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RESEARCH

Estimating Crop Evapotranspiration in Data-Scare Regions: A Comparative Analysis of Eddy Covariance, Empirical and Remote-Sensing Approaches

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Abstract
Maximizing water productivity amid agricultural water scarcity demands accurate crop evapotranspiration (ET_c) estimation. While the Penman–Monteith method is standard, its dependence on extensive meteorological data restricts use in data-scarce regions. Eddy covariance offers precise ET_c estimation but is resource-intensive. Satellite remote sensing, like MOD16, offers a promising alternative for ET estimation. Several empirical models are also available, out of which suitable alternatives can also be identified for the regions with limited weather data availability, where eddy covariance and remote sensing techniques become limitations. Consequently, a study was undertaken to investigate the performance of eddy covariance method (Eddy Tower based), empirical models, and a remote sensing technique for computing crop evapotranspiration under rice–wheat cropping system at Naraingarh Seed Farm of Punjab Agricultural University, Ludhiana, for the years 2022–2023. The performance evaluation of all the methods was performed using statistical indicators, including mean absolute error, mean bias error, root mean squared error, coefficient of determination, and index of agreement. The eddy covariance method, selected empirical models, and remote sensing technique demonstrated a good correlation with FAO Penman–Monteith ET, with coefficient of determination values greater than 0.85. The eddy covariance tower gives precise ET_c estimates, with MOD-16 satellite data closely trailing. When Eddy Tower data is inaccessible, MODIS products provide a reliable alternative on a broader scale. In the absence of MODIS data, such as during cloud cover, empirical models offer effective ET_o and hence ET_c estimation. Moreover, for regions lacking weather data, models like Hargreaves and Samani (1985) or Priestley and Taylor (1972) stand out as optimal choices for accurate ET_o and thereafter ET_c estimation.

Keywords Agriculture · Energy balance closure · Models · Remote sensing · Water management

Introduction

Earth's demand for finite water resources has escalated due to population growth, industrialization, and water-intensive agriculture practices. Water is essential for human survival and is used for domestic, drinking, agricultural, and industrial purposes [1]. The agriculture sector is the largest consumer of freshwater, followed by industry and domestic usage [2]. This demand is expected to continue rising, with projections indicating that approximately 6 billion people may suffer from food and water scarcity by 2050 [3, 4]. The imbalance between water supply and demand is a growing concern, and there is an urgent necessity for more efficient water management strategies. Thus, there is a need to enhance the efficiency of water utilization in food production [5, 6]. Numerous studies have concentrated on water management [7], water delivery scheduling [8], groundwater level monitoring [9], the effective allocation of water resources [10], and the resolution of conflicts among water consumers [7, 11]. Irrigation agriculture emerges as a significant water consumer in arid and semi-arid regions, and its allocation directly influences yield production, food security, and system efficiency [12–14].

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Evapotranspiration (ET) is a crucial indicator for assessing crop water requirements, consisting of the vaporized movement of water from the land to the atmosphere through soil evaporation and plant transpiration [15–17]. It is essential to accurately assess evapotranspiration to avoid excessive and insufficient irrigation, ensuring the sustainable utilization of water resources while meeting agricultural demands. Achieving this goal involves employing models for measuring and predicting evapotranspiration rates or utilizing advanced instruments for direct measurements. However, the complex nature and high costs associated with direct measurement have led to the development of estimation models designed for versatile applications across different contexts [18–21].

Numerous models have been proposed for evapotranspiration estimation utilizing diverse meteorological data. Broadly, ET estimation methods fall into five primary categories: pan evaporation-based, temperature-based, mass-transfer-based, radiation-based, and combined methods [22, 23]. Nevertheless, these models differ in assumptions, data requirements, complexity, and reliability. The FAO Penman–Monteith method, endorsed by the Food and Agriculture Organization of the United Nations (FAO) and the World Meteorological Organization, is recommended as a standard model for calculating evapotranspiration and evaluating other models' accuracy [24, 25]. This standardized approach involves intricate mathematical calculations with various meteorological variables, often challenging to obtain from local weather stations in developing countries. Consequently, simpler alternative methods based on empirical equations are being explored for ET computation with limited data [26]. Due to the complex relationships between meteorological factors, time, and predictability, these alternative models must undergo scrutiny against the standard FAO Penman–Monteith method before practical application. It is emphasized that a site-specific assessment is essential to ascertain the predictive performance of alternative methods for a given region [27, 28].

Eddy covariance (EC) method stands out as a state-of-the-art, scientifically grounded micrometeorological approach for assessing evapotranspiration (ET) exchanges in cropping systems [29–31]. This method involves estimating net ecosystem exchanges of CO_2 (Net Ecosystem Exchange) and water vapor (ET) by monitoring and measuring the turbulent transport of eddies carrying CO_2 and water vapor within the plant canopy boundary layer of the atmosphere [32–34]. Although the EC approach proves to be a scientifically robust, easy-to-install, and maintainable technology for accurately quantifying ET in cropping systems, it does not account for the spatial variability and provides field-scale evapotranspiration values [34]. To understand this element of ET, remote sensing models are important. Several models are currently available to estimate ET using remote sensing data, ranging from local and regional scales such as Surface Energy Balance System (SEBS) [35, 36], Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC) [37], and Atmosphere Land Exchange (ALEXI) [38] to continental and global scales such as MOD16 [39], disaggregated Atmosphere-Land Exchange (ALEXI/DisALEXI) [38], Jet Propulsion Laboratory Priestley-Taylor (JPL-PT) [40], and Global Land Evaporation Amsterdam Model (GLEAM), spanning a wide range of temporal scales. MODIS Global Terrestrial evapotranspiration Product is a frequently used technique to calculate ET at both a continental and global scale. The technique is based on the Penman–Monteith equation to compute ET's temporal and spatial variations over the world's land surface areas. ET data obtained through satellite remote sensing observations on regional or global scales is integral to hydrology and ecology studies due to its spatial coverage advantages [41–43].

