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Comparison of smart applications for evapotranspiration assessment automation with manual estimation using the Thornthwaite method

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Abstract. Evapotranspiration assessment is critical for effective agricultural water management, as it is the primary factor influencing decisions regarding the amount, location, timing, and method of crop irrigation. Manual evapotranspiration calculations are time-consuming and labor-intensive, particularly for long-term assessments. Consequently, various automated approaches have been developed in recent decades to improve the speed and accuracy of evapotranspiration estimation. However, not all automated methods demonstrate sufficient reliability for practical applications. The primary objective of this study was to evaluate the performance of widely used and innovative evapotranspiration calculation tools, namely EVAPO, AgSAT, and Evapotranspiration Calculator (Ukraine), and compare their results with the reference Thornthwaite method. The study was conducted in Kherson Oblast from September 2022 to June 2025, utilizing the data from the regional hydrometeorological center and the default settings of the applications. The statistical analysis involved generating evapotranspiration distribution plots, box plots, scatter plots, residual plots, and Bland-Altman plots for each application, alongside calculations of mean differences, root mean square error (RMSE), mean absolute error (MAE), R-squared, and Nash-Sutcliffe Efficiency (NSE). The overall comparisons were conducted using Repeated Measures ANOVA or the Friedman Test, with the Bonferroni correction applied for multiple paired comparisons. The results revealed that the EVAPO application provided the closest evapotranspiration estimates to the reference method (RMSE = 0.78 mm, MAE = 0.60 mm, R-squared = 0.74, NSE = 0.72), while the AgSAT application exhibited the poorest performance. Additionally, AgSAT tended to underestimate evapotranspiration, whereas Evapotranspiration Calculator (Ukraine) tended to overestimate it. These tendencies should be considered when using these applications without prior calibration. The results yielded by ANOVA confirmed that all the evaluated approaches significantly differed from the reference manual estimations using the Thornthwaite method, indicating that even the best-performing application, EVAPO, requires refinement before practical implementation in irrigation scheduling.

Keywords: agricultural meteorology; digital agriculture; irrigated agriculture; statistical analysis.

Introduction

Evapotranspiration (ET) assessment is crucial for agriculture, especially as climate change, aridization, and freshwater scarcity intensify pressures on water resources. Evapotranspiration represents the combined loss of water through evaporation and plant transpiration, making it a key variable in understanding and managing the agricultural water cycle and ensuring food security under changing climatic conditions (Fisher et al., 2017). Accurate ET estimation enables efficient irrigation scheduling, helps prevent overuse of limited water supplies, and supports the development of climate-smart agricultural practices that build resilience to drought and shifting weather patterns (Lakhiar et al., 2024). In arid and semiarid regions, where the effects of water scarcity on the agroecosystems are most pronounced, advanced ET assessment methods – such as remote sensing, machine learning, and UAV-based monitoring – provide high-resolution, timely data to optimize water use, and adapt to local conditions (Abdel-Fattah et al., 2023; Elkatoury et al., 2024). These technologies are essential for identifying areas of high water demand, evaluating the impacts of climate change on crop water needs, and informing policy decisions on land and water management based on long-term and operational ET forecasts and their possible adverse effects on certain crops (Babaeian et al., 2022). Moreover, integrating ET assessment into agricultural planning helps balance ecosystem health with food production, guiding strategies such as water-saving irrigation and appropriate land use scaling. As climate change alters precipitation patterns and increases the frequency of extreme weather events, robust ET monitoring becomes even more vital for sustaining agricultural productivity and conserving freshwater resources. To provide for the best dynamic ET monitoring and forecasting, it is crucial to develop and implement robust tools for the automation of ET assessment.

