioned into latent heat ( $LE$ ) and sensible heat ( $H$ ) fluxes [1]. These two energy fluxes are the main components of the surface energy balance (SEB) [1,2]. The processes of convection, mass, and heat transfer from the surface to the free atmosphere are linked to the  $H$ . At the same time,  $LE$  is a key component of the surface water balance, responsible for the evapotranspiration ( $ET$ ) process [2], which is defined as the energy available to transport water from the soil and plant leaves to the atmosphere [3,4].

Understanding the behavior of the energy balance components related to  $ET$  (i.e.,  $LE$ ) is fundamental for irrigation support, especially in agro-ecosystems such as citrus groves in the Mediterranean climate region, whose productivity depends mainly on irrigation [3,5–7]. Therefore, qualifying the SEB components is fundamental for determining  $ET$ , and, thus, improving the irrigation support in semi-arid regions of the Mediterranean basin [4,5,7].

The EC technique has become the reference method for directly measuring SEB fluxes [2,8]. By capturing high-frequency exchanges of energy, water, and momentum between ecosystems and the atmosphere, EC allows direct assessment of surface energy balance dynamics [9,10]. Typically, an EC system combines a three-dimensional sonic anemometer with an infrared gas analyzer [11]. Despite its robustness, the EC method presents several challenges, including limited spatial representativeness compared to satellite approaches, incomplete energy balance closure, and underestimation of SEB under thermal stratification or non-stationary turbulence, which necessitate detailed corrections for accurate estimates. [9]. According to the author, these challenges often necessitate adjustments to ensure energy balance conservation. Other issues include the sensitivity of sensors to environmental conditions, such as atmospheric stability and surrounding vegetation, which can affect the transfer of heat and mass between the Earth's surface and the atmosphere, resulting in information gaps [12]. Alternatives, such as remote sensing, have been explored to fill these gaps, providing spatiotemporal information at different wavelengths

of the electromagnetic spectrum over the Earth's surface and allowing the behavior of energy fluxes to be estimated through SEB models [13].

Mediterranean climates are characterized by irregularity and scarcity of water supplies, which affect water availability levels for irrigation [7,14,15]. Several studies have evaluated the temporal behavior of SEB fluxes, mainly for the *ET* process determination, in Mediterranean regions, contributing to the proper management of water resources, particularly in the context of climate change scenarios [16], for which water scarcity and the increased recurrence and intensity of droughts are expected. The climate change effects exacerbate the shortage of water resources in these affected regions. This fact negatively impacts irrigated agriculture, leading to the need to monitor crop water consumption to achieve sustainable water management [8]. This objective can be pursued through tools that determine the SEB components at the agro-ecosystem level [17]. One of these tools is the SAFER model, which utilizes remote sensing to estimate the SEB components at different spatial and temporal scales. SAFER has already been used in different climatic conditions. For example, a study calibrated the algorithm for conditions in California [8], United States, for grape cultivation. Additionally, Teixeira et al. [4,18] used the model to estimate the *ET* fluxes in lemon orchards, as well as in soybean and corn crops. A recent work quantified *ET* for orange and lime crops in the Amazon Region [19]. This study applied the SAFER algorithm, utilizing satellite (Landsat 7 and 8) and meteorological data. The SAFER algorithm determined *ET* with an overall accuracy of 75%, showing higher accuracy for lime crops. These findings highlight the value of satellite imagery as an effective tool for estimating *ET* with this algorithm.

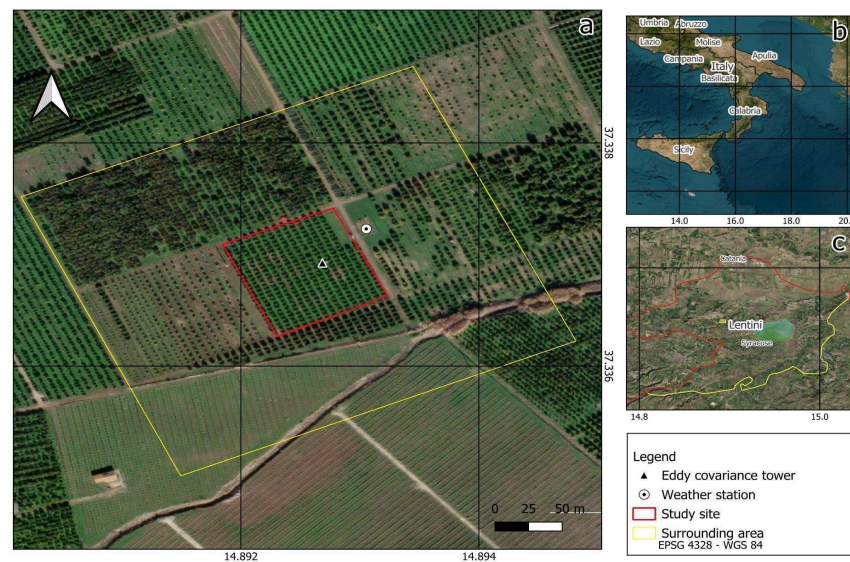
This study assesses the potential of the SAFER model as a tool to enhance irrigation support and water resource monitoring in semi-arid and Mediterranean agricultural systems, particularly considering the drought challenges in the region. The study also seeks to demonstrate the model's usefulness for water resource management. In parallel, the study calibrated the algorithm for Mediterranean conditions, as it was initially calibrated for other crops and in different geographical conditions. The SAFER model, with Sentinel-2 imagery and agrometeorological data, was used to estimate the main components of the SEB and *ET* in a citrus crop under the Mediterranean climatic conditions of Lentini, Sicily (Italy). These estimates were compared with SEB measurements obtained using an EC system, which are representative of the fluxes in the orange grove.

## **2. Materials and Methods**

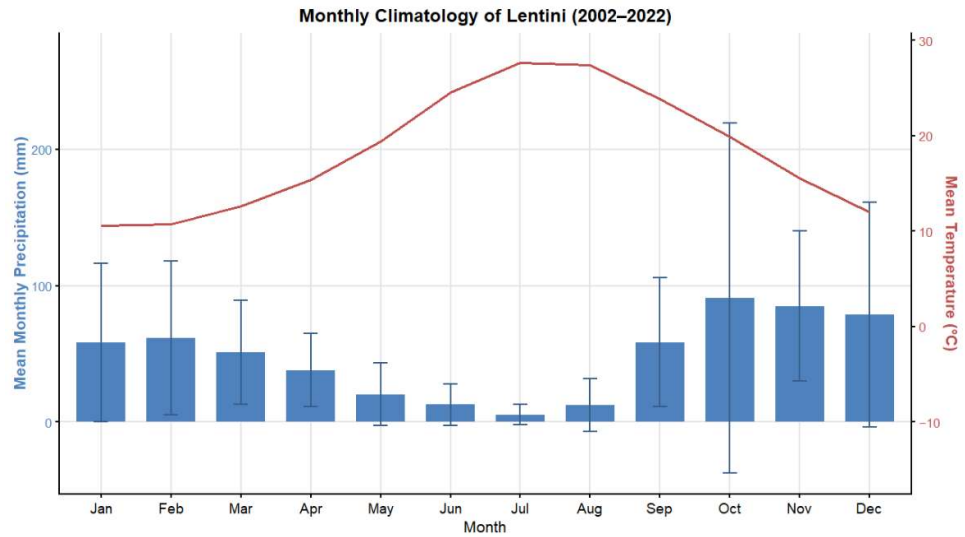
### **2.1. Study Site**

The study site comprises a 0.7-hectare orange orchard located in eastern Sicily (Italy), specifically in Lentini (Figure 1). It is managed by the “Consiglio per la ricerca in agricoltura e l’analisi dell’economia agraria, Centro di ricerca Olivicoltura, Frutticoltura e Agrumicoltura” (CREA-OFA) of Acireale. The study area is characterized by a Mediterranean warm-summer climate (Köppen Csa Code) that features a rainy season during winter [20,21]. Figure 2 shows the monthly average precipitation and the mean air temperature from 2002 to 2023 recorded at Lentini agrometeorological station managed by the Agrometeorological Information Service of Sicily (SIAS).

During the reference period (2002–2023), the monthly average air temperatures ranged from 12.7 °C, 18.3 °C, and 24.8 °C for minimum, mean, and maximum temperatures, respectively. The winter months (DJF) exhibited lower temperatures and higher precipitation compared to the summer months (JJA), which were characterized by higher temperatures and lower precipitation. The average observed monthly and annual rainfall at the station was approximately 47.7 mm and 572.6 mm, respectively. July (5.3 mm) and October (90.0 mm) were the months with the lowest and highest average monthly precipitation, respectively, during the reference period.



**Figure 1.** (a) Overview of the study site, including the surrounding area (37°20′12.65″ N, 14°53′33.04″ E, WGS84, 50 m), (b) a map of Italy, and (c), a map of Lentini.



**Figure 2.** Average monthly precipitation and air temperature values from 2002 to 2022, recorded at the Lentini weather station managed by the Sicilian Agrometeorological Information Service (SIAS).

The orchard under study consists of orange trees (*Citrus sinensis* (L.) Osbeck cv. “Tarocco Sciara”), planted in 2010, with a 6 m × 4 m spacing. The soil is sandy loam, with a field capacity and permanent wilting point of  $0.28 \text{ m}^3 \text{ m}^{-3}$  and  $0.14 \text{ m}^3 \text{ m}^{-3}$ , respectively, and a density of approximately  $1.25 \text{ g cm}^{-3}$  [5,22]. An EC flux tower, installed at the study site in 2016, was used for collecting the turbulent fluxes, using a three-dimensional sonic anemometer (CSAT3-3D, Campbell Scientific Inc., Logan, UT, USA) and an open-path infrared gas analyzer (Li-7500, Li-cor Biosciences Inc., Lincoln, NE, USA) to measure high-frequency (10 Hz) wind components and  $\text{H}_2\text{O}$  and  $\text{CO}_2$  concentrations, respectively. The low-frequency (30 min), net radiation ( $R_n, \text{W m}^{-2}$ ), and soil heat flux ( $G, \text{W m}^{-2}$ ) were measured using a net radiometer, located at 7 m above the ground (CNR-1 Kipp and Zonen, Delft, Netherlands), and three soil heat flux plates (HFP01SC, Hukseflux, Delft, Netherlands), respectively. The H and LE fluxes were calculated using the covariances between vertical wind velocity and air temperature, as well as between vertical wind velocity and water vapor density, according to the methodology provided in Saitta et al. [23]

Within the reference period (2021–2022), a qualitative and quantitative analysis of the local EC fluxes and agrometeorological data records from the SIAS Lentini weather station was carried out in R version 4.5.1 using the AGRIWATER [23] package version 1.0.2, together with the acquisition and processing of Sentinel-2 satellite images using the Google Earth Engine (GEE) tool.

## 2.2. EC Footprint Analysis

The EC footprint analysis is a crucial method in micrometeorology for interpreting turbulent flow measurements from EC flux towers. Ideally, these

towers should be installed on homogeneous, flat terrain with a uniform tree species distribution and similar thermal properties [9]. However, many locations do not meet these criteria, requiring a thorough understanding of the source zone and its impact on the measured signal [24]. The footprint is the surface area contributing to measurements at a specific point during a certain period [10]. It varies depending on measurement height, wind direction, atmospheric stability, and terrain roughness [25]. Advanced models, including analytical models, stochastic Lagrangian particle simulations, and extensive eddy simulations, are employed to address flow heterogeneities. These models and their parameters are essential for accurately estimating the contribution of different source areas to flow and vertical concentration measurements [9].

### 2.3. Description of the SAFER Model

The SAFER model is an alternative to the SEB Algorithm for Land (SEBAL) [13] that requires no anchor pixels or thermal strips, enhancing its practicality and operational applicability. It integrates radiometric data from satellite images with agrometeorological data such as reference ET, global solar radiation, and air temperature to estimate ET on a large scale. Designed for satellite-based applications, such as Landsat 8, Sentinel-2, and MODIS, which lack thermal bands, the model applies the SAFER algorithm to spatialize mass and SEB fluxes, where the spatial resolution depends on the set of images used. For the experiment, Sentinel-2 images with a spatial resolution of  $10 \text{ m pixel}^{-1}$  were utilized. These data were accessed through the Agriwater version 1.0.2 an R package [26], which provides the radiation\_s2 function for estimating *ET* using remote sensing data. It should be noted that, for optimal results, the model requires simple calibration to local conditions [4].

The modeling approach includes as input the planetary albedo for the entire solar spectrum, calculated as a weighted sum of the reflectance in narrow spectral bands. ( $r_p$ ):

$$a_p = \sum w_b r_p \quad (1)$$

where  $w_b$  (0.32, 0.26, 0.25, and 0.17) represent the weights for the blue, green, red, and infrared bands, respectively, depicting the proportion of incident solar radiation in each band relative to the total incoming radiation [18].

Then, the daily surface albedo is calculated using a regression equation:

$$a_0 = aa_p + b \quad (2)$$

In which 1.70 and 0.13 are regression coefficients  $a$  and  $b$ , derived from planetary albedo for 24 h, found by Teixeira et al. [18].

The daily surface temperature is estimated as a residual in the daily radiation balance:

$$T_0 = \sqrt[4]{\frac{R_G S - a_0 R_G + \varepsilon_A \sigma T_a^4 - R_n}{\varepsilon_s \sigma}} \quad (3)$$

where  $R_n$  is the daily Net Radiation,  $\varepsilon_s$  is the Surface Emissivity, and  $\sigma$  is the Stefan-Boltzmann Constant  $5.67 \times 10^{-8} \text{ Wm}^{-2} \text{ K}^{-4}$  [18,26].

The surface emissivity is calculated as:

$$\varepsilon_s = a_s \ln(NDVI) + b_s \quad (4)$$

In which  $a_s = 1.0035$  and  $b_s = 0.0589$  are regression coefficients [17,18].

$$\varepsilon_a = a_A (-\ln \tau_{sw})^{b_A} \quad (5)$$

where  $a_A = 0.9634$ ,  $b_A = 0.1135$  are regression coefficients, and  $sw$  is the shortwave atmospheric transmissivity, calculated as the ratio of daily incoming solar radiation  $R_G$  to incident solar radiation at the top of the atmosphere [27].

$R_n$  is calculated using the Slob equation [18]:

$$R_n = (1 - a_0) R_G - a_L \tau_{sw} \quad (6)$$

where  $a_L$  is a coefficient related to the air temperature ( $T_a$ ):

$$a_L = c T_a - d \quad (7)$$

The values of  $c$  and  $d$  are 6.99 and 39.93, obtained as regression coefficients in the past experiments [28,29]. We retained the physically based coefficients  $c$  and  $d$ . These have been extensively validated over Mediterranean-type agroecosystems and orchard canopies. These coefficients encode radiative-thermal constraints that are expected to be transferable across sites with comparable climates, canopy architectures, and background reflectance's. In contrast, the empirical pair  $a$  and  $b$  in Equation (9) with local tower and Sentinel-2 data from Lentini was calibrated to account for site-specific phenology and stress responses. This hybrid strategy preserves physical consistency and transferability for the radiative terms (via  $c$ ,  $d$ ), while ensuring local representativeness of the  $ET_{fr}$  relationship (via  $a$ ,  $b$ ).

Regarding the satellite component, the  $NDVI$  is calculated as:

$$NDVI = \frac{r_{NIR} - r_{RED}}{r_{NIR} + r_{RED}} \quad (8)$$

where  $r_{NIR}$  and  $r_{RED}$  are the reflectances in the near-infrared and red infrared bands, respectively.

The evaporative fraction, which is the ratio of the actual  $ET$  to the reference  $ET$ , is calculated as:

$$ET_{fr} = \exp \left[ a + b \left( \frac{LST}{a_0 NDVI} \right) \right] \quad (9)$$

where  $a = -0.463$  and  $b = -0.002$  represent the regression coefficients between the calculated evaporative fraction and the one estimated by satellite. These values were estimated in this study during the calibration process under the specific conditions of Sicily, Italy.

Finally, the actual daily  $ET$  is calculated as:

$$ET_a = ET_{fr} * ET_0 \quad (10)$$

where  $ET_0$  is the reference evapotranspiration, calculated using the standard FAO Penman-Monteith method [30], and calculated using the BrazilMet 0.4.0 R package. The  $ET_a$  and  $ET_{fr}$  are actual evapotranspiration and observed evaporative fraction, respectively.

#### 2.4. Model Calibration and Validation

Data sources and preprocessing:

- (i) EC data (at 30 min resolution) and  $H$ ,  $LE$ ,  $Rn$ ,  $G$  data from the Lentini tower (Section 2.1) were quality-controlled following standard practice (spike removal, tilt correction, frequency-response, and WPL density corrections), screened by nighttime  $u^*$  thresholds, and aggregated to daily values when data coverage  $\geq 80\%$ . Energy-balance closure was monitored as  $EBC = (H + LE)/(Rn - G)$ ; days with poor closure were flagged and excluded from calibration but kept for sensitivity checks.
- (ii) Meteorological records from SIAS provided daily  $ET_0$  (FAO-56 Penman-Monteith) and auxiliary variables.
- (iii) Sentinel-2 MSI images (cloud-masked and atmospherically corrected) supplied  $a_0$ , NDVI, and the variables needed for Equations (1)–(8); only scenes with cloud cover  $\leq 10\%$  over the footprint were retained. All satellite quantities were extracted as the footprint-weighted mean within the 50–90% EC footprint contours for each date.

The SAFER model requires internal calibration to determine the optimal empirical coefficients  $a$  and  $b$  in Equation (9), following the methodology proposed by Teixeira et al. [17] and further applied by Venâncio et al. [31]. This calibration is achieved through linear regression analysis, in which the relationship between the remote sensing-based variable  $LST a_0^{-1} NDVI^{-1}$  and the natural logarithm of the ratio of observed  $ET$  to  $ET_0$   $\ln(ET ET_0^{-1})$  is

established for each flux tower within the study area. This procedure enables the model to be locally parameterized, enhancing its representativeness under site-specific conditions. This hybrid strategy preserves physical consistency while adapting the evaporative fraction ( $EF$ ) relationship to local agro-meteorological conditions. Additional methodological details and applications of the SAFER model using Agriwater R can be found in Silva et al. [26] and Safre et al. [8], who provide comprehensive insights into its structure and implementation.

The SAFER model was calibrated for the Lentini site (37.337° N, 14.893° E) using flux tower measurements and remote sensing data. The observed evaporative fraction  $ET_{fr}$  was derived as the ratio between  $ET_a$ , measured by the EC system, and  $ET_0$ , estimated using the FAO Penman-Monteith method [30]. Then, a linear relationship is established between the remote sensing parameters Land Surface Temperature ( $LST$ ), albedo ( $a_0$ ), ( $NDVI$ ) and the observed values of  $\ln(ET_{fr})$ , using the independent variable ( $LST a_0^{-1} NDVI^{-1}$ ). Through a linear regression, the coefficients  $a$  (intercept) and  $b$  (slope) are obtained, which are incorporated into Equation 9. Finally, the calibrated model is validated by comparing  $ET_a$  estimates with flux tower measurements, ensuring its accuracy for regional applications.

The SAFER model was calibrated using a combination of remote sensing data and ground-based observations. Harmonized Sentinel-2 MSI images, listed in Table 1, were utilized to derive the necessary remote sensing parameters ( $LST a_0^{-1} NDVI^{-1}$ ) for the calibration process. These images correspond to specific dates throughout 2021 and 2022, ensuring a representative temporal coverage of the study area. Additionally, meteorological data from the Lentini weather station and flux tower measurements from the Micro Tower site were incorporated to provide observed  $\ln(ET_{fr})$  values. The integration of these datasets enabled the development of a robust linear regression model, which is essential for determining the optimal coefficients  $a$  and  $b$  in Equation (9).

**Table 1.** Harmonized Sentinel-2 MSI images used for model calibration.

| Year | 2021 |     |     |     |     |     | 2022 |     |     |     |     |     |     |     |     |
|------|------|-----|-----|-----|-----|-----|------|-----|-----|-----|-----|-----|-----|-----|-----|
| DOY  | 87   | 207 | 137 | 209 | 219 | 222 | 152  | 154 | 187 | 197 | 204 | 207 | 214 | 359 | 362 |

To validate the SAFER model, a comprehensive dataset was employed, including agrometeorological records from the SIAS Lentini weather station, Sentinel-2 MSI imagery (see Table 2), and SEB flux measurements obtained from the micrometeorological tower. These data sources provided reference values of actual  $ET$ ,  $H$ , and  $LE$ , which were directly compared to SAFER model simulations. The validation spanned the years 2021 and 2022, encompassing a broad range of seasonal variability and environmental conditions. Model performance was

quantitatively evaluated using standard statistical indicators: the coefficient of determination ( $R^2$ ), root mean square error ( $RMSE$ ), and mean bias error ( $MBE$ ). These metrics were applied to assess the accuracy of SAFER in estimating  $H$ ,  $LE$ , and  $ET$ . Observed  $ET$  values derived from the EC technique were used as ground truth for the evaluation. This multivariable, multi-temporal validation framework demonstrated the model's reliability and predictive skill in capturing  $ET$  dynamics and energy flux partitioning under Mediterranean climatic conditions, supporting its applicability for operational monitoring and hydrological modeling in similar environments.

**Table 2.** Harmonized Sentinel-2 MSI images used for model validation.

| Year | DOY |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 2021 | 87  | 129 | 139 | 194 | 197 | 207 | 209 | 212 | 219 | 222 | 224 | 259 | 262 | 294 | 324 |     |     |     |     |     |     |     |
| 2022 | 84  | 99  | 137 | 142 | 152 | 154 | 172 | 179 | 184 | 187 | 197 | 204 | 207 | 214 | 227 | 247 | 297 | 299 | 342 | 359 | 362 | 362 |

### 2.5. Additional Performance Metrics

In addition to the  $R^2$ , we now report  $RMSE$  and  $MBE$  for model validation. These metrics are widely used for evaluating models, as seen in recent studies [32,33], and were employed in this research to provide a more comprehensive evaluation of SAFER performance, which is included in the results section.

#### Validation Metrics

Together with the  $R^2$  (Equation (11)), we evaluated model skill using  $RMSE$  (Equation (12)) and  $MBE$  (Equation (13)). Let  $y_i$  and  $\hat{y}$  be the daily and average be the daily EC-derived  $ET$  and the corresponding SAFER estimate for day  $i = 1, \dots, n$ . Metrics are defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\underline{y} - y_i)^2} \quad (11)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (12)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (13)$$

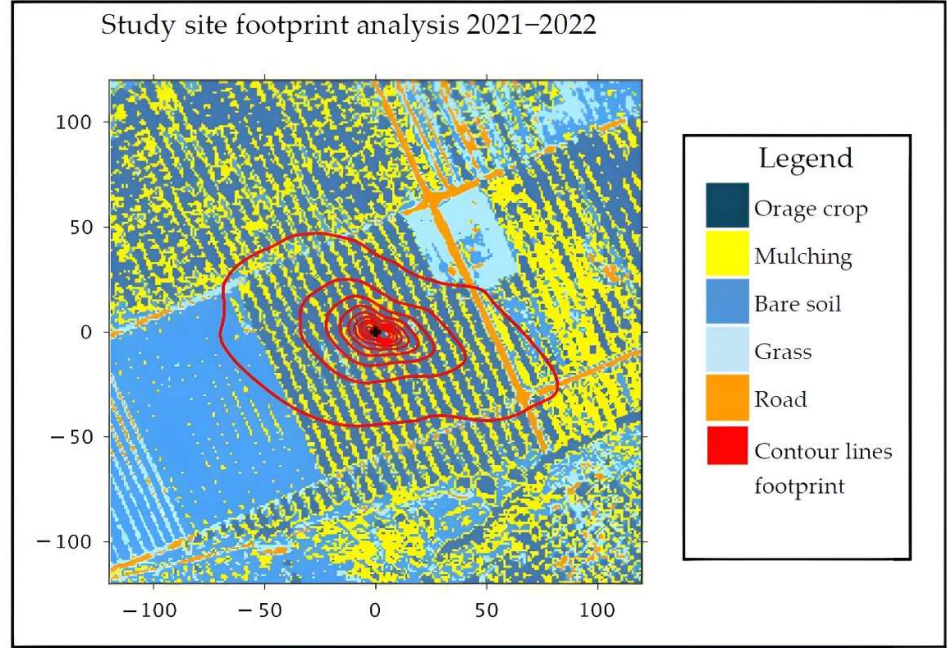
Errors are reported in  $\text{mm d}^{-1}$  (consistent with  $ET$  units); negative  $MBE$  indicates underestimation by SAFER relative to EC. Metrics are computed for (i) all valid dates, and (ii) stratified by wet vs. dry season.

## 3. Results

### 3.1. Footprint Analysis

The footprint area was calculated using the widely applied micrometeorological model by Kljun [25]. This method combines equations based on principles of atmospheric turbulence and mass transport to calculate the impact of meteorological conditions, terrain characteristics, and surface properties on the extent and shape of the footprint. For this purpose, we utilized the online program developed by Kljun et al. [25] for processing our data. Figure 3 presents a map of the study area overlaid with the automatic land cover classification and the flux tower footprint contour lines, calculated in 10% intervals from 10% to 90%. The title of each panel in the figure annotates the footprint-weighted contribution of each land cover class to the measured flux. This analysis reveals that the largest contribution comes from the orange crop,

at 64.2%, followed by mulching at 27.2%. Other land covers, such as bare soil (6.9%), grass (1.3%), and roads (0.4%), contribute marginally to the total measurements. The elongated shape of the footprint aligns with the predominant wind direction pattern during the analyzed period (2021–2022), confirming that most of the footprint area effectively represents the crop of interest.



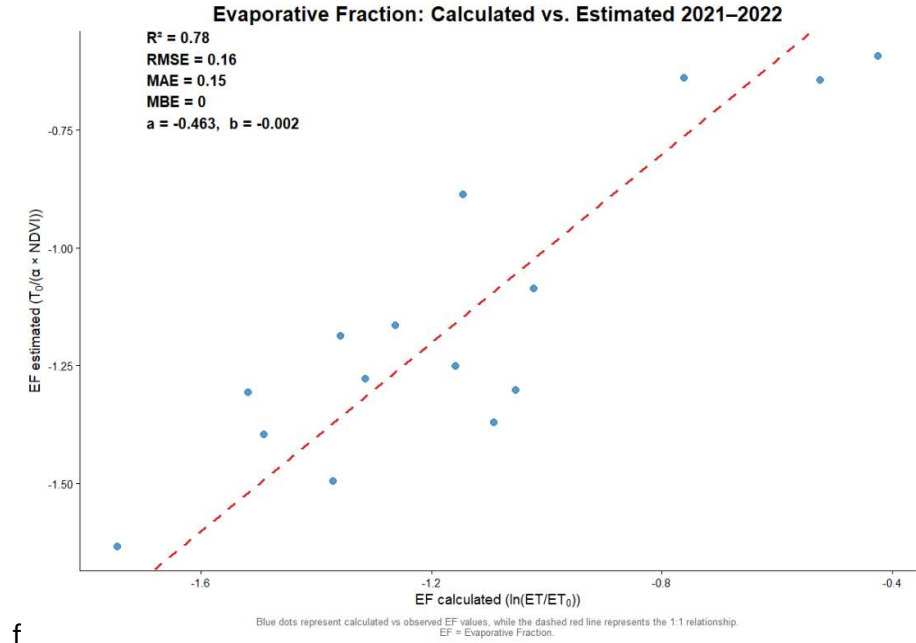
**Figure 3.** EC footprint 2021–2022 map with land cover classification and footprint contour lines from 10% to 90%, in 10% steps. The contribution from each land cover class to the measured flux, weighted by the footprint, is annotated in the title of each panel.