This research focuses on estimating evapotranspiration (ET) in rice–wheat rotations using alternative approaches. It determines the most suitable empirical model for the study area, especially under conditions of limited meteorological data. Additionally, it evaluates the effectiveness of the eddy covariance (EC) method for in situ ET determination and explores the applicability of remote sensing models for estimating ET in the region. This approach not only fills a critical gap in understanding ET dynamics in agricultural systems but also offers practical solutions for water management in areas with resource constraints. By combining traditional empirical models, micrometeorological techniques, and remote sensing technology, the study provides a comprehensive framework for improving water resource management in agriculture, addressing a pressing global challenge.

Materials and Methods

Site Description

The eddy covariance flux tower is situated in Naraingarh village, in the Amloh tehsil of Fatehgarh Sahib district in Punjab, India. The site's geographical coordinates are between latitude 30˚60'N and longitude 76˚19'E, and it has an elevation of 268 m above mean sea level, as illustrated in Fig. 1. The predominant crops in this region are rice and wheat. Notably, June emerges as the hottest month, characterized by an average temperature of 31.4 °C, while January is the coldest month with an average temperature of 12.6 °C. The annual mean temperature in Naraingarh is recorded at 23.2 °C. The area experiences an annual rainfall of approximately 769 mm. The study covers the period from December 2021 to April 2023 for rice–wheat rotation.

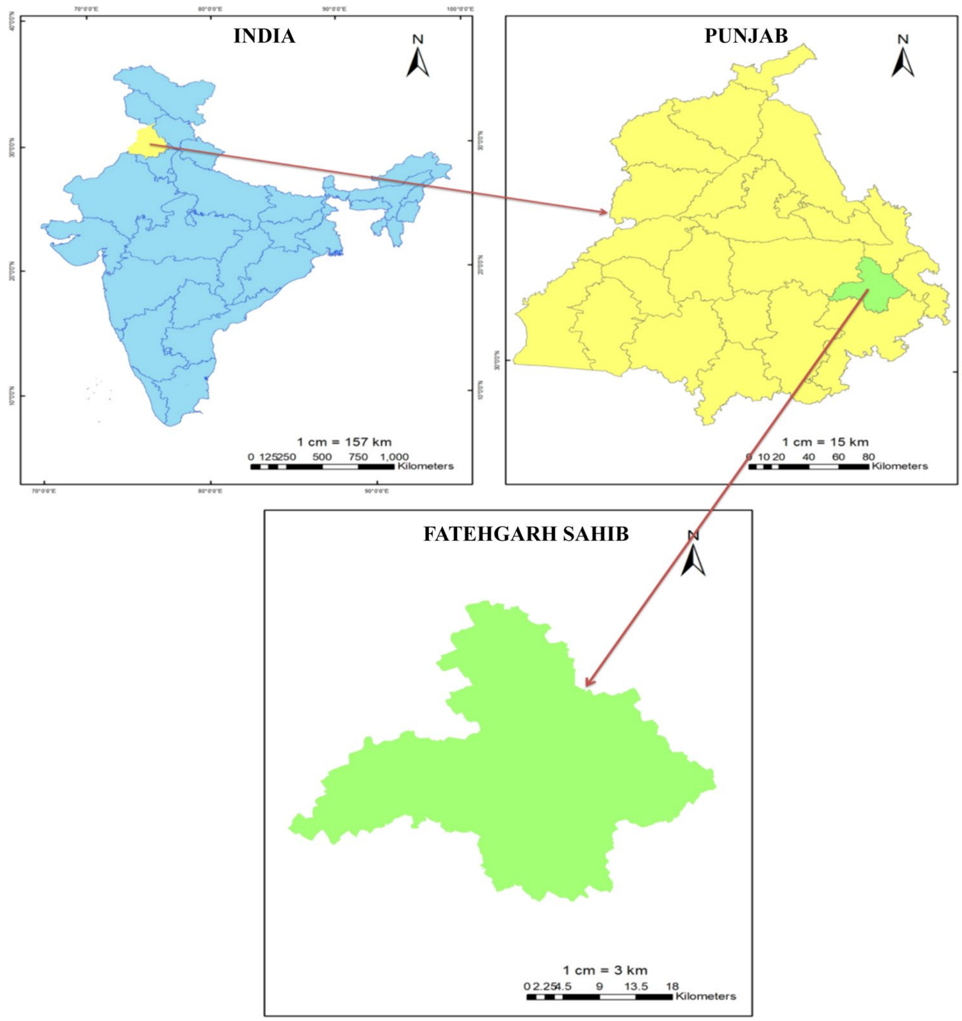


Fig. 1 Map of the study area

Selection of the Crop

The experimental crop chosen for investigation within the designated study area comprised wheat (varieties: Punjab Wheat Chapati 1) during winter (*Rabi*) season and rice (varieties: Punjab Rice 121 and Pusa Basmati 1509) during monsoon (*Kharif*) season. The cultivated land spanned 2.5 hectares. Wheat sowing occurred on the fourth night of November whereas the rice crops, including Punjab Rice, in late June and Pusa Basmati on the fourth night of July. The study period included two wheat crops (November to April) and one rice crop (June to October) in rotation. Conventional flood-based irrigation and fertigation methodologies were uniformly applied to both crops. Wheat harvest transpired in April for both Rabi seasons, while rice harvesting took place at the beginning of November. The research period also consisted of a fallow period, during which no crop was cultivated. The eddy covariance flux tower is situated in the study region.

ETo Methods

Different methods have been analyzed for the calculation of evapotranspiration. These are described below with their corresponding equation.