Automation in ET calculations is increasingly vital for modern agriculture, as it enables precise, efficient, and scalable water management – key for addressing water scarcity, climate variability, and the need for higher crop yields. Automated approaches, particularly those integrating machine learning (ML) and artificial intelligence (AI) with traditional computation methodologies and remote sensing data, can deliver highly accurate ET estimates with minimal manual intervention, outperforming manual expertise in both accuracy and speed. Modern deep learning approaches are widely implemented for modeling ET for various crops under different cultivation practices and climate (Cemek et al., 2023; Pagano et al., 2023). Moreover, such tools can provide highly accurate ET forecasts, which are essential for rational agricultural water management and irrigation planning (Ravindran et al., 2022). The integration of automated systems, such as AutoML frameworks and advanced algorithms, such as Random Forests and neural networks, allows for rapid model development and adaptation to local conditions, even with limited input data, thus supporting cost-effective and site-specific irrigation planning. Automation also facilitates the use of high-resolution data from UAVs and satellites, enabling real-time, field-scale ET mapping that supports precision agriculture and optimizes water use (Wanniarachchi & Sarukkalige, 2022). These advancements help prevent overirrigation, reduce water waste, and improve crop productivity, while also supporting sustainable groundwater management and resilience to drought (Li & Tartakovsky, 2023). Overall, automating ET estimation is transforming agricultural water management by making it more data-driven, adaptive, and resource-efficient.

At the same time, the automation of ET evaluation for irrigated agriculture encounters several challenges, including the use of diverse methodological approaches and input data for estimating agrometeorological indices. Currently, ET is primarily estimated using meteorological data rather than direct field measurements with lysimeters. Methodological approaches to ET calculation vary significantly in terms of input data requirements, data types, and computational methods. Therefore, it is critical to identify the automation tool that yields results most closely aligned with standardized, scientifically validated manual methods of ET calculation, such as the FAO-endorsed Penman-Monteith, Hargreaves, or Thornthwaite equations.

One of the most effective automation tools for evapotranspiration (ET) estimation is the mobile application EVAPO. This application employs the FAO-endorsed Penman-Monteith algorithm to estimate ET based on meteorological data retrieved for specific geolocations from NASA-POWER servers. The application generally performs well; however, preliminary studies conducted in Ukraine have highlighted the need for calibration to align EVAPO's calculations with those of the FAO-developed ETo Calculator software, which uses the standardized Penman-Monteith method (Vozhehova & Lykhovyd, 2021).

Another notable, though less recognized, tool within the scientific community is the AgSAT application. It calculates daily water requirements using the ASCE-Penman-Monteith method and integrates vegetation indices derived from satellite imagery to determine the basal crop growth coefficient. Beyond ET estimation, AgSAT provides guidance on gross irrigation requirements for crops and optimizes water use in agricultural production. The developers of AgSAT compared its ET estimates with *in situ* measurements from 18 meteorological stations, reporting a correlation coefficient of 0.90 and a root mean square error (RMSE) of 1.27 mm (Jaafar et al., 2022). Despite these promising results, independent validation by other researchers is limited, primarily due to the application's low visibility within the scientific community.

Similarly, Evapotranspiration Calculator (Ukraine), developed by Ukrainian scientists, is a cross-platform, cloud-based application that employs a unique ET estimation methodology based solely on mean temperature values, utilizing a robust regression modeling approach involving over 20,000 data inputs from 1971 to 2020 was used to derive models for temperature-based ET computation. Tailored for optimal accuracy across Ukraine's regions, it demonstrated satisfactory performance in the preliminary tests (Lykhovyd, 2022). However, due to its limited adoption within the scientific community, there is a paucity of studies comparing its efficacy with standardized manual computation methods.

Therefore, the main objective of this study was to compare the three abovementioned tools for ET assessment automation in terms of their accuracy and correspondence to the Thornthwaite manual calculations.

Materials and methods

The study was conducted from September 2022 to June 2025 in Kherson Oblast. Evapotranspiration (ET) was estimated daily. Meteorological data for the ET estimations were obtained from the regional hydrometeorological center and used both in the Evapotranspiration Calculator (Ukraine) application and for the manual calculations employing the adapted Thornthwaite methodology to produce daily estimates (Chang et al., 2019). Days with incomplete meteorological records or missing data from any of the tested platforms (EVAPO, AgSAT) were excluded from the analysis. Consequently, the final dataset comprised 792 ET records evaluated using the EVAPO, AgSAT, and Evapotranspiration Calculator (Ukraine) applications, as well as manual calculations based on the Thornthwaite methodology (1):

$$ET = 16 \times (\frac{10 \times T}{I})^a \quad (1)$$

where ET is a potential evapotranspiration (mm), T is an average air temperature (°C), I is a heat index, and a is a coefficient derived from I.

The Thornthwaite equation was employed to calculate evapotranspiration (ET), utilizing meteorological inputs and criteria derived from the most recent meteorological averages for Kherson Oblast, updated through 2018. The heat index was determined to be 51.38, with the exponent set at 1.301. All the calculations using the Thornthwaite reference method were performed manually, without reliance on auxiliary software. By contrast, the ET estimations in automated tools—namely AgSAT, EVAPO, and Evapotranspiration Calculator (Ukraine)—were conducted using default settings. For AgSAT and EVAPO, the calculations were performed for identical geolocations, with AgSAT configured for grass cover. Evapotranspiration Calculator (Ukraine) utilized default calculation outputs, without applying the intrinsic calibration option for relative air humidity.

Statistical processing of the data was performed to provide unbiased comprehensive comparison of all the studied automation tools with the reference method. In order to provide the deepest insights into the differences among the approaches used in different applications, we constructed ET value distribution plots, box plots, scatter, residual, and Bland-Altman plots (Kalra, 2017), and also calculated the mean differences, RMSE, MAE, R-squared and Nash-Sutcliffe Efficiency (NSE) (Chicco et al., 2021; Melsen et al., 2025). The overall comparison was performed using Repeated Measures ANOVA / Friedman Test, while multiple comparisons correction for the paired tests was performed using the Bonferroni method (Sedgwick, 2012). The data analysis and visualization were performed using Python 3 with external libraries pandas, NumPy, matplotlib, seaborn, SciPy, statsmodels.

Results

First, general statistics of the dataset need to be analyzed. The distribution plots have been developed to illustrate the frequency of occurrence of various ET values in mm across their respective datasets (Fig. 1).

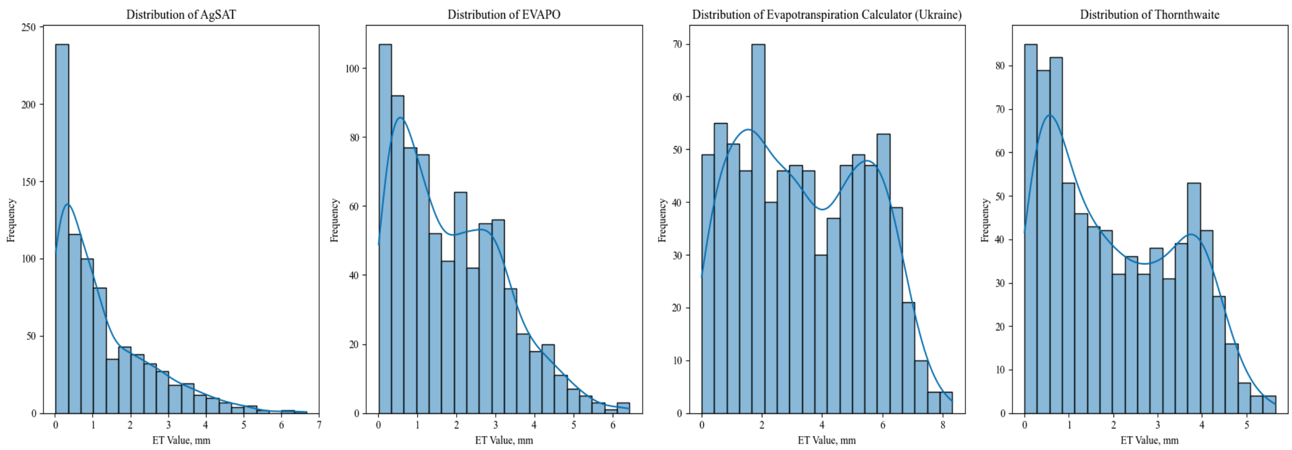

Fig. 1. The distribution of different evapotranspiration (ET) metrics: AgSAT, EVAPO, Evapotranspiration Calculator (Ukraine), and Thornthwaite

All four distributions are right-skewed, indicating that lower ET values are more frequent across all the methods. The AgSAT and Thornthwaite methods show the most pronounced skewness, with a strong concentration of data at the lower end (0–1 mm). The EVAPO application and Evapotranspiration Calculator (Ukraine) exhibit broader ranges, with secondary peaks and a broader range of values, suggesting greater variability or sensitivity to different conditions. The overlaid curves in each histogram likely represent a fitted model (e.g., kernel density estimate), aiding in visualizing the underlying distribution shape. Differences in range and peak frequencies may reflect variations in the methodologies, geographic regions, or time periods used to derive these ET estimates. This analysis suggests that evapotranspiration estimates are generally low across these methods, with AgSAT and Thornthwaite showing the most consistent low-value dominance, while EVAPO and Evapotranspiration Calculator (Ukraine) capture a wider range of conditions. The boxplot comparing the ET values across four studied methods revealed other valuable insights (Fig. 2), in particular the distinct differences in evapotranspiration estimates across the four methods. Evapotranspiration Calculator (Ukraine) exhibits the highest median (ET = 5.0 mm) with the widest interquartile range (IQR = 4.5–6.0 mm) and significant outliers (up to 8.0 mm), suggesting greater variability and sensitivity to local conditions. The AgSAT shows the lowest median of 2.0 mm with the narrowest IQR (1.5–2.5 mm) and moderate outliers, indicating consistent but occasionally extreme estimates. Thornthwaite (standard method) and EVAPO both have similar medians of about 3.0 mm with narrower IQRs (2.5–3.5 mm) and no outliers, reflecting more uniform distributions. These variations highlight methodological and contextual differences, necessitating careful selection based on specific research or application needs. Based on the results of boxplot analysis, EVAPO exhibits the best correspondence to the Thornthwaite method due to its matching median and similar IQR, which reflect comparable distributional characteristics.

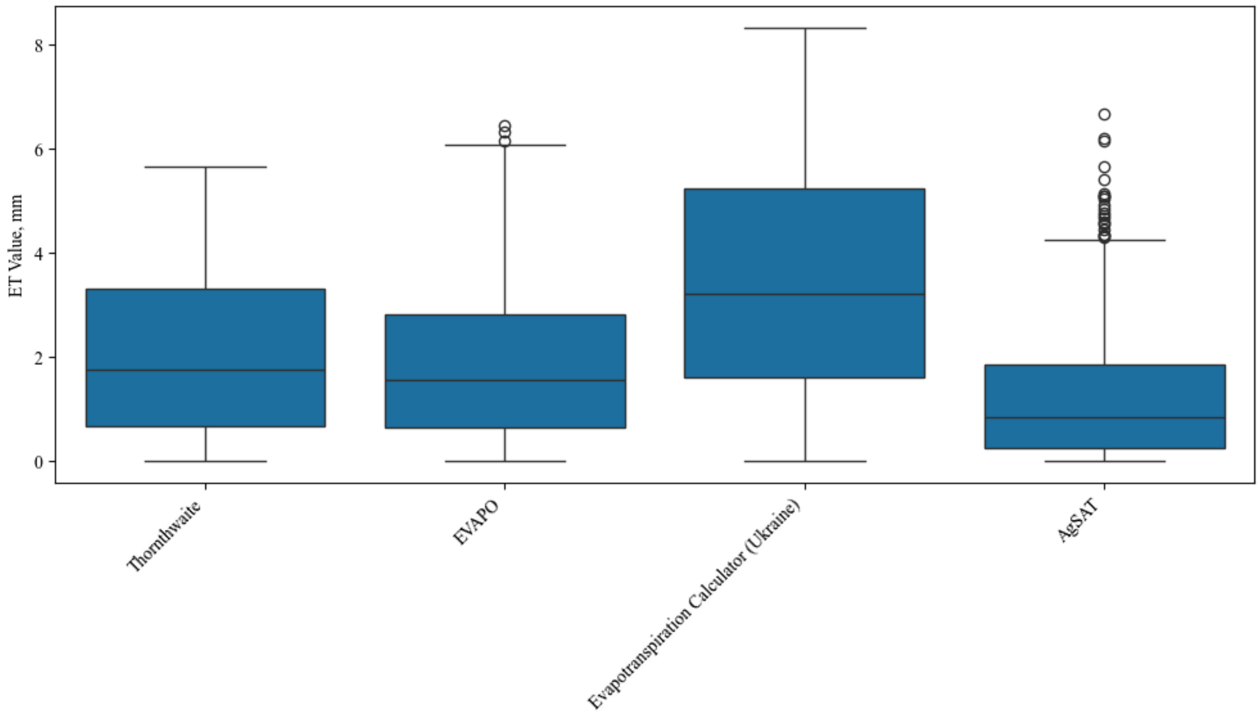

Fig. 2. The boxplot of different evapotranspiration (ET) methods: AgSAT, EVAPO, Evapotranspiration Calculator (Ukraine), and Thornthwaite

The scatter plot and residual plot compare the EVAPO and Thornthwaite ET estimates (Fig. 3). The scatter plot shows a strong positive correlation, with the data points closely aligned along the line of equality (y = x), indicating good agreement between methods across ET values (0–6 mm). The residual plot reveals a mean difference near zero, with residuals symmetrically distributed around the zero-difference line, suggesting minimal systematic bias. However, slight deviations and scattered residuals indicate minor variability, particularly at higher ET values, reflecting some method-specific differences. In general, the EVAPO's approach to ET estimation is close enough to the reference methodology.

The scatter plot and residual plot comparing Evapotranspiration Calculator (Ukraine) with Thornthwaite ET estimates (Fig. 4) provided the following insights. The scatter plot shows a strong positive correlation, with the data points clustering near the line of equality (y = x) across ET values (0–8 mm), indicating good overall agreement. The residual plot reveals a positive mean difference (0.5–2.5 mm) above the zero-difference line, suggesting a systematic overestimation by the Evapotranspiration Calculator method as compared with Thornthwaite, with residuals increasing with ET values, indicating method-specific bias at higher estimates. Such an overestimation might lead to excessive irrigation water applied to the fields. Consequently, in arid and semiarid climates, where freshwater resources are limited, this may exacerbate irrational wastage of water. Besides, it might lead to an increase in soil salinity, and in edge cases promote waterlogging, posing significant agronomic and environmental challenges.

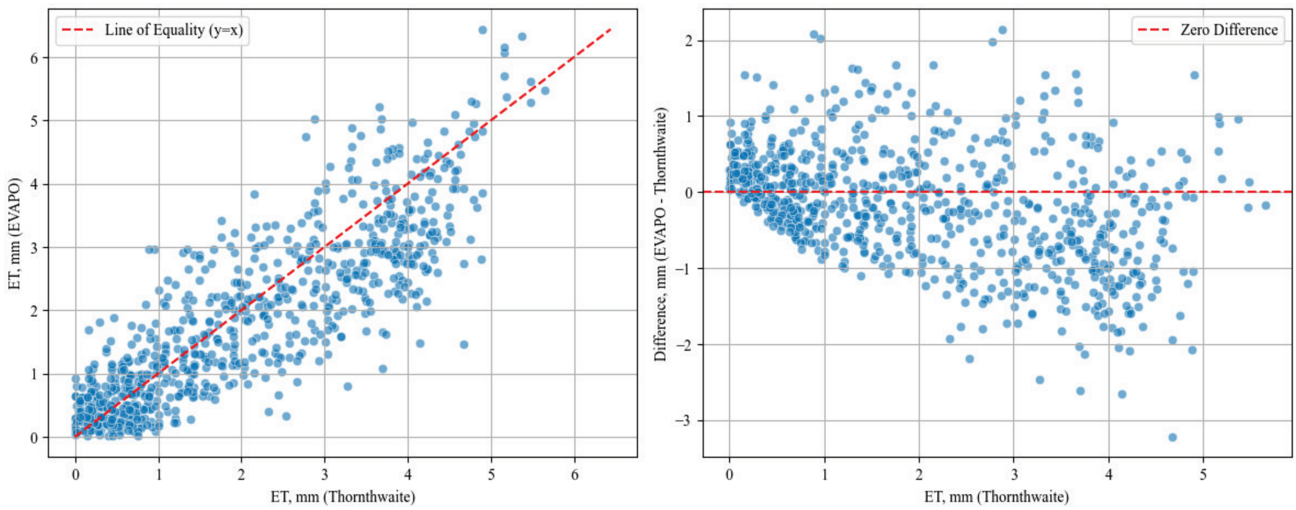

Fig. 3. The scatter and residual plot of different evapotranspiration (ET) methods: EVAPO versus Thornthwaite

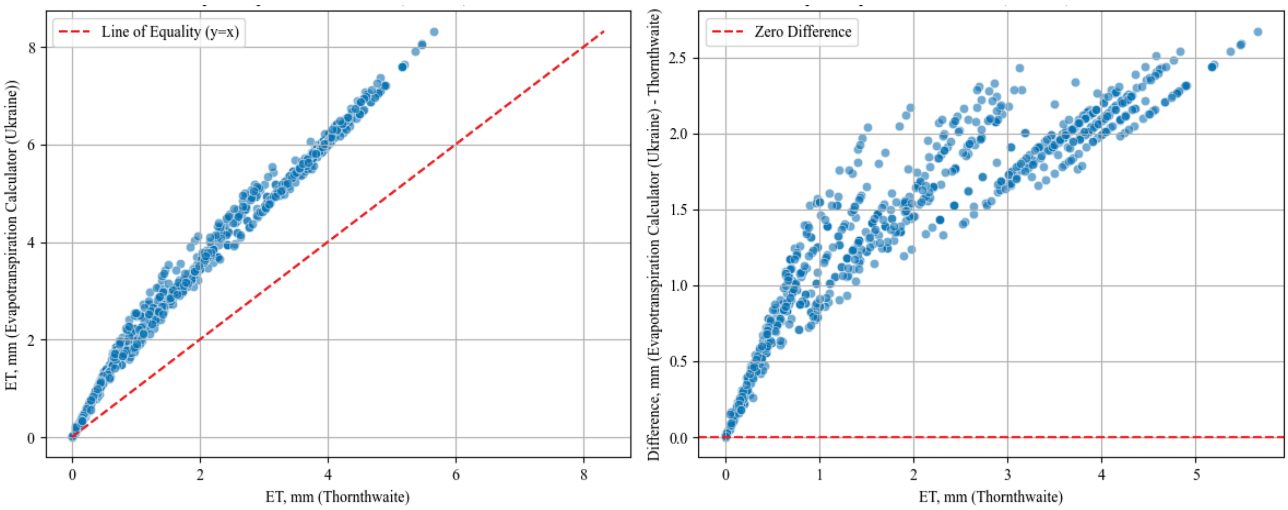

Fig. 4. The scatter and residual plot of different evapotranspiration (ET) methods: Evapotranspiration Calculator (Ukraine) versus Thornthwaite

The scatter plot and residual plot comparing the AgSAT and Thornthwaite ET estimates (Fig. 5) revealed a strong positive correlation between the two methods, with data points closely following the line of equality (y = x) across ET values (0–7 mm), indicating good agreement. The residual plot reveals a mean difference near zero, with residuals symmetrically distributed around the zero-difference line, suggesting minimal systematic bias. However, slightly negative residuals at higher ET values indicate a minor underestimation by the AgSAT compared with Thornthwaite. The observed underestimation could pose risks for irrigation management. If this underestimation is consistent, it may lead to miscalculation of required volumes of irrigation water, leading to insufficient water allocation, potentially causing inadequate humidification and subsequent crop losses, particularly in arid and semiarid climate conditions, where irrigation is crucial for sustainable crop production.

The Bland-Altman plots (Fig. 6) compare AgSAT, EVAPO, and Evapotranspiration Calculator (Ukraine) with the reference Thornthwaite method. Each plot displays the difference between the test method and Thornthwaite with their average ET values, with the mean difference and 95% limits of agreement (LoA) indicated. First, the comparison of AgSAT and Thornthwaite estimations reveals that the mean difference is –0.78 mm, with 95% LoA from –0.87 to –0.69 mm. The negative mean difference indicates a systematic underestimation by AgSAT compared with Thornthwaite, as was claimed above. The narrow LoA suggests consistent bias, with most differences clustering around –0.78 mm, implying reliable but lower estimates, posing significant risks of insufficient irrigation supply if irrigation rates are based on the AgSAT ET estimates. As for EVAPO versus Thornthwaite, the mean difference reached –0.18 mm, with 95% LoA from –0.23 to –0.13 mm. The slight negative mean difference reflects a minor underestimation by EVAPO, with a narrow LoA indicating high consistency. The small bias suggests close alignment with Thornthwaite. Evapotranspiration Calculator (Ukraine) had the highest mean difference of 1.39 mm, with 95% LoA from 1.35 to 1.44 mm. The positive mean difference indicates a systematic ET overestimation, with a wider LoA reflecting greater variability. This suggests a consistent but significant deviation from Thornthwaite in the direction of possible overwatering and consequent environmental challenges. At the same time, use of Evapotranspiration Calculator (Ukraine) poses minimal risks of drought stress as underwatering is almost impossible with this method of ET estimation.

Considering Thornthwaite as the reference, the method with the smallest mean difference and narrow LoA is preferable for ET assessment. The EVAPO app demonstrated the closest correspondence to Thornthwaite, with a minimal mean difference (–0.18 mm) and narrow LoA, indicating high accuracy and consