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A comparative study of crop evapotranspiration estimation in maize using empirical methods, pan evaporation and satellite-based remote sensing technique

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Abstract

A research study was conducted at the Agricultural College and Research Institute, Coimbatore to estimate the evapotranspiration (ET) of maize crop (*Zea mays*) over 2 consecutive seasons in 2022-2023. Among the different methods used to estimate crop evapotranspiration, the Food and Agricultural Organization Penman-Monteith model (FAO P-M) is widely recognized as the standard approach for ET estimation. This study aimed to compare the effectiveness of three alternative methods - Thornthwaite (TW), NDVI-based and pan methods against the FAO Penman-Monteith (P-M) model in estimating maize evapotranspiration. Meteorological data were collected from the TNAU weather station spanning the period from 2022 to 2023.The performance of the estimation methods was assessed using statistical metrics such as coefficient of determination (R^2), root mean squared error (RMSE), percentage error and mean bias error. The findings revealed that the NDVI-based method, relying on satellite data, provided higher accuracy in estimating maize evapotranspiration compared to the FAO PM method. Specifically, the NDVI-based method achieved the highest coefficient of determination (R^2) of 0.87 and 0.89, the lowest RMSE of 12.44 mm/month and 15.5 mm/month, the lowest percentage error of 4.8 % and 9.00 % and the lowest mean bias error of 5.5 and 7.85 for the first and second seasons respectively. This study highlights the effectiveness of the NDVI-based ET estimation method for accurately assessing maize evapotranspiration. While the FAO-56 Penman-Monteith method is highly regarded for its accuracy in both theoretical and practical contexts, the comparative evaluation presented in this paper offers valuable insights for selecting alternative methods that require less data, particularly in regions with limited data availability.

Keywords

Maize; Evapotranspiration; FAO Penman Monteith method; Thornthwaite method; NDVI method; Pan Evaporation method

Introduction

A key obstacle in precision agriculture involves maximizing the efficiency of irrigation water usage, especially for crops grown in open fields. Farmers are tasked with addressing uncertainties in weather conditions and water availability particularly in light of climate change (1). In many regions globally, where open-field crops are cultivated during dry seasons with limited rainfall, the demand for irrigation water is chiefly influenced by crop evapotranspiration. Evapotranspiration refers to the concurrent transfer of water from soil to the atmosphere by virtue of evaporation and transpiration within the soil-plant system (2). Initially, water tends to evaporate primarily from the soil in agricultural fields during the early phases of crop development. However, as the crop progresses and its canopy completely covers the soil, transpiration takes precedence as the principal mechanism for water loss. The complexity of this dual process poses a significant challenge for efficient water resource management, necessitating more precise and adaptive approaches in precision agriculture to mitigate the adverse effects of climate variability on crop yield and water use efficiency.

The productivity of crops has a major impact on water movement via soil-plant-atmosphere continuum (3). Crop evapotranspiration (ET_c) holds immense importance in land hydrology, irrigation scheduling and the allocation of water resources (4). It serves as an essential element of the hydrological cycle, exerting critical influence on the energy cycle concerning the exchange of latent heat (5).

Evapotranspiration contributes a vital role in both hydrological and climatological processes, representing approximately 70 % of land precipitation and harnessing over 50 % of the solar radiation retained by the Earth (6). Accurately predicting crop evapotranspiration can be instrumental in conserving irrigation water, particularly in regions where irrigation is heavily relied upon for crop growth (7). Therefore, precise forecasting of crop evapotranspiration can enhance both water use efficiency and reduce water consumption in crops.

While evapotranspiration holds crucial significance across various applications, direct measurement proves impractical. Instead, it must be inferred by observing energy and water exchange above vegetated surfaces using micrometeorological techniques or as a residual term in the hydrological balance through methods like lysimeter and soil water budget analysis.

Quantifying evapotranspiration poses a challenge. On a smaller scale, evapotranspiration can be directly measured using tools such as lysimeter, soil moisture balance techniques or sap flow measurement devices. While lysimeter provide a direct means of measuring ET, their global utilization is constrained by high costs and labour-intensive upkeep (8). While these methods provide precise data, they are often limited practical constraints, such as the need for regular maintenance, high cost and the requirement for specific conditions. Consequently, direct measurement is not feasible over larger areas or regions with limited resources. An alternative other approach to estimate evapotranspiration involves employing physical-mathematical models, which rely on meteorological data to compute the evapotranspiration rate for a standard reference crop (ET_o). The term ETo specifically refers to the maximum rate of evapotranspiration achievable by a well-watered grass surface (9, 10). Numerous models have been formulated to accommodate a range of climates and timeframes. These models utilize crop coefficients (K_c) to estimate evapotranspiration for diverse vegetation types. However, their effectiveness is heavily dependent on the presence of meteorological stations, which are often scarce in remote areas or regions of lesser economic importance.

The method is widely regarded as the most accurate means of quantifying evapotranspiration from real land surfaces under specific meteorological circumstances (11). In fact, ET_o has been a crucial component in numerous hydrological models for a significant period, as opposed to actual ET (12). ET_o plays a pivotal role in the hydrological process by determining water needs in agriculture (13) and facilitating precision farming through the utilization of meteorological parameters (14).

Different models for estimating ET_o are categorized by the specific climate input they require. These encompass mass-transfer-based techniques, temperature-driven approaches, radiation-focused techniques and combined methods integrating principles of mass transfer, energy balance and the FAO P-M equation. Several scientists have advocated for the P-M method as a highly efficient approach for estimating reference evapotranspiration compared to other methods (15). The P-M ET_o method integrates a wide array of meteorological variables such as air temperature, humidity, wind speed and solar radiation. Nonetheless, not all-weather stations have access to such extensive meteorological parameters.

Consequently, it seems practical to consider replacing it with alternative ET_o methods that necessitate fewer meteorological variables (16). The precision of a specific ET_o methodology relies significantly on the environmental conditions of the study area (17). In regions characterized by humid subtropical climates, the P-M ET_o approach is typically advised (18).

Several studies have found that temperature and radiation-driven methods for estimating evapotranspiration (ET_o) result in the highest values, while methods relying on pan-coefficients tend to produce lower values (19). It has been inferred that in dry and semi-arid climates, methods dependent on solar radiation for ET_o estimation may yield inadequate outcomes (20). However, the Thornthwaite method remains widely utilized as it only requires monthly average air temperature data (21).

Remote sensing methods are highly effective for estimating evapotranspiration over extensive areas providing a comprehensive view of vast land expanses over different time periods (22). Remote sensing-based methodologies have been widely employed for calculating and monitoring evapotranspiration in croplands, spanning from regional to global extents (23). Remote sensing methods commonly applied in estimating actual evapotranspiration are mainly grounded in two fundamental concepts: energy balance and water balance. The energy balance technique determines actual evapotranspiration by analyzing the temperature difference between the air and the land surface. These techniques using thermal infrared images, known for their suitable spatial and temporal resolution, to obtain the land surface temperature (24). Although this method offers advantages, it frequently faces spatial and temporal under sampling challenges. This is due to the difficulty in capturing the substantial variability of land surface temperature with current satellite sensors.

Conversely, water balance methods employ remotely sensed vegetation indices to evaluate biomass levels, which typically demonstrate more temporal stability. This provides a depiction of vegetation transpiration under favourable water conditions (25). The utilization of vegetation indices for estimating fractional vegetation cover and related crop coefficients (26). In a similar way, another study aimed for a comparable objective by utilizing digital imagery (27). A modification to the NDVI method was suggested for estimating daily evapotranspiration in areas with limited water resources (28). The ability to estimate daily ET using these indices allows for more precise monitoring and management of water resources enabling better decision-making in regions with constrained water availability.

Utilizing remote sensing technology enables the efficient and cost-effective estimation of crop evapotranspiration at both regional and local scales, leading to significant savings in time and resources (29). Remote sensing facilitates the calculation of crop coefficients by analyzing the spectral reflectance obtained from different vegetation indices (VIs) (30). Out of the numerous vegetation indices available, the NDVI is notable as one of the most frequently used indices (31). It functions based on the reflectance properties of red and near-infrared wavelengths. In red waveband, chlorophyll in upper leaf layers predominantly absorbs light, while in healthy vegetation, the near-infrared waveband is reflected by the internal mesophyll structure, entering deeper into the leaf layers (32). Consequently, a high NDVI score indicates robust, dense vegetation. This is distinguished by pronounced reflectance in the near-infrared (NIR) waveband and minimal reflectance in the red waveband (33). Crop coefficients derived from vegetation indices (VIs) offer a more dependable measure of evapotranspiration (ET_c) compared to tabulated kc values, as they mirror the actual growth conditions of crops and adapt to spatial differences across various fields (34).

A research investigation spanned two successive seasons to estimate crop evapotranspiration in maize, employing diverse methodologies including the Thornthwaite method, Penman-Monteith method, pan evaporation method and NDVI-based remote sensing technique. The principal aim was to evaluate the effectiveness of the Thornthwaite, NDVI-based remote sensing approaches and pan evaporation methods by validating them against the FAO Penman-Monteith method.

Materials and Methods

Experimental site

The experimental site was situated at the Eastern Farm of the Agricultural College and Research Institute, Tamil Nadu Agricultural University, Coimbatore, with geographical coordinates approximately 11.0086°N latitude and 76.09385°E longitude. Soil preparation involved initial cultivation with a cultivator followed by further refinement using a rotavator to ensure optimal tilth. The laterals were positioned at intervals of 60 cm and seeds of the Co (H) M6 variety were sown at a rate of 25 kg/ha, spaced 25 cm apart within the laterals. Fertilization followed TNAU recommendations for hybrid maize, with a composition of 250:75:75 kg/ha of NPK respectively. The experiment was conducted over 2 consecutive seasons, specifically during the summer and *Kharif* seasons of 2023.

Evapotranspiration methods

Penman - Monteith (PM) Method

The Penman-Monteith method is commonly used as a reference for estimating evapotranspiration (ET_o). Various studies have shown that this method is dependable for estimating ET0 across diverse weather conditions (35). The Penman-Monteith (PM) method (36), serves as the approach for determining potential evapotranspiration (ET_o).

$$ET_o = \frac{0.408\,\Delta\,(R_n - G) + \gamma \frac{900}{T + 273} u_{2(e_s - e_a)}}{\Delta + \gamma(1 + 0.34u_2)}$$

In this context, ET_0 represents the reference evapotranspiration (mm day^{-1}). R_n indicates net radiant energy received at the crop's surface ($MJ/m^2/d$), while G denotes the soil heat flux density ($MJ/m^2/d$). T represents the air temperature at a height of 2 m, measured in degrees Celsius (°C). The variable u_2 denotes the wind speed measured at 2 m above the ground, expressed in meters per second (m/s).

The term “e_s” denotes the vapor pressure when the air is completely saturated with moisture (kPa), while “e_a” represents the actual vapor pressure (kPa). The difference between e_s and e_a, e_s - e_a, represents the saturation vapor pressure deficit. Δ indicates the change rate of saturation vapor pressure with temperature (kPa/°C) and γ is the psychrometric constant, which quantifies the relationship between heat and moisture (kPa/°C).

Thornthwaite Method

A formula developed to estimate potential evaporation (PET) by taking into account the mean air temperature and the duration of daylight hours for each month (37, 38).