Eddy Covariance

The eddy covariance (EC) method is widely recognized as a key technique for estimating evapotranspiration (ET) [44]. This method determines the latent heat of evapotranspiration (LE) by analyzing the covariance between vertical wind velocity and specific humidity. The accuracy of the LE flux estimate is assessed through the energy flux balance equation at the land surface, denoted as follows:

$$Rn = LE + H + G \tag{1}$$

where Rn is net radiation, H is sensible heat flux, and G is ground heat flux. All components are denoted in W/m^2. In Eq. (1), minor flux terms such as energy storage in the canopy or energy conversion by photosynthesis are not considered. The Energy Balance Closure (EBC) calculation utilized all available filtered half-hourly flux data about the four terms in Eq. (1). Three criteria were employed to assess the EBC. Firstly, we computed the slope and intercept using ordinary linear regression (OLR) for turbulent fluxes (H + LE) against available energy (Rn − G). In an ideal situation where the energy balance is fully closed, the slope and intercept of the linear regression should ideally be 1 and 0, respectively [45]. The EBC is calculated as follows:

$$EBCratio = \frac{LE + H}{Rn - G} \tag{2}$$

Latent and Sensible Heat

Employing the eddy covariance (EC) measurement, we estimate latent heat (LE) and sensible heat (H) within a footprint extending over hundreds of meters. We apply the fetch area thumb rule of 100:1 m in our case. The local surface layer grows at approximately one vertical meter per hundred horizontal meters. The fetch area covers 30 m by keeping sensors at a 3-m height. Each EC system comprises a fast-response 3D sonic anemometer, a rapid open-path infrared gas analyzer measuring H_2O and CO_2 concentrations, a fine-wire thermocouple, an air temperature/humidity sensor, and a micro logger. The calculation of flow terms includes constant air density measurements. The EC system measures turbulent flows at a frequency of 20 Hz, and 30-min mean LE and H fluxes are subsequently computed and corrected. The correction, referred to as the Webb, Pearman, and Leuning (WPL) correction, as outlined by EK [46] and detailed by Leuning [47], plays a crucial role, potentially rectifying scalar fluxes by up to 50%, as highlighted by Mauder and Foken [48]. The significance of WPL correction is underscored by its capacity to address significant differences in flux measurements. Coordinate rotation corrections, recommended by Moore [49], when nearly correct pickup separation is achieved. The 30-min LE fluxes are further converted to evapotranspiration by the eddy covariance (ET EC) in millimeters per day, as determined by the following:

$$ECET = \frac{1}{\rho w} \sum_{i=0}^{48} \frac{LE30min}{\lambda(T)} \tag{3}$$

where ρw (kg/m^3) is the density of water. The heat of vaporization λ (MJ/kg) is a function of the temperature T (°C) described by the equation given by Ding et al. [50]:

$$\lambda = (2.501 - 0.00236T) \tag{4}$$

Empirical Approaches

FAO-56 Penman–Monteith

This is a combination of the Penman [51] method and is based on the principle of the Bowen ratio (includes radiation, wind, and humidity factors) and Monteith [52], a method that takes into account resistance factors (including surface drag and aerodynamic drag). The equation was used by Allen [37] on an hourly basis, while the resistance term has a constant value of 70 s/m all day and night and recommended FAO-56 Penman–Monteith equation as the only standard method of determining reference evapotranspiration in all climates, especially if it was available data. The equation is given as follows:

$$PET = \frac{0.408\Delta(Rn - G) + \Upsilon(\frac{900}{T+273}U2)(es - ea)}{\Delta + \Upsilon(1 + 0.34U2)} \tag{5}$$

where PET is the potential evapotranspiration (mm/day), R_n is the net radiation at the crop surface (MJ/m^2/day), G is the soil heat flux (MJ/m^2/day), T is the daily mean temperature at 2 m height ($^{\circ}$C), U_2 is the wind speed at 2 m height (m/s), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), (e_s-e_a) is the saturated vapor pressure deficit (kPa/°C), Δ slope vapor pressure curve (kPa/°C), and ϒ is the psychrometric constant (kPa/°C).

Papadakis

The Papadakis [53] method is based on saturated vapor pressure corresponding to monthly temperatures for ETo estimation (mm/month). The equation is presented as follows:

$$PET = 0.5625(eaTmax - ed) \tag{6}$$

where e_{aTmax} is the water pressure corresponding to the average maximum temperature (kPa) and e_d is the saturation water pressure corresponding to the dewpoint temperature (kPa).

Priestly and Taylor

Priestly and Taylor (PT) [54] approach has proved to be a good alternative in many climatic regions. According to Priestly and Taylor, the equation is defined as follows:

$$PET = \alpha * \left(\frac{\Delta}{\Delta + \Upsilon}\right) * \left(\frac{Rn}{\lambda}\right) \tag{7}$$

where,

$$\Delta = \frac{4098 * (0.6108 * \exp(\frac{17.27*Tmean}{Tmean+237.3})}{(Tmean + 237.3)^2} \; and \; \Upsilon = \frac{Cp * Patm}{\in * \lambda} = 0.665 * 10^3 * Patm \tag{8}$$

where α is the Priestley-Taylor parameter (1.26), Rn is the net radiation at the crop surface (MJ/m2/day), Tmean is the mean air temperature (○C), λ is the latent heat of vaporization of water (λ = 2.501 MJ/kg), and Patm is the atmospheric pressure (kPa).

Hargreaves and Samani

Hargreaves and Samani [55] proposed a method where only daily mean maximum, mean minimum temperature, and extra-terrestrial solar radiation are required. The Hargreaves-Samani (HS) method has been widely used for its simplicity in evaluating and calibrating its parameters.

$$PET = 0.0135 * 0.16 * \left(\frac{Ra}{\lambda}\right) * (Tmean + 17.8) * \sqrt{(Tmax - Tmin)} \tag{9}$$

where R_a is the extra-terrestrial radiation (MJ/m^2/day), λ is the latent heat of vaporization of water (λ = 2.501 MJ/kg), T_{max} is the maximum air temperature ($^{\circ}$C), T_{min} is the minimum air temperature ($^{\circ}$C), and T_{mean} is the mean air temperature ($^{\circ}$C).

Jensen and Haise

Jensen and Haise [56] estimated evapotranspiration from solar radiation. The equation is given as follows [57]:

$$PET = (0.014Ta - 0.37)(Rs * 0.000673) * 25.4 \tag{10}$$

where T_a is the average daily air temperature ($^{\circ}$C) and R_s is incident solar radiation (MJ/m^2/day).

Calculation of Actual Evapotranspiration

Actual evapotranspiration or evapotranspiration (ET) is calculated using the crop coefficient (Kc) calculated for different crops at different growth stages [37]. The ET is calculated as follows [58]:

$$ET = Kc * PET \tag{11}$$

where ET = actual evapotranspiration (mm/day) and Kc = crop coefficient PET = potential evapotranspiration (mm/day).

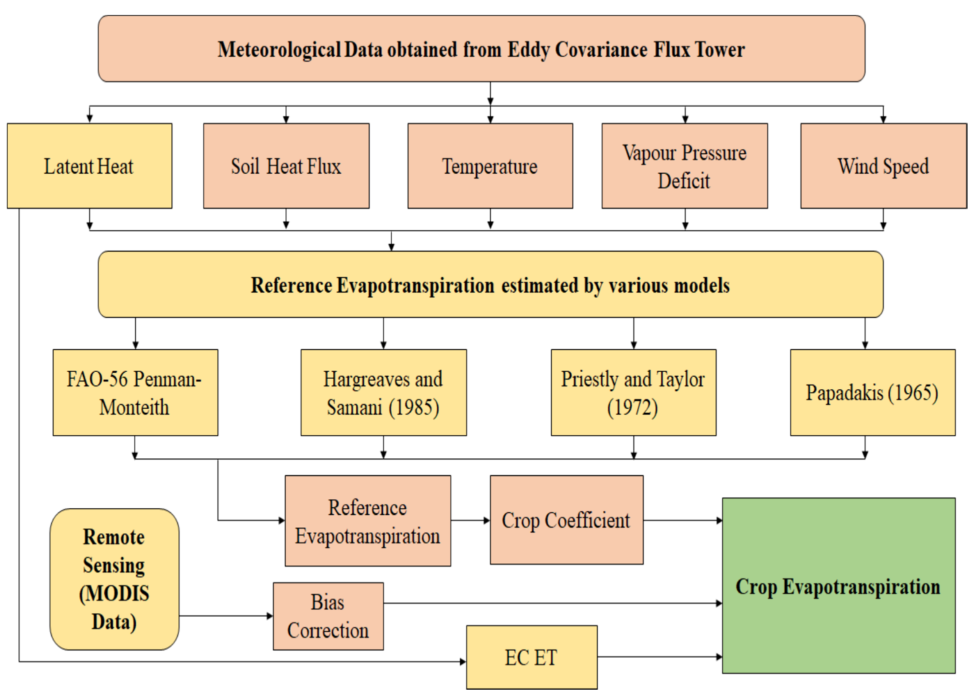


Fig. 2 Flowchart of the MOD16 ET algorithm

MOD 16

The MOD16 model, proposed by Mu et al. [39, 59], calculated potential evaporation [60] by estimating ET using the Penman–Monteith equation. It distributes the available energy across surface soil and vegetation constituents through fractional total vegetation cover. The evaporation from the wet and saturated soil surfaces is thus included in the soil evaporation. Moreover, canopy water loss includes transpiration from the dry surface and evaporation from the wet canopy surface. Finally, it uses meteorological and physiological aspects related to vegetation to reduce potential ET to actual ET (Fig. 2). In MOD16, the total of wet canopy evaporation (E_{wet} mm/day), bare soil evaporation (E_s, mm/day), and vegetation transpiration (E_T, mm/day) throughout the day and night is equal to evapotranspiration (E, mm/day). The equations in their model are given below [61]:

$$Ewet = \frac{\left(\Delta * Rnc + \rho * Cp * fc * \frac{VPD}{rhrc}\right) * \frac{fwet}{\lambda}}{\Delta + \frac{Pa*Cp*rcv}{\lambda*\varepsilon*rhrc}} \tag{12}$$

$$Es = \frac{(\Delta * Rns + \rho * Cp * (1 - fc) * \frac{VPD}{ras})/\lambda}{\Delta + \Upsilon * rtot/ras} * [fwet + (1 - fwet) * fsm] \tag{13}$$

$$ET = \frac{\left(\Delta * Rnc + \rho * Cp * (1 - fc) * \frac{VPD}{ra}\right) * (1 - fwet)/\lambda}{\Delta + \lambda * (1 + rs)/ra} \tag{14}$$

$$E = Ewet + Es + ET \tag{15}$$

The MOD16 evapotranspiration (ET) dataset utilized in this study was an 8-day composite dataset with a 500-m (m) pixel resolution spanning from December 2021 to April 2023.

Statistical Analysis

The various statistical performance indicators, namely root mean squared error (RMSE), Willmott index of agreement (d), coefficient of determination (R^2), mean absolute error (MAE), mean bias error (MBE), and Nash Sutcliffe model Efficiency coefficient (NSE) were used, keeping Penman–Monteith evapotranspiration as observed (Table 1).

Results and Discussion

Energy Balance Closure (EBC)

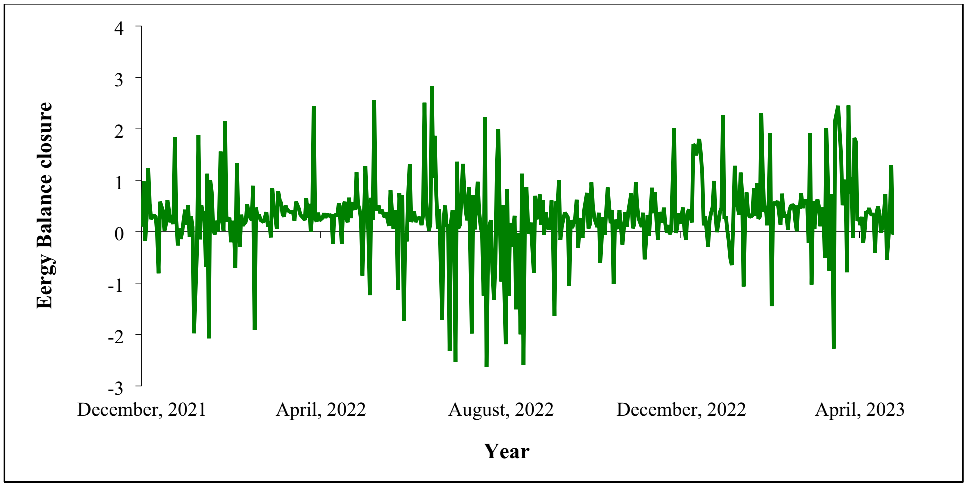
The energy balance closure (EBC) was assessed for the study period from December 2021 to April 2023, representing the rice–wheat cropping cycle in the study area (Fig. 3). The analysis revealed a maximum EBC of 2.84 and a minimum of − 2.64, resulting in an average EBC of 0.30. Despite its prominence, the EC method often fails to achieve energy balance closure. Several authors reported the same results [68–70]. Typically, the available energy, represented by the difference between incoming Rn and outgoing G, exceeds the sum of the outgoing turbulent fluxes of H and LE [71]. The relative energy balance closure ratio (Eq. 2) reflects the imbalance in the in- and outgoing energy fluxes. Depending on the surface type, EBC_{ratio} values between 70 and 90% are frequently reported [69, 72]. Energy balance closure in rice fields presents unique challenges due to various factors. The multi-layered canopy, including the water surface, rice plants, and underlying soil, poses difficulties in accurately

Table 1 Parameters of statistical analysis

S. No	Analysis	Equation	Range	References
1	Mean absolute error	$MAE = \frac{1}{n}\sum_{i=1}^{N} \lvert(ETobs - ETcal)\rvert$	0 to ∞	[62]
2	Mean bias error	$MBE = \frac{1}{N}\sum_{i=1}^{N}(ETCal - ETObs)$	− ∞ to ∞	[63]
3	Root mean square error	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(ETObs - ETCal)^2}$	0 to ∞	[64]
4	Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^{N}(ETObs - ETCal)^2}{\sum_{i=1}^{N}\left(ETObs - \overline{ETCal}\right)^2}$	0 to 1	[65]
5	Nash–Sutcliffe efficiency coefficient	$NSE = 1 - \frac{\sum_{i=1}^{N}(ETobs - ETcal)2}{\sum_{i=1}^{n}(ETobs - \overline{ETobs})2}$	− ∞ to 1	[66]
7	Index of agreement	$d = 1 - \frac{\sum_{i=1}^{N}(ETObs - ETCal)^2}{\sum_{i=1}^{n}\left(\lvert ETCal - \overline{ETObs}\rvert + \lvert ETObs - \bar{ETObs}\rvert\right)^2}$	0 to 1	[67]

ET_{Obs} observed evapotranspiration, ET_{Cal} evapotranspiration calculated using selected methods

Fig. 3 Energy balance closure of wheat rice cycle

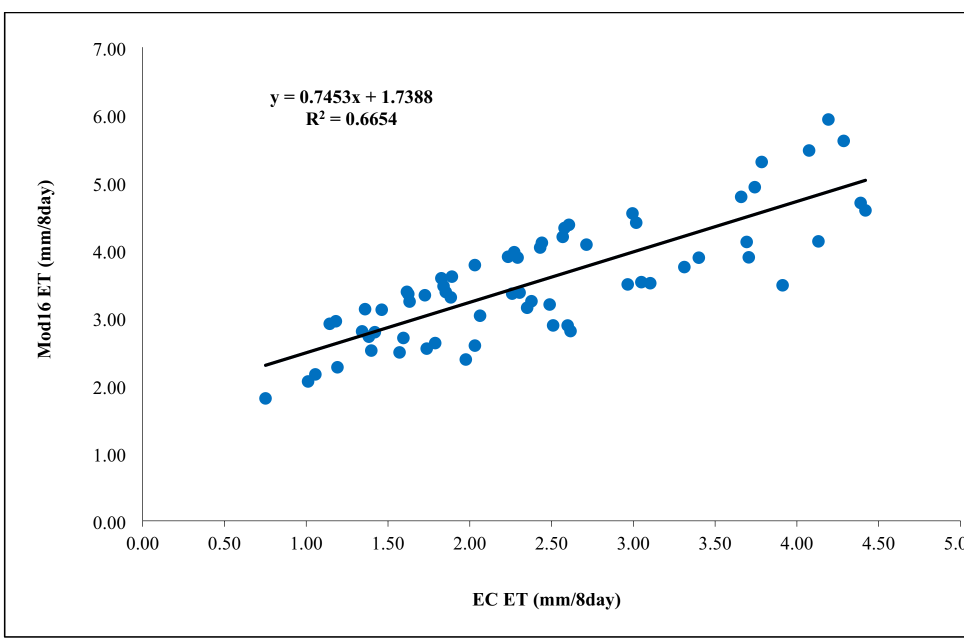


measuring energy fluxes. The changing growth stages and flooded nature of rice fields further complicate the energy balance, affecting energy absorption, reflection, and emission. The fluctuating water depth and high humidity contribute to inconsistencies in energy balance measurements. Additionally, the heterogeneous surface created by water, vegetation, and bare soil patches leads to spatial variability in energy fluxes—a challenge for accurate measurement. Some researchers also suggest that undetected vertical transport of LE and H at large spatial and temporal scales could contribute to the energy balance issue [71, 72], particularly with the involvement of large-scale eddies related to landscape heterogeneity [73]. All this implies an incomplete understanding of the system's physics, leading to an underestimation of actual ET.

Comparison of MOD 16 ET with Eddy Covariance ET

The comparative analysis involved the MOD16-derived ET with in situ ET calculated from latent heat flux measured via eddy covariance. To align with the temporal resolution of MOD16, the available eddy covariance measurements were processed to derive 8-day averages. The bias correction is further done to adjust systematic errors or biases in a dataset. The assessment revealed consistent underestimation by the MOD16 model compared with eddy covariance ET throughout most of the temporal domain. Statistical indicators, including a mean absolute error (MAE) of 1.15, mean bias error (MBE) of 1.13, and root mean square error (RMSE) of 1.27, underscore significant differences between the modelled and observed ET values.

Fig. 4 Comparison of ECET (measured) and MOD 16 ET (modelled) for the rice wheat crop cycle



Furthermore, the Nash Sutcliffe efficiency coefficient of – 0.39 indicates a pronounced deficiency in the MOD16 model's ability to capture the observed ET variability. The index of agreement (Willmott index), registering a value of 0.63, reinforces the substantial lack of similarity between the two datasets. The coefficient of determination, 0.67, indicates a positive linear relationship, highlighting the differences between modelled and observed ET (Fig. 4).

Several factors lead to the uncertainties of ET obtained from MOD 16. One of the reasons is spatial and temporal resolution. Since MOD16 ET operates at a relatively coarse spatial resolution of 500 m, compared to the point measurements obtained by eddy covariance systems, this inconsistency may lead to difficulty accurately capturing the heterogeneity of land surface characteristics, such as vegetation type, topography, and land use, which can significantly influence evapotranspiration [74]. Similar uncertainties in MOD16 ET were also found compared to EC ET due to spatial scale mismatch between the fine vegetation data and coarse meteorological forcing data. MOD16 ET relies on a specific model/calculation that incorporates various assumptions about the land surface, vegetation properties, and meteorological inputs. These assumptions may not perfectly align with the specific conditions of the study area, introducing uncertainties in the estimation process. Differences in the parameterization of the underlying physical processes, such as stomatal conductance, soil moisture dynamics, and canopy interception, can contribute to the underestimation. Mu et al. [39], Chi et al. [75], and Aguilar et al. [76] also reported a similar underestimation of MOD 16 ET. EC measurements directly capture these processes at a specific location, while the model relies on generalized parameterizations. Eddy covariance systems are susceptible to local variations in land surface characteristics, whereas MOD16 ET may smooth out these variations due to its coarser resolution. This can lead to differences in the evapotranspiration in regions with significant spatial heterogeneity.

Eddy covariance measurements are not without uncertainties, and local site conditions, instrument calibration, and data processing can introduce errors. When not accounted for in the comparison, these uncertainties may contribute to anticipated underestimations by MOD16. Several authors [75, 76] also reported underestimation due to calibration errors. Also, an underestimation of MOD16 ET when compared to EC ET was observed. Wang et al. [77] compared MOD16 ET with EC ET observed that MOD16 ET showed relatively significant differences when compared with EC ET datasets in cold seasons and barely vegetated regions making it difficult to use them for making country-wide estimates. Li et al. [78], also found uncertainties in remote sensing models compared with in situ flux methods. All of these results suggest that the MOD16 model might not accurately reflect the actual evapotranspiration in the studied area; hence, using MOD16 ET estimates should not be solely dependent.

Comparison of Eddy Covariance with Penman ET

Evapotranspiration, as determined through different empirical models and eddy covariance, has been systematically compared with the PM model as standard due to its wide acceptance and incorporation of physical and physiological factors (Fig. 5). Notably, the evapotranspiration values derived from the eddy covariance overestimated with those obtained from Penman–Monteith (Table 2). These differences can be attributed to the enhanced complexity of the Penman–Monteith model, which operates on a more comprehensive and physically grounded framework, incorporating various meteorological parameters such as temperature, humidity, wind speed, and solar radiation. The model

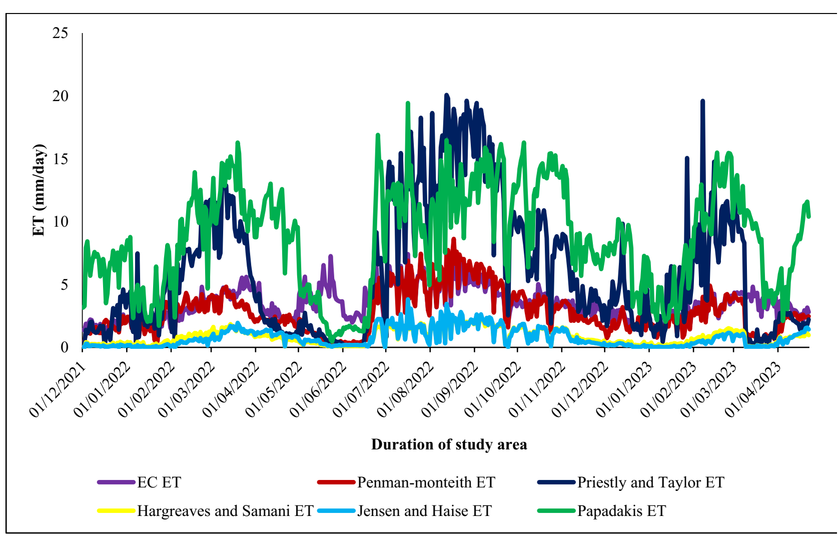


Fig. 5 Comparison of daily evapotranspiration of the selected methods

Table 2 Statistical analysis

Models/parameters	EC ET	Hargreaves and Samani	Priestley and Taylor	Jensen and Haise	Papadakis	MODIS
MAE	0.94	1.98	3.49	2.03	5.86	1.29
MBE	0.60	− 1.98	3.26	− 2.03	5.86	0.56
RMSE	1.40	2.27	4.88	2.33	6.65	1.48
R^2	0.85	0.85	0.87	0.70	0.87	0.86
NSE	0.30	− 0.85	− 7.55	− 0.94	− 14.86	0.14
Willmott index	0.75	0.44	0.57	0.44	0.31	0.50

suitably addresses both aerodynamic and radiative components of evapotranspiration. In contrast, eddy covariance directly measures actual fluxes but relies on the assumption of horizontal homogeneity and stationarity, conditions that may only be sometimes upheld. The sensitivity of eddy covariance systems to the representativeness of the measured area contributes to the observed disparities.

Inconsistencies arising from distinctions in spatial and temporal scales, particularly under dynamic environmental conditions, align with findings from prior studies by Hargreaves & Samani [55], Migliaccio and Barclay Shoemaker [79], and Priestly and Taylor [54]. Also, the differences are due to the intensive sensitivity of Penman–Monteith evapotranspiration estimates to surface conductance. An overestimation of surface conductance can lead to concurrent overestimates of evapotranspiration, as verified by studies conducted by Hughes et al. [80]. Noteworthy inconsistency in daily evapotranspiration estimates between Penman–Monteith and eddy covariance is observed due to increased vapor pressure deficit (VPD), particularly during the June to August period, where the rice crop is dominant. The energy imbalance can influence the accuracy of evapotranspiration estimates and potentially lead to overestimations. Furthermore, aerodynamic limitations may also play a significant role. The eddy-covariance relies on the assumption that the atmosphere above the canopy is well-mixed, which may not hold in fields due to stagnant air pockets near the water surface. These air pockets obstruct water vapor exchange between the canopy and the atmosphere, resulting in an overestimation of evapotranspiration. This observation has been corroborated by Wilson et al. [50], Sun et al. [81], and Denager et al. [73].

Evapotranspiration in Fellow Period

Evapotranspiration (ET) calculations were conducted using eddy covariance, MOD-16, and various empirical models during the fallow period, from mid-April after the wheat crop harvest to the rice transplanting phase. The outcomes are presented in Fig. 6. Differences in ET were noted among MOD-16, Penman ET, and the empirical models, primarily attributed to the unaccountability of

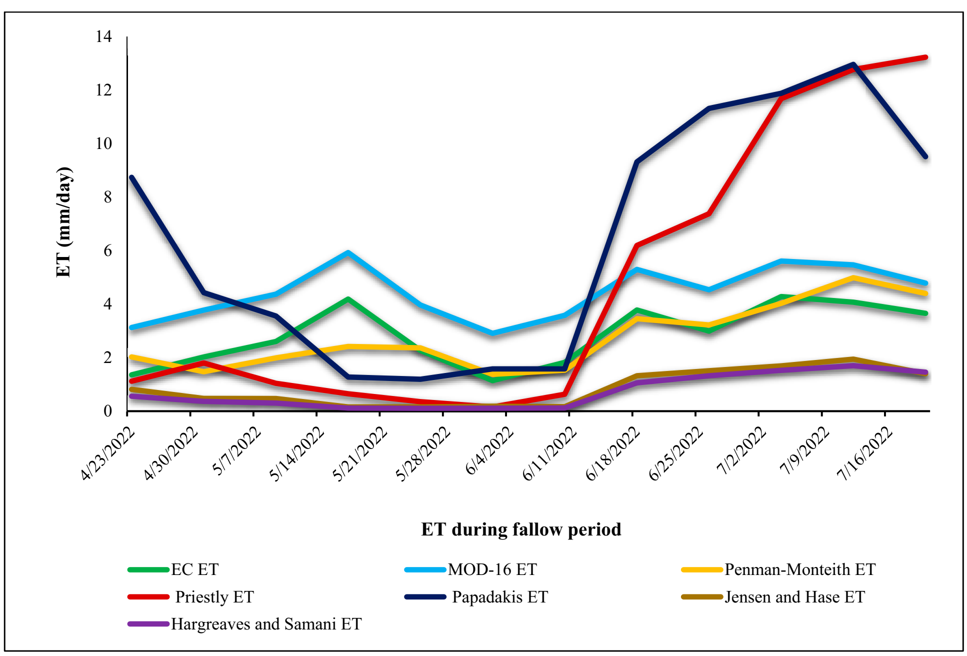


Fig. 6 ET comparison from different models of the fellow period

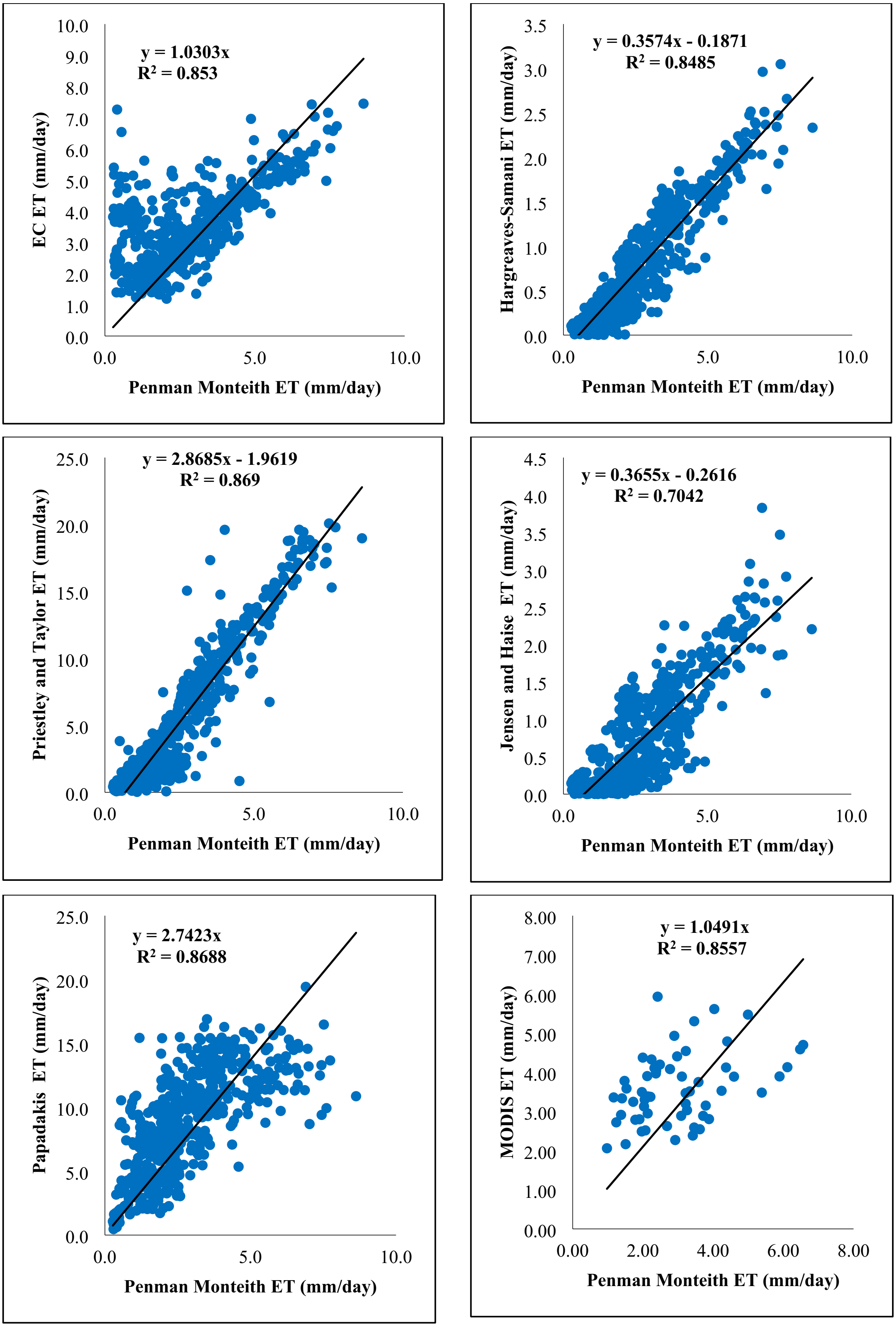


Fig. 7 Correlation of ET estimated using each technique with Penman–Monteith-based ET

soil evaporation in MOD-16, which tends to over-estimate soil evaporation under conditions of elevated soil wetness (MAE 0.47; MBE 0.47; RMSE 0.98). The MODIS approach relies on satellite-based observations of land surface properties and exhibits sensitivity to variations in soil moisture content and land surface temperature. In contrast, eddy covariance (MAE 0.15; MBE 0.02; RMSE 0.37) persists in capturing residual fluxes associated with lingering vegetation or soil processes even in the absence of an active crop during the fallow period. These findings highlight the essential factors influencing ET variations and emphasize the importance of accounting for vegetation dynamics in ET estimation methodologies.

Evapotranspiration from Different Empirical Methods

While comparing the evapotranspiration of Penman–Monteith with other empirical models, it was observed that the Hargreaves-Samani (HS) and Jensen-Haise methods have consistently underestimated evapotranspiration compared to the Penman–Monteith (PM) reference equation (Allen, 1998), with the mean bias error (MBE) of – 1.98 and – 2.03 respectively. This underestimation has also been documented by several authors [82–84]. Both HS and Jensen-Haise models, based on a reduced set of meteorological parameters primarily relying on air temperature, exhibit limitations compared to the more comprehensive Penman–Monteith equation. These methods incorporate empirical coefficients derived from historical weather data, introducing potential biases in estimating evapotranspiration due to their inability to represent site-specific conditions accurately.

In contrast, an overestimation of evapotranspiration (ET) was noted with the Priestley and Taylor (PT) ET and Papadakis ET models, making them unsuitable for application in the current study area, as indicated in Table 2. Previous studies conducted by Bottazzi et al. [85], Vishwakarma et al. [86], and Proutsos et al. [87] have also reported uncertainties associated with both models in the determination of evapotranspiration. This overestimation can be attributed to the Priestley and Taylor model's assumption of a constant ratio between latent heat flux and net radiation under non-limiting conditions, implying an equal energy partitioning between sensible and latent heat fluxes. However, this simplification neglects the impact of aerodynamic resistance and stomatal regulation, which can constrain actual evapotranspiration. On the other hand, Papadakis incorporates temperature as an additional factor, but the temperature dependence may not accurately capture plant physiological responses under diverse environmental conditions. Moreover, both PT and Papadakis models need to explicitly consider the influence of wind speed on controlling the transfer of sensible heat from the surface to the atmosphere, potentially leading to an overestimation of evapotranspiration, particularly under calm atmospheric conditions.

Figure 7 illustrates the coefficient of determination by comparing various models with Penman–Monteith evapotranspiration (ET). The highest coefficient of determination was distinguished for Priestley and Taylor and Eddy covariance (R^2 0.87), succeeded by Hargreaves-Samani (R^2 0.85) and Jensen and Haise (R^2 0.70). This ranking highlights the suitability of the Priestley and Taylor model and Eddy covariance ET, followed closely by Hargreaves-Samani and Jensen and Haise, as alternatives in the absence of Penman–Monteith within the current study area. Singh et al. [88] examined multiple empirical models for different seasons. They also observed that Hargreaves and Samani are the best substitutes for FAO Penman–Monteith, particularly during winter.

Conclusions

The study identified suitable alternatives to the Eddy covariance (EC) method for estimating evapotranspiration (ET) within the study area, focusing on five empirical models and one remote sensing model across a rice–wheat crop cycle. The Penman–Monteith (PM) method, recognized as the most physically sound and reliable approach, requires extensive meteorological data. Due to data limitations, alternative methods with less demanding data requirements were explored. The MOD-16 ET model exhibited a coefficient of determination (R^2) of 0.86 compared to the PM method (primary method), establishing its suitability as a remote sensing model for the study area. However, cloud cover often hinders the utility of remote sensing data, necessitating the disaggregation of spatial and temporal resolutions. The Priestley-Taylor and Hargreaves-Samani methods emerged as the most promising empirical alternatives, with R^2 values of 0.82 and 0.78, respectively. These methods require only temperature data, which is readily available in many regions. The study highlights the potential of Priestley-Taylor and Hargreaves-Samani methods as cost-effective substitutes for EC in data-scarce regions. Further validation across diverse climatic zones and crop types is recommended. The exploration of additional remote sensing models, such as Surface Energy Balance for Land (SEBAL), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), and Simplified Surface Energy Balance Index (SSEBI), alongside machine learning models, is also suggested. Enhanced crop diversification is needed to develop models capable of determining evapotranspiration more accurately under varying conditions.

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Author Contribution NGC: data collection, data analysis, and writting rough draft of the manuscript. SK: planning and xcecution of the study and editing of the manuscript. MCS: planning and execution of the research trial, data collection, and editing of the manuscript. NS: providing the facilities for conducting the research trial on rice–wheat crop sowing and management. AM: assisted in planning and ececution of the study and installation of Eddy Covariance Flux Tower.

Data Availability The dataset generated and used in this study may be available from the corresponding author on a reasonable request.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Conflict of Interest The authors declare no competing interests.

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