### 3.2. Calibration

The linear regression results showed a good model fit, show figure 4, with a  $R^2$  of 0.7823, indicating that approximately 78% of the variability in  $\ln(ET_{fr})$  is explained by the independent variable ( $LST a_0^{-1} NDVI^{-1}$ ). The intercept  $a$  was  $-0.463143$ , and the coefficient of the independent variable  $b$  was  $-0.002310$ , both of which were statistically significant ( $p < 0.01$ ). The model exhibited a low Root Mean Square Error (RMSE) of 0.16 and a Mean Absolute Error (MAE) of 0.15. Furthermore, a Mean Bias Error (MBE) of zero indicates the absence of any systematic overestimation or underestimation in the model calibration, demonstrating its unbiased nature. The residual standard error was 0.1752, suggesting that the model has acceptable accuracy in predicting the evaporative fraction under Lentini's conditions. These results allow calibrating Equation (9) to estimate  $ET_{fr}$  more accurately in the Mediterranean condition of the region.

Our results highlight the need for local calibration of parameters  $a$  and  $b$  to represent site-specific evaporation under dry conditions. This is consistent with

the notion that radiative constraints are more portable than empirical  $EF$  slopes, which reflect canopy physiology and stress. We therefore recommend re-estimating  $a$  and  $b$  whenever canopy composition or hydroclimate differ markedly from the calibration setting.



**Figure 4.** Linear regression of evaporative fraction calculated with meteorological and micrometeorological data and evaporative fraction estimated with satellite data.

### 3.3. Model Validation Results

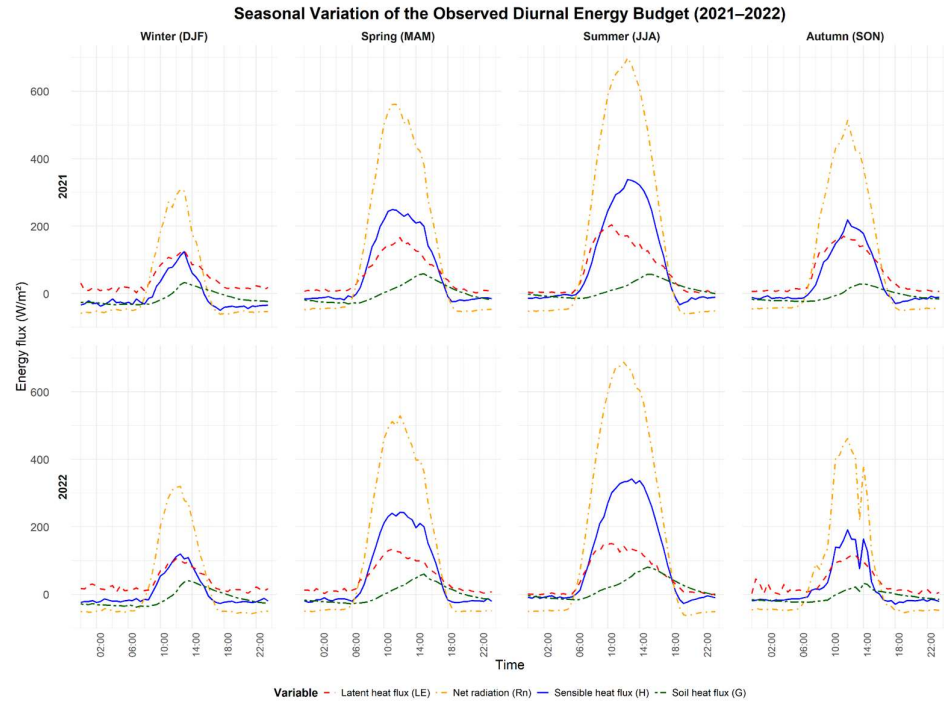
Analysis of daily energy flows (Figure 5) reveals a marked seasonal contrast in the behavior of the citrus orchard. During the summer (JJA), the annual maximum values of all components of the energy balance are observed, with  $R_n$  reaching  $699 \text{ W m}^{-2}$ ,  $H$  of  $338 \text{ W m}^{-2}$ , and  $LE$  of  $172 \text{ W m}^{-2}$ . However, this season is characterized by a clear dominance of  $H$  over  $LE$ , with an  $H/LE$  ratio exceeding 1.6 during the midday period. This imbalance, more pronounced in 2022 than in 2021, is a direct indicator of severe water stress that limits  $ET$  and explains the greater challenges for modeling during this period.

In spring (MAM), the system exhibits more balanced behavior, with  $R_n$  values reaching up to  $561 \text{ W m}^{-2}$ ,  $H$  of  $249 \text{ W m}^{-2}$ , and  $LE$  of  $166 \text{ W m}^{-2}$ , maintaining an  $H/LE$  ratio of approximately 1.5. The transition from negative nighttime values to daytime maximums occurs gradually and predictably, creating ideal conditions for modeling. This stability in the energy balance, combined with adequate water availability, allows the SAFER model to achieve its maximum accuracy during the spring season.

Autumn (SON) exhibits a marked reduction in all energy fluxes, with  $R_n$  decreasing to  $469 \text{ W m}^{-2}$ ,  $H$  to  $219 \text{ W m}^{-2}$ , and  $LE$  to  $160 \text{ W m}^{-2}$ , accompanied by

notable interannual variability. The differences between 2021 and 2022 are particularly evident in  $LE$  fluxes, which show a 30% reduction in the drier year. This season is also characterized by nocturnal condensation events, evidenced by positive  $LE$  values during the night, which adds complexity to modeling processes.

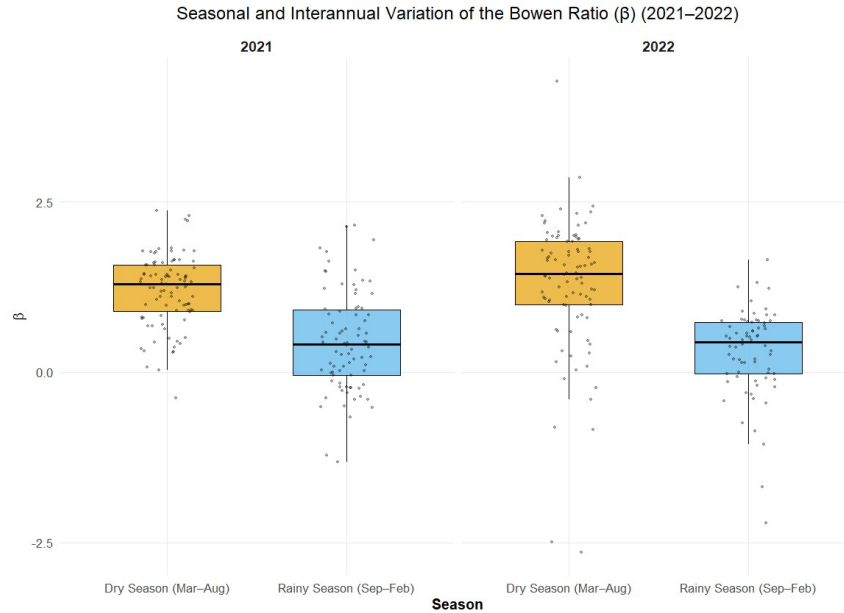
Winter (DJF) represents the most stable scenario for modeling, with the lowest annual values in all energy fluxes:  $R_n$  of  $320 \text{ W m}^{-2}$ ,  $H$  of  $125 \text{ W m}^{-2}$ , and  $LE$  of  $129 \text{ W m}^{-2}$ , along with prolonged nighttime periods with negative fluxes. Low evaporative demand and predictable system behavior allow the model to operate with high accuracy under these conditions. Significant heat loss from the ground, indicated by negative  $G$  values down to  $-35 \text{ W m}^{-2}$ , completes the picture of this season of minimal biological activity and maximum environmental stability.



**Figure 5.** Components of the SEB on a seasonal and annual scale for the experimental site.

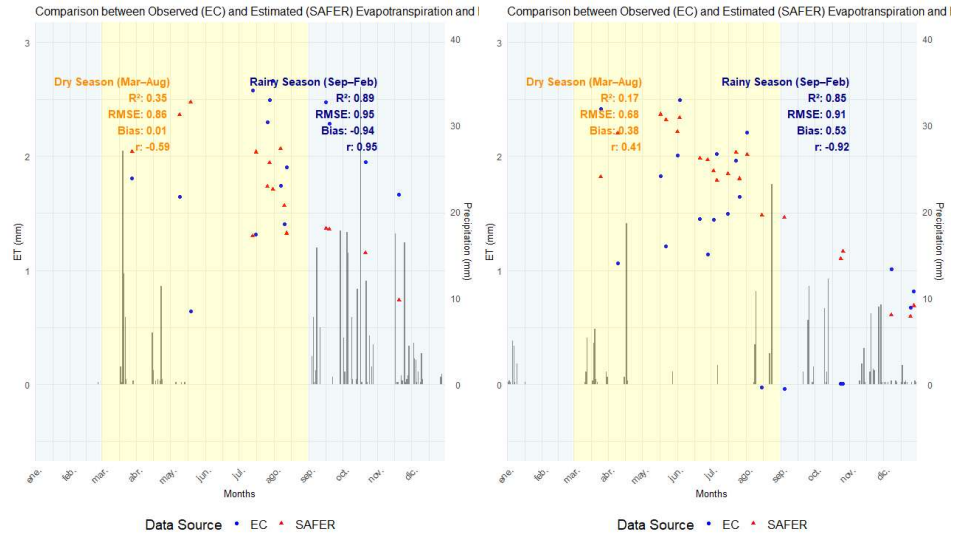
In Figure 6, the analysis of the Bowen ratio ( $\beta$ ) reveals a clear difference in the performance of the SAFER model between dry and rainy seasons during the years 2021 and 2022. In the rainy season, consistently low  $\beta$  values ( $\beta = 0.45$  in 2021;  $\beta = 0.29$  in 2022) reflected conditions of high-water availability and  $LE$  dominance, allowing the model to achieve high accuracy ( $R^2 = 0.89$  in 2021;  $R^2 = 0.85$  in 2022) due to the predictable linear relationship between remote sensing variables and  $ET_a$ . In contrast, during the dry season, high and variable  $\beta$  values ( $\beta = 1.19$  in 2021;  $\beta = 1.29$  in 2022) indicated a dominance of  $H$  and severe water

stress, resulting in lower model accuracy ( $R^2 = 0.35$  in 2021;  $R^2 = 0.17$  in 2022) due to the nonlinear nature of energy flows under water-limited conditions. This marked seasonal difference highlights the need to incorporate water stress parameters to improve  $ET_a$  estimates in dry periods.



**Figure 6.** Bowen ratio box plot for 2021–2021 and seasons.

The validation of the SAFER model against EC-derived  $ET_a$  (Figure 7) revealed marked seasonal variability in performance. During the dry season (March–August), model accuracy was substantially lower, with  $R^2$  of 0.35 in 2021 and 0.17 in 2022, indicating limited explanatory power (35.2% and 16.7%, respectively). This decline was attributed to extreme climatic conditions, which intensified plant water stress and limited  $ET$ . Consequently, the model tended to underestimate  $ET$ , as evidenced by RMSE values of  $0.86 \text{ mm day}^{-1}$  (2021) and  $0.68 \text{ mm day}^{-1}$  (2022) and low correlation coefficients ( $r = -0.59$  and  $0.41$ , respectively), reflecting its reduced sensitivity to water-limited conditions. The global analysis for 2021 ( $n = 15$  days) yielded an  $R^2$  of 0.18, an RMSE of  $0.88 \text{ mm day}^{-1}$ , and an MBE of  $-0.25 \text{ mm day}^{-1}$ , indicating a slight overall underestimation.



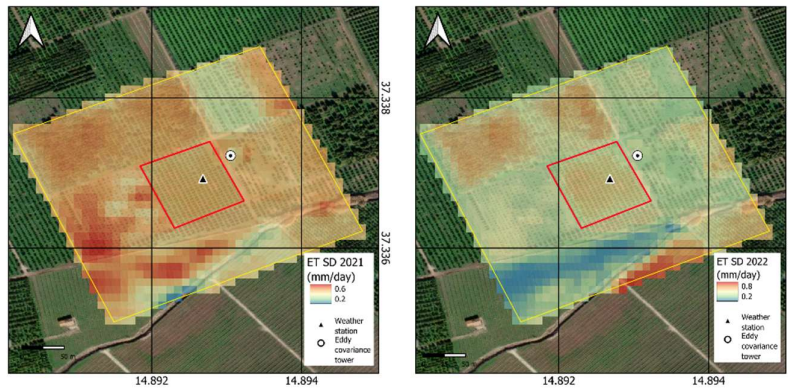
**Figure 7.** Observed EC and simulated (SAFER) ET behavior for 2021 and 2022 at the experimental site illustrates the spatial distribution of the standard deviation (SD) of average daily ET for 2021 (left) and 2022 (right) in comparison to EC-based ET fluxes.

Conversely, model performance improved significantly during the rainy season (September–December), with  $R^2$  values of 0.89 (2021) and 0.85 (2022), indicating strong agreement between modeled and observed  $ET$ . More favorable atmospheric conditions contributed to increased water availability and reduced thermal stress, enhancing model reliability. However, the model exhibited a negative  $MBE$  of  $-0.94 \text{ mm day}^{-1}$  in 2021 and a positive  $MBE$  of  $0.53 \text{ mm day}^{-1}$  in 2022, indicating a tendency to under- or overestimate  $ET$  depending on the year. Despite these biases, correlation coefficients remained high ( $r = 0.95$  in 2021 and  $r = -0.92$  in 2022), indicating a strong temporal alignment between the modeled and observed fluxes. The global analysis for 2022 ( $n = 21$  days) showed improved integrated performance, with an  $R^2$  of 0.38, an  $RMSE$  of  $0.75 \text{ mm day}^{-1}$ , and an  $MBE$  of  $0.42 \text{ mm day}^{-1}$ .

Normalized Difference Vegetation Index ( $NDVI$ ) dynamics further explain seasonal  $ET$  patterns. During the rainy season,  $NDVI$  values increased markedly (up to 0.93), reflecting enhanced vegetation activity and canopy development, which supported higher  $ET$  rates. In contrast,  $NDVI$  values declined during the dry season (as low as 0.41), consistent with reduced photosynthetic capacity and vegetation cover under drought stress. These findings underscore that while  $NDVI$  is incorporated into the  $ET_{fr}$  calculation of the SAFER model, its current parameterization does not fully capture the complex interactions between vegetation dynamics and water stress under extreme climatic conditions. The model's performance limitations during the dry season suggest that the relationship between  $NDVI$  and evaporative fraction becomes nonlinear under moisture-limited regimes, where vegetation indices alone cannot adequately

represent stomatal regulation and soil moisture constraints. This underscores the need for improved model formulations that better account for the dynamic coupling between vegetation status and water availability, potentially through the integration of additional stress indices or modified parameterizations of the *NDVI-ET* relationship during periods of meteorological drought.

In Figure 8 color scale represents *ET* variability in  $\text{mm day}^{-1}$ , ranging from approximately  $0.2 \text{ mm day}^{-1}$  (blue) to higher values of  $0.6 \text{ mm day}^{-1}$  in 2021 and up to  $0.8 \text{ mm day}^{-1}$  in 2022 (red). The study site is outlined in yellow, with the flux tower (black triangle) and a specific region of interest marked by the red square.



**Figure 8.** *ET* daily standard deviation at the study site (square red) and the surrounding area (yellow square) in 2021–2022.

In 2021, *ET* variability is more pronounced in the southwestern section, where values exceed  $0.6 \text{ mm day}^{-1}$ , while the central and northeastern parts exhibit lower variability, ranging from  $0.2$  to  $0.4 \text{ mm day}^{-1}$ . In contrast, the 2022 map shows a more homogeneous distribution of *ET* variability across the study site [34], with slightly increased values in the southern region ( $\sim 0.8 \text{ mm day}^{-1}$ ). The decrease in localized hotspots of high variability and the more uniform spatial distribution in 2022 suggest potential shifts in land cover characteristics, atmospheric conditions, or differences in irrigation and crop growth patterns between the years. Additionally, the variability within the red-marked region near the flux tower appears lower in 2022 than in 2021, indicating possible changes in energy flux dynamics or measurement conditions.

#### Model Validation with Error Metrics

Beyond  $R^2$ , we now report *RMSE* and *MBE* to provide a more comprehensive assessment of *SAFER* performance. Over the whole validation period, *SAFER* yielded *RMSE* ( $0.88 \text{ mm day}^{-1}$  and  $0.75 \text{ mm day}^{-1}$ ), and *MBE* ( $-0.25 \text{ mm day}^{-1}$  and  $0.42 \text{ mm d}^{-1}$ ), with  $R^2$  ( $0.18$  and  $0.38$ ) for 2021 and 2022,

respectively. When stratified by season, dry-season errors increased RMSE, and *MBE* patterns, indicating inconsistent model behavior under water-limited conditions (Table 3). In 2021, the slightly positive *MBE* (0.01 mm d<sup>-1</sup>) suggested minor overestimation during dry periods, while in 2022 the negative correlation coefficient ( $r = -0.59$ ) revealed inverse patterns between observed and modeled *ET*. These patterns are consistent with the energy-partition shift observed during the dry season.

**Table 3.** Validation metrics for SAFER against EC-derived *ET* (daily scale).

| Season | Year | <i>n</i> Days | $R^2$ | <i>RMSE</i> | <i>MBE</i> | <i>r</i> |
|--------|------|---------------|-------|-------------|------------|----------|
| Dry    | 2021 | 11            | 0.35  | 0.86        | 0.01       | -0.59    |
| Rainy  | 2021 | 4             | 0.89  | 0.95        | -0.94      | 0.95     |
| All    | 2021 | 15            | 0.18  | 0.88        | -0.25      | -0.42    |
| Dry    | 2022 | 15            | 0.17  | 0.68        | 0.38       | 0.41     |
| Rainy  | 2022 | 6             | 0.85  | 0.91        | 0.53       | -0.92    |
| All    | 2022 | 21            | 0.38  | 0.75        | 0.42       | 0.62     |

The results are presented for the entire period, as well as separately for the rainy and dry seasons. Metrics include  $R^2$ , *RMSE*, and *MBE*. Values are reported in mm d<sup>-1</sup> (*MBE* < 0 indicates underestimation).

#### 4. Discussion

The calibration and validation of the SAFER model under Mediterranean conditions revealed its strong potential for estimating  $ET_a$  in citrus orchards. When calibrated with local flux tower data and remote sensing imagery, the model demonstrated reliable agreement with observed *ET* values, especially during the rainy season. The model achieved high  $R^2$  (0.89 in 2021 and 0.85 in 2022) under cooler and wetter conditions, suggesting that SAFER performs optimally when soil moisture is not a limiting factor. These findings align with previous research conducted in tropical conditions [19] where the SAFER algorithm demonstrated an overall accuracy of approximately 75% in citrus orchards under humid climates in the eastern Amazon. Both studies highlight the model's effectiveness across diverse climatic conditions if sufficient calibration is performed. A simple log-linear regression was adopted to demonstrate SAFER's applicability and ensure reproducible calibration with limited data. This choice enhances model interpretability and transferability across sites. Nevertheless, future work should systematically test alternative calibration strategies to further improve robustness, including nonlinear regression (e.g., generalized additive models or polynomial terms), regularized linear models (ridge/LASSO) to handle multicollinearity, and machine-learning

approaches (e.g., tree-based ensembles or kernel methods). Any such extensions should be evaluated with strict out-of-sample cross-validation, assessed for extrapolation risk, and accompanied by model-agnostic diagnostics to preserve interpretability in operational contexts.

However, our study also revealed a marked decline in SAFER performance during dry summer months (March–August), with substantially lower  $R^2$  values (0.35 in 2021 and 0.167 in 2022), along with high  $RMSE$  and negative or low correlation coefficients. These periods are characterized by intense solar radiation, elevated air temperatures, and reduced precipitation, all of which contribute to water stress in citrus crops. Under these conditions, SAFER tended to underestimate. This limitation can be attributed to the model's reliance on vegetation indices, particularly  $NDVI$ , which may not promptly reflect physiological stress when the canopy remains green. Similar limitations were observed by Abou Ali et al. [3], who reported reduced model performance under semi-arid conditions due to difficulties in capturing the reduction in transpiration caused by soil moisture deficits.

Addressing the lower performance of the SAFER model during the dry season is essential for enhancing its operational reliability. The elevated Bowen ratio values ( $\beta > 1.2$ ) confirm that energy partitioning was dominated by sensible heat flux, a regime where the empirical relationship between  $NDVI$  and the evaporative fraction becomes nonlinear. If model improvements remain limited after implementing adjustments for water stress, the underlying cause may be structural. The model's foundation on linear regressions may be inherently constrained in capturing the complex, threshold-driven physiological responses of citrus trees to severe soil moisture deficit, where stomatal regulation decouples transpiration from both vegetation indices and atmospheric demand.

Despite these seasonal limitations, the SAFER model effectively represented the spatial heterogeneity  $ET_a$  across the orchard. In 2021,  $ET_a$  variability was more pronounced, particularly in the southwestern portion of the field, possibly reflecting variations in irrigation distribution, plant development, or microclimatic influences. By contrast,  $ET_a$  it was more uniformly distributed in 2022, likely due to consistent irrigation and vegetative coverage. These spatial differences emphasize the utility of SAFER in identifying zones of differential water use, supporting precision agriculture strategies.

Our findings are consistent with other SAFER-based studies in diverse cropping systems. Teixeira et al. [4] applied the model in Mediterranean lemon orchards. They found that it accurately reproduced mid-season  $ET$  values (3–4 mm day<sup>-1</sup>) and crop coefficients in the 0.5–0.8 range, which were comparable to our estimates. Similarly, Do Nascimento Leão et al. [19] observed  $ET$  rates in citrus crops that aligned with lysimetric and eddy covariance-based values in the

humid tropics, further supporting the robustness of the SAFER model across climatic zones.

From a practical standpoint, these results reinforce the applicability of SAFER as a decision-support tool for irrigation recommendations. Its ability to estimate  $ET_a$  using satellite imagery facilitates near-real-time monitoring of crop water needs, reducing dependence on extensive field instrumentation. This capability is particularly critical in Mediterranean regions, where water scarcity requires an efficient irrigation tool. SAFER estimates enable growers to anticipate peak water demand during the summer and adjust irrigation volumes accordingly, thereby minimizing over-irrigation and enhancing water use efficiency.

Nevertheless, the current model configuration has key limitations. The lack of a mechanism to detect physiological plant responses, such as stomatal closure under stress, may mean that  $ET_a$  it may be overestimated in drought scenarios. Integrating indicators of plant water status, such as stem water potential or stomatal conductance, as suggested by Anderson et al. [35], could improve model responsiveness. Likewise, incorporating soil moisture data or coupling SAFER with a soil water balance model may help correct  $ET_a$  estimates when water availability limits transpiration. Abou Ali et al. [3] and Agam & Berliner [36] emphasize the importance of accounting for dew formation and nighttime condensation, which may affect latent heat fluxes and are often underrepresented in remote sensing-based models.

Another issue is model transferability. Although the SAFER model was successfully calibrated for this Mediterranean orchard, its empirical coefficients (a and b) differed from those used in other studies, indicating the need for site-specific adjustments. The ability to apply the model to other crops, climates, or management systems may require localized recalibration. As noted by Trambly et al. [16], variability in regional climate responses requires robust calibration frameworks to ensure accurate modeling.

Future enhancements to the SAFER model should include:

Integration of physiological crop indicators to account for drought-induced transpiration reduction.

Coupling with soil moisture sensors or remote sensing of surface wetness to detect water deficits.

Phenological modeling to capture seasonal shifts in canopy function, particularly in evergreen species like citrus.

Expansion of calibration efforts across different orchard systems to develop region-specific coefficients.

The persistent challenges in estimating  $ET_a$  during the dry season, as evidenced by the low  $R^2$  and high RMSE of the SAFER model, underscore a

fundamental limitation of linear regression-based approaches in capturing the nonlinear dynamics of water-stressed ecosystems. Our findings suggest that the relationship between remote sensing indices (like NDVI) and evaporative fraction becomes highly nonlinear under moisture deficits, a complexity that simple empirical models struggle to represent. This limitation highlights a promising avenue for future research: the integration of advanced machine learning (ML) algorithms that are explicitly designed to model such nonlinear relationships. Recent studies strongly support this direction. For instance, Wang et al. [37] demonstrated that ensemble ML frameworks, such as XGBoost, significantly outperformed physical models in estimating latent heat flux. Meanwhile, Haonan et al. [38] found that Back Propagation Neural Networks (BP) achieved high accuracy in predicting ET for crops in challenging saline-alkali soils. Furthermore, Amani et al. [39] showed that algorithms like Random Forest (RF) and Support Vector Machine (SVM) could provide robust, climate-adaptive  $ET_a$  estimates using minimal satellite inputs, with RF identifying land surface temperature as a critical predictor—a variable highly sensitive to water stress. Therefore, future iterations of ET models for Mediterranean agroecosystems could be substantially improved by adopting or hybridizing with these advanced ML techniques to better capture the complex interplay between vegetation, soil moisture, and atmospheric demand, especially under the water-limited conditions that are becoming increasingly prevalent.

## 5. Conclusions

This study confirms SAFER's reliability for estimating  $ET_a$  and surface energy balance components in Mediterranean citrus orchards. The model performed well under non-stressed, wet season conditions, producing high  $R^2$  values and realistic  $ET_a$  estimates when validated against eddy covariance flux tower data. However, its accuracy declined significantly during the dry season, highlighting limitations in capturing crop water stress with current vegetation index-based approaches.

The results emphasize the critical role of local calibration to improve SAFER's accuracy under different environmental conditions. Our findings align with previous studies in both tropical and semi-arid climates, confirming the broad applicability of SAFER when site-specific calibration is undertaken. Spatial variability analyses further demonstrated the model's ability to support irrigation by identifying areas with differing water demands.

Moreover, the SAFER model offers a practical and cost-effective alternative to traditional ET estimation methods, especially in areas lacking continuous ground-based measurements. Its compatibility with freely available satellite data (e.g., Sentinel-2) and its integration into open-source tools make it accessible for operational use by farmers, researchers, and policymakers alike. This

democratization of *ET* monitoring tools can contribute to more equitable and efficient water distribution strategies, particularly in regions facing increasing water scarcity due to climate change.

Despite these strengths, further refinement is necessary to improve the model's sensitivity to biophysical changes during drought stress. Enhancing the model to account for physiological responses and soil moisture dynamics would significantly bolster its reliability across diverse climatic conditions and cropping systems. Continued research and development are also essential for establishing generalized calibration protocols that support large-scale implementation.

In conclusion, the SAFER model shows great promise as a remote sensing-based decision-support tool for sustainable water resource management in Mediterranean agriculture and beyond. Its capacity to deliver accurate, spatially explicit *ET* estimates provides a foundation for precision irrigation, adaptive drought response, and informed water policy, all of which are vital for building resilience in agricultural systems under a changing climate.

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