The Monthly Heat Index (i) can be computed using the following formula:

$$i = (T/5)^{1.514}$$

Here, t - mean monthly temperature

The cumulative sum of Monthly Heat Indices (i) equates to the value of the Annual Heat Index.

$$I = \sum_{i=1}^{n} i$$

Potential Evapotranspiration (PET) for each month is calculated based on the assumption of a 30 days month and theoretically 12 h of sunlight per day. The following formula is applied to estimate PET

$$PET_{\text{non corrected}} = 16(10T/I)^{a}$$

Where;

$$a = 6.75 \times 10^{-7} I^{3} - 7.71 \times 10^{-5} I^{2} + 1.792 \times 10^{-3} I + 0.49239$$

The calculated values are then adjusted according to the actual number of days in the month and the expected sunshine duration specific to the latitude. This adjustment employs a formula to refine the initial estimate in accordance with these real-world factors.

$$PET = PET_{\text{non corrected}} \times N/12 \times d/30$$

Pan evaporation

Evapotranspiration can be estimated using the pan evaporation method, utilizing the following formula:

$$ET_o = E_{pan} \times K_p$$

ET_o represents reference evapotranspiration (mm/day), where K_p denotes the pan coefficient (typically around 0.7) and E_{pan} stands for pan evaporation, also measured in millimeters per day.

Evapotranspiration based on NDVI

The extent of live green vegetation can be quantitatively measured using the NDVI, which ranges from -1 to +1. A higher NDVI value indicates a greater presence of live green vegetation in the area. Landsat's Band 4 captures reflectance in the near-infrared (NIR) range, with wavelengths from 0.77 to 0.90 microns, while Band 3 measures reflectance in the red portion of the spectrum, spanning from 0.63 to 0.69 microns. The method for computing the NDVI for individual pixels in a classified map is outlined as follows.

$$NDVI = \frac{NIR - R}{NIR + R}$$

NDVI was computed for each pixel of the image and subsequently it was averaged to obtain Fractional Vegetation Cover.

Estimation of Fractional Vegetation Cover: The fraction of vegetation cover can be assessed by adjusting the NDVI, estimating it based on values that range from a complete vegetation canopy to bare soil (39). It can be computed using the following formula.

$$N^* = (NDVI - NDVI_0) / (NDVI_{max} - NDVI_0)$$

In this context, the NDVI value for bare soil as captured by Landsat is denoted as $NDVI_0$, while the maximum NDVI value for dense vegetation cover is represented as NDVImax. The fractional vegetation cover is determined using the formula.

$$Fr = (N^*)^2$$

The fractional vegetation can be obtained by squaring the N* value.

Estimation of Reference Evapotranspiration: The reference evapotranspiration for the period of NDVI estimation can be computed using the weather data collected from a nearby weather station.

Estimation of Actual Evapotranspiration: The actual evapotranspiration can be computed by multiplying the reference evapotranspiration value by the fractional vegetation cover derived from NDVI (Fig. 1).

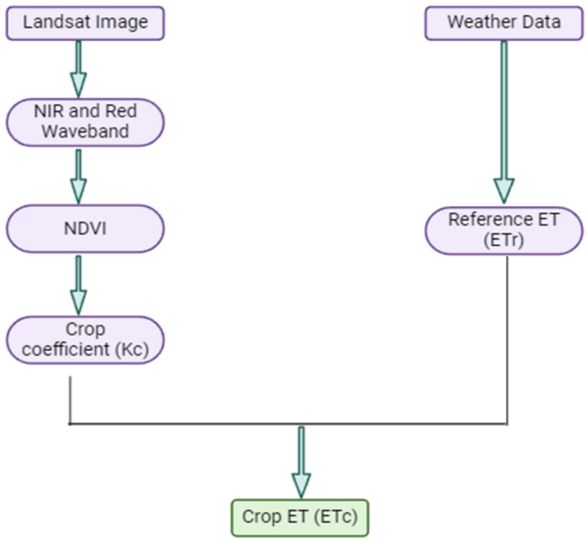


Fig. 1. Flowchart for estimation of ET using NDVI method.

$$AET = \text{Fraction of vegetation} \times \text{Ref ET}$$

Evaluation criteria

The accuracy of each evapotranspiration estimation method was assessed by comparing it with the evapotranspiration estimates derived from the FAO P-M for the specified period. In this analysis, various metrics are employed to assess the accuracy of evapotranspiration calculation methods. These metrics comprise the Root Mean Square Error (RMSE), Percentage Error (PE), Mean Bias Error (MBE) and the Coefficient of

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(P_{i-O_i}\right)^2}{n}}$$

$$\%PE = \left[\frac{\bar{P} - \bar{O}}{\bar{O}}\right] X\ 100$$

$$MBE = \frac{\sum_{i=1}^{n}\left(P_{i-O_i}\right)}{n}$$

$$R^2 = \frac{\left[\sum_{i=0}^{n}(P_i - \bar{P})(O_i - \bar{O})\right]^2}{\sum_{i=1}^{n}\left(P_i - \bar{P}\right)^2 \sum_{i}^{n}\left(O_i - \bar{O}\right)^2}$$

Determination (R^2). The formulas for RMSE, PE, MBE and R^2 are as follows

Results and Discussion

The accuracy of evapotranspiration methods such as Thornthwaite, NDVI and pan evaporation is assessed against the FAO standard Penman Monteith method using statistical analysis. It is not practical to evaluate the overall performance of these methods based solely on a single parameter, such as the coefficient of determination, because accurately assessing their accuracy is a multifaceted challenge. Evaluating these methods solely on a single parameter like the coefficient of determination is impractical due to the complexity involved in assessing their accuracy. Experimental data, despite its value, has limitations due to the difficulty in replicating the precise conditions required for accurate evapotranspiration estimation. Therefore, evaluating these methods should prioritize their physical and dynamic characteristics, particularly how closely their estimates correspond with standard ET values. Table 1 and Table 2 depict the statistical comparison of the evapotranspiration methods for 2 consecutive seasons. The coefficient of determination between those methods was given in Fig. 2.

Comparison between Thornthwaite and Penman-Monteith method:

Crop evapotranspiration was computed using the FAO crop coefficient method with reference evapotranspiration determined using temperature data via the Thornthwaite method. In Season I (summer season), maize was sown in March and harvested in June. In Season II (*Kharif* season), the crop was sown in August and harvested in November 2023. The weather data for the study period is represented in Fig. 3. Monthly calculations of crop evapotranspiration were performed using these four methods, with cumulative totals computed for each season. For the months of March, April, May and June, evapotranspiration estimated by the Thornthwaite method was 419.3 mm, while the FAO standard Penman-Monteith method yielded approximately 476 mm. The comparison between these methods was statistically analyzed using Root Mean Square Error (RMSE), Percent Error (PE), Mean Bias Error (MBE) and the coefficient of determination (R^2). This comprehensive statistical evaluation provided insights into the relative performance and accuracy of each method under varying seasonal conditions. The Thornthwaite method, while simpler and reliant on fewer meteorological inputs, demonstrated discrepancies when compared to the more robust FAO P-M method which integrates a wider range of climatic variables. The findings underscore the necessity of selecting appropriate ET estimation method based on the specific climatic and agricultural contexts to ensure accurate water resource management.

During summer season, the highest evapotranspiration occurred in May, recording 148.9 mm using the Thornthwaite method and 171.8 mm using the Penman Monteith method. In contrast, the lowest evapotranspiration was observed during the vegetative stage in March, measuring 58.4 mm with the Thornthwaite method and 40.9 mm with the Penman Monteith method, respectively. Notably, the Thornthwaite method tends to overestimated evapotranspiration in the first three months (March, April, May) and underestimated it in the last month (June) of Season I. In Season II (*Kharif*), the Thornthwaite method overestimated evapotranspiration in the first month (August) and underestimated it during the last three months (September, October and November) when compared to the FAO PM method. The Thornthwaite method was developed for conditions where temperature measurements are taken under optimal circumstances, depicting potential evaporation in the absence of soil moisture stress (21). It was reported that Thornthwaite method may result in an overestimation of potential evaporation in arid regions. Moreover, the coefficient of determination (R^2) obtained from comparing these two methods was 0.62 for Season I (Summer) and 0.63 for Season II (*Kharif*). A higher R^2 value indicates greater accuracy in evapotranspiration estimation when compared to the FAO P-M method.

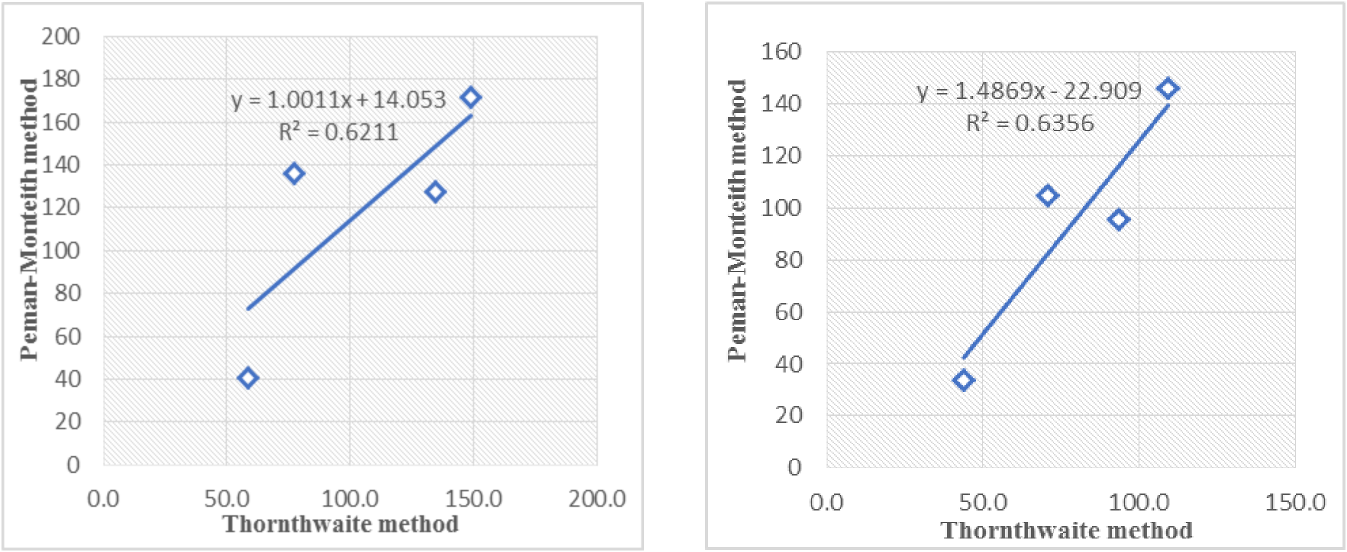
The comparison between the Thornthwaite and Penman Monteith methods yielded RMSE values of 32.8

Table 1. Statistical analysis for Season I.

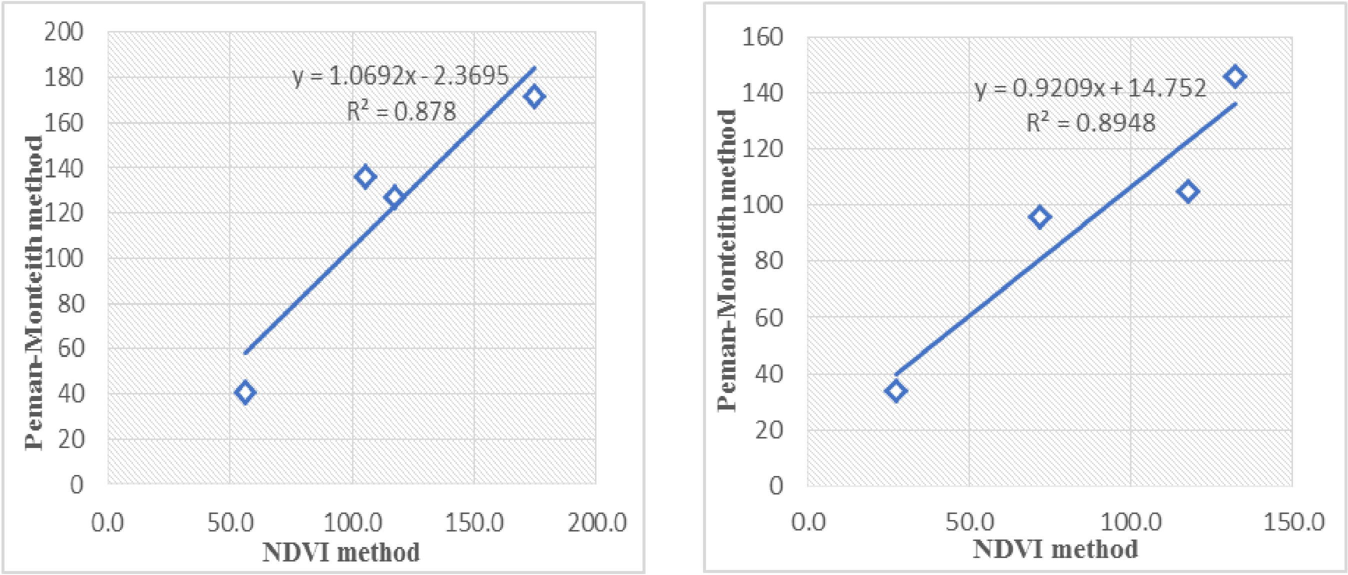
Estimation Methods	Regression equation	R^2	RMSE	Percentage Error	Mean bias error
Thornthwaite method	y = 1.0011x + 14.053	0.6211	32.805	13.50	14.2
NDVI Method	y = 1.0692x - 2.3695	0.878	12.44	4.8	5.5
Pan evaporation Method	y = 0.969x + 26.189	0.5721	39.11	24.24	23.2

Table 2. Statistical analysis for Season II.

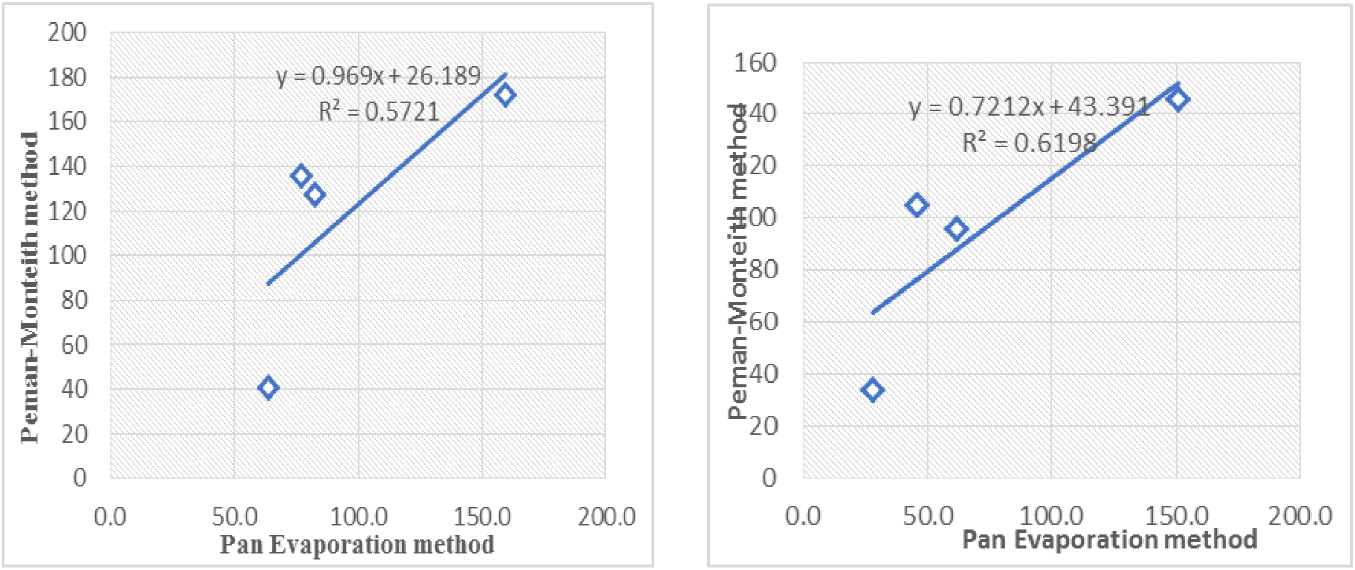
Estimation Methods	Regression equation	R^2	RMSE	Percentage Error	Mean bias error
Thornthwaite method	y = 1.4869x - 22.909	0.6356	25.62	19.82	15.72
NDVI Method	y = 0.9209x + 14.752	0.8948	15.54	9.00	7.85
Pan evaporation Method	y = 0.7212x + 43.391	0.6198	34.25	32.70	23.42



Thornthwaite method vs Penman Monteith method



NDVI method vs Penman Monteith method



Pan evaporation method vs Penman-Monteith method

Fig. 2. Co-efficient of differentiation for maize crop during Season I and Season II.

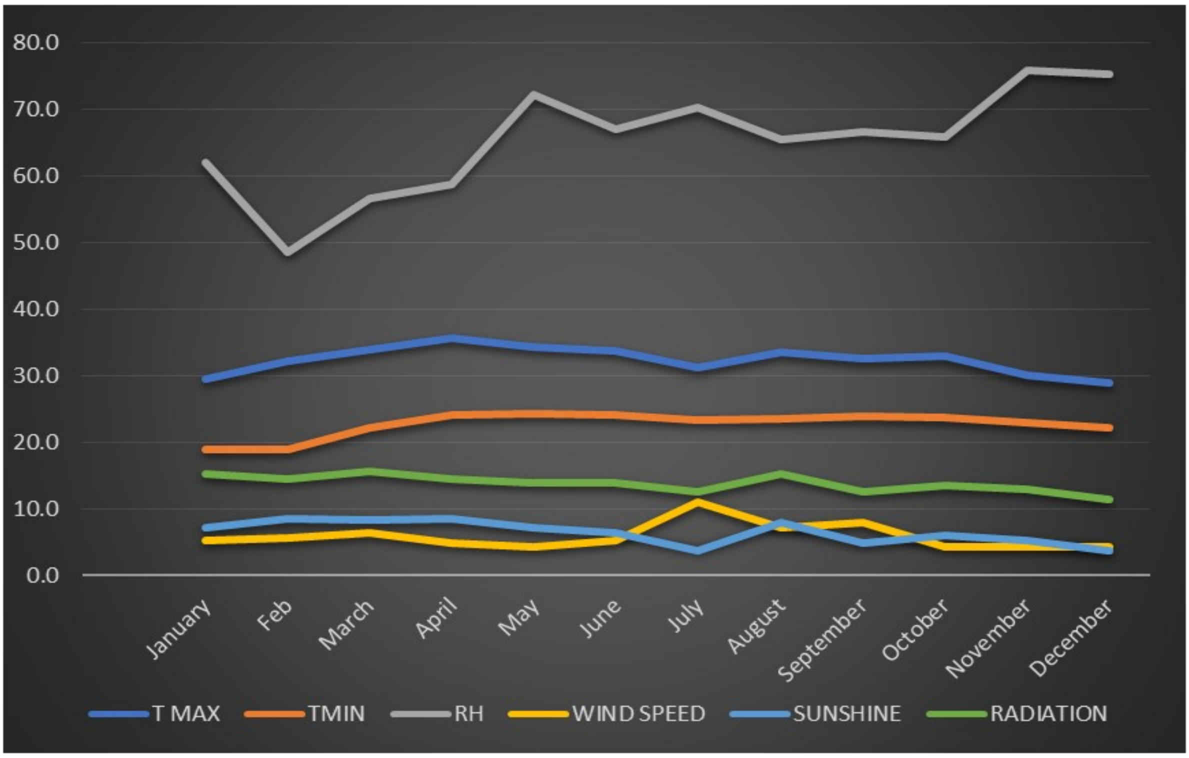


Fig. 3. Weather data for the year 2022-2023.

mm/month for Season I and 25.6 mm/month for Season II. Additionally, the percentage errors were 13.5 % in Season I and 19.82 % in Season II when using the Thornthwaite method compared to the PM method. The Mean Bias Error (MBE) values computed for Season I and Season II were 14.2 and 15.7 respectively, indicating the average deviation between the Thornthwaite method and the FAO P-M method across the 2 seasons. When comparing the Thornthwaite method with the FAO Penman-Monteith, it was observed that the Thornthwaite method tends to underestimate crop evapotranspiration. This discrepancy may be attributed to the fact that the Thornthwaite method relies solely on temperature as an input parameter. A study was conducted on different evapotranspiration methods, validating them against the FAO Penman-Monteith method. The findings revealed that temperature-based methods, such as the Thornthwaite method, performed inadequately compared to the FAO P-M method (40).

The Thornthwaite method for estimating evapotranspiration underestimates by 15-19 % compared to the FAO Penman-Monteith method (13). This highlights the need for additional parameters beyond temperature alone to achieve accuracy comparable to the PM method. Temperature-based methods typically yield correlation coefficients between 0.32 to 0.35, indicating a weak relationship. This finding contrasts with another study, which demonstrated reasonable error analysis and correlation between the Thornthwaite and P-M methods but noted a poor correlation specifically with evapotranspiration (41). According to The low correlation coefficient of the Thornthwaite method suggests its unsuitability for accurately predicting evapotranspiration (42). The Thornthwaite method showed very poor results when compared to the FAO Penman-Monteith method, with root mean square error (RMSE) values ranging from 0.38 to 0.65 mm/day (43). Similarly, another study reinforced the limitations of the Thornthwaite method in estimating evapotranspiration, finding comparable results when compared to more comprehensive methods like the FAO Penman-Monteith (26).

Comparison of NDVI-based ET method with FAO Penman-Monteith Method

Based on NDVI, a satellite-based method for estimating evapotranspiration, the maize crop shows highest accuracy when compared to the Thornthwaite and pan evaporation methods, particularly aligning closely with the FAO Penman Monteith method. ETc maps were generated by multiplying pixel-wise K_c maps with estimated reference evapotranspiration (ET_o) using ARC GIS software. During the first season, NDVI calculated a maximum ET of 7.83 mm/day in April, with an NDVI-based Kc factor of 0.85. The K_c values obtained from the NDVI-based method for the maize field started low at the initial stage of the crop (0.2). Subsequently, K_c increased to a maximum of 0.85 during the mid-season stage of the crop. In the first season, the K_c values derived from NDVI for the maize crop started at 0.2 during the initial stage, peaked at 0.85 in mid-season, decreased to 0.65 and finally dropped to 0.37 by the end of the cropping season. In the second season, the initial K_c was 0.2, reached a maximum of 0.90 and then decreased to 0.3 by the season end. The NDVI-derived K_c curves observed by researchers exhibited low values in the early stages, increased during the middle of the season and then slightly declined towards the end of the season. The NDVI curves and the K_c values derived from NDVI is given in Fig. 4. The NDVI curves for forage corn gently increasing from early to mid-season and then stabilizing until the end of the season (44). This consistency in NDVI derived K_c values underscores

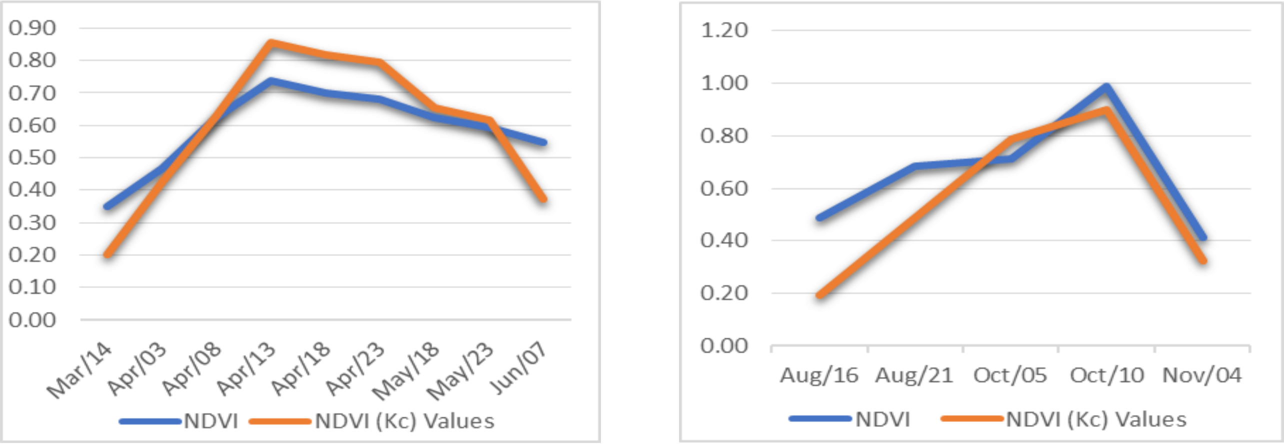


Fig. 4. NDVI curves and NDVI Kc for Season I and II in maize.

the method's reliability in capturing the temporal dynamics of the crop growth stage, making it a valuable tool for accurately estimating crop water usage and ET.

During the first season of maize cultivation, the maximum evapotranspiration was recorded in the third month (May), measuring 174.8 mm, which exceeded the evapotranspiration measured by the FAO P-M method (171.8 mm) by 3 mm. In the first season, the NDVI method overestimated the P-M method in the first and third months (March and May) and underestimated it in the second and fourth months (April and June). In the second season of the crop, the NDVI method underestimated the Penman-Monteith method in the first 3 months (August, September and October) and overestimated it in the last month (November). During the Tasseling and Silking stage of the maize crop, the maximum evapotranspiration was observed with values of 132.1 mm and 145.8 mm using the NDVI and Penman-Monteith methods respectively. The total seasonal ET estimated by the NDVI method were approximately 468.1 mm in season I and 348.8 mm in season II respectively. In comparison, using the Penman-Monteith method, the maximum evapotranspiration was 476 mm and 380.2 mm in the first second season respectively. The statistical comparison between the NDVI method and the FAO Penman -Monteith method indicates that the NDVI method exhibits higher accuracy. It achieved an R^2 of 0.87, an RMSE of 12.44 mm/month, a percentage error of 4.8 % and a mean bias error of 5.5 during the first season. In the second season, the NDVI method obtained an R^2 value of 0.89, an RMSE of 15.5 mm/month, a percentage error of 9.00 % and a mean bias error of 7.85. This pattern in the coefficient of determination has been consistently noted in research conducted by other investigators (45). It's important to recognize that inconsistent or unreliable NDVI values can lead to inaccuracies in estimating crop evapotranspiration (46). Similar methods of evapotranspiration estimation have been reported by other researchers. They computed evapotranspiration using the alfalfa-reference crop coefficient and NDVI values. The highest R^2 value signifies the highest accuracy in evapotranspiration estimation. This suggests that K$_c$ values derived from vegetation indices can be dependable parameters for calculating actual crop evapotranspiration (47-49). The K$_c$ values derived from vegetation reflectance decrease with soil water content. Similar conclusions were reached by other researchers, who noted that lower moisture content resulted in reduced kc values (45, 50). In the maize crop, the minimum crop evapotranspiration of 3 mm/day was observed during the initial stage, while the maximum of crop evapotranspiration 7.8 mm/day occurred during the mid-season stage. This variation is attributed to the crop's lower water requirement in the initial stage and increased water demand during mid-season growth. The ET$_c$ results obtained in this study align with findings from other research studies such as that also utilized K$_c$ values obtained through remote sensing-based vegetation indices to create ET$_c$ maps (51-53). Other researchers have proposed that kc values obtained from canopy reflectance-based vegetation indices can accurately estimate crop evapotranspiration at both regional and field scales (54). This approach demonstrates the utility of RS techniques is providing detailed, stage specific ET$_c$ estimates, which are crucial for precise irrigation management and water resource planning in Agriculture.

This observation was consistent with findings from other studies, which demonstrated the minimum and maximum ET$_c$ values throughout different crop growth phases, noting that the highest evapotranspiration rates generally occur during the mid-season growth stage, while the lowest rates are seen during the early growth stage (55, 56). During the early to mid-development phases, ET$_c$ values were lower, indicating that farmers can implement water-saving measures during these times. This was because the crop's water requirements are relatively smaller, especially when the crop canopy has not yet fully developed. Similar results were found when estimating average crop evapotranspiration values in wheat crops (51). NDVI varies by crop at each pixel, while K$_c$ represents the conditions of specific crop growth in the field. The coefficients of determination (R^2) for all crops illustrate the robustness of the models developed. NDVI serves as an indicator of healthy and dense vegetation cover and plant vigor. It measures surface reflectance and offers a quantitative estimation of vegetation growth and biomass (57). This indicates that NDVI captures a significant portion of the variation seen in crop coefficients under conditions where there is no water stress. The findings demonstrate a strong positive correlation between ET$_c$ (crop evapotranspiration) and NDVI, implying that greater crop canopy or biomass production results in higher evapotranspiration rates. This suggests that NDVI can effectively predict green vegetation at each stage of crop development throughout the entire growth cycle. Therefore, NDVI serves as a dependable indicator of crop canopy, biomass and crop evapotranspiration in maize.

The study's findings indicate a notable logarithmic positive correlation between crop evapotranspiration, estimated via the Penman-Monteith method and NDVI values derived from satellite imagery. This implies that NDVI data can effectively assess crop health when water availability is sufficient. One advantage of establishing the NDVI-ET_c relationship is the elimination of the need to individually identify each crop and determine its acreage. This approach leverages satellite imagery to provide a broader understanding of crop evapotranspiration across large areas without the need for ground-based crop-specific information. Instead, it necessitates a broad understanding of the predominant crops, their acreage and their growth stages during data collection, alongside crop coefficients specific to the region. In conclusion, crop coefficients (K_c) derived from NDVI are valuable for tasks such as scheduling of irrigation, evaluating the efficiency of irrigation, managing water resources and estimating the water use efficiency. This approach allows for efficient water management practices based on satellite-derived data, enhancing agricultural sustainability and productivity.

Comparison of Pan Evaporation method with FAO Penman -Monteith Method

Crop evapotranspiration using the open pan evaporation method was computed by adopting the crop coefficient specified by FAO for maize. Subsequently, ETc was evaluated against the FAO Penman-Monteith method to assess the pan evaporation method's accuracy compared to FAO P-M. During the first season of the crop, the Pan evaporation method overestimates evapotranspiration in March and underestimates it in all subsequent months. In the season II of the crop, the pan evaporation method overestimates the FAO Penman-Monteith (P-M) method in the third month (October), which coinciding to the mid-season stage when the maximum ET (150.7 mm) was recorded. However, for the remaining months (August, September and November), the pan method underestimates the P-M method. According to the statistical analysis comparing these 2 methods, in the first season of the maize crop, the coefficient of determination (R^2) obtained was 0.57,indicating a moderate correlation. The root mean square error (RMSE) was 39.11 mm/month, suggesting significant overall error. The percentage error was 24.24 %,indicating a considerable deviation from the P-M method, and the mean bias error (MBE) was 23.2,highlighting a systematic discrepancy. Meanwhile in the second season of the crop. Meanwhile, at the second season of the crop the R2 was 0.61,RMSE 34.25 mm/ month, percentage of error 32.7 % and the mean bias error was 23.42.The crop evapotranspiration obtained by the maize crop during the entire season (season I) was 383.1 mm and 476 mm by the pan evaporation and P-M method respectively. With respect to the second season of the crop the crop evapotranspiration was 286.5 mm (pan evaporation method) and 380.2 (P-M method). The study indicates that the accuracy of crop evapotranspiration estimation was notably lower in the pan evaporation method compared to the Penman- Monteith method, in contrast to other ET estimation methods such as NDVI and Thornthwaite. In a similar investigation, it was noted that the Class A pan showed a weak correlation with the FAO P-M method, with an R value of 0.37.This weak correlation might be due to the Class A pan lacking a surrounding ring at the agro-meteorological station where the study took place, potentially causing the pan to tilt when filled with water. Frogs and birds were occasionally seen around the pan, indicating that these animals likely consumed the water. This activity could have led to a decrease in the water level, thereby potentially affecting the ETo estimation values of the pan (58).The accuracy of evapotranspiration estimation using the open pan evaporimeter was relatively lower compared to the FAO P-M method (59).The Penman-Monteith method may have underestimated evapotranspiration due to substantial advective energy transfer from areas where sensible heat was produced. Past research has demonstrated that sensible heat advection can markedly augment evapotranspiration (60). Several studies have highlighted that in certain irrigated regions, well-watered crops can transpire more water and consume more energy than what is evaporated from free-water surfaces. Although evaporation from a pan is influenced by the same climatic factors as crop transpiration, there are notable differences between water loss from an open water surface and from a vegetated surface. The reflection of solar radiation from water in a shallow pan may differ from the standard assumption of 23 % for a grass reference surface. Heat storage within the pan can be considerable, potentially causing notable nighttime evaporation, whereas crops predominantly transpire during daylight hours. Moreover, there are variations in the temperature, turbulence and humidity of the air immediately above each surface type. Heat transfer through the sides of the pan also influences the overall energy balance. Evapotranspiration was notably higher and more intense than the net radiation value. The Penman - Monteith method demonstrates superior predictive capability compared to evaporation-based methods (61).These findings are consistent with those of previous research (62). Furthermore, a study found that evapotranspiration estimation using the pan evaporation method exhibits the highest percentage of error when compared with the FAO P-M method (63).

Conclusion

The current research assessed the effectiveness of various evapotranspiration approaches (Thornthwaite, NDVI-based and pan evaporation method) compared to the standard FAO Penman - Monteith method for maize during 2 seasons from 2022-2023. Statistical analysis revealed that the NDVI-based ET estimation method exhibited the least error compared to the Penman-Monteith method, while the highest error was observed in ET estimation using the pan evaporation method. The study reported the highest coefficient of determination (R^2) and the lowest root mean square error, percentage error and mean bias error for the NDVI-based method among the evaluated approaches. Remote sensing-based evapotranspiration presents a robust approach for rapid hydrological monitoring, agricultural management and climate change research. ET_c was computed by multiplying reference evapotranspiration with the crop coefficient corresponding to crop development stages aligned with satellite data dates. The study unequivocally demonstrates that NDVI serves as a dependable predictor of maize crop water usage and evapotranspiration. Therefore, remotely sensed NDVI can effectively monitor maize crop water utilization in areas where on-site measurements are impractical. Estimating evapotranspiration using vegetation indices provides reliable insights for agricultural crops in arid regions, potentially playing a pivotal role in guiding land and water management where on-site data is lacking. The comparative assessment of these four ET estimation techniques presented in this study is site-specific, and results may vary in different locations. Nevertheless, such research aids decision-makers in selecting the most suitable ET estimation method based on factors like data availability, cost constraints or accuracy requirements. Conducting similar studies on a larger scale across various agro-climatic zones will contribute to developing standardized guidelines for choosing the optimal ET estimation technique, taking into account available data and financial resources.

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Authors' contributions

MRK: conceptualization, data curation, writing - original draft. SP: conceptualization, supervision, funding acquisition, writing - review and editing. MR: writing - original draft, methodology, validation. RK: software, formal analysis. VR: resources, visualization. AS: methodology, writing - review and editing.

Compliance with ethical standards

Conflict of interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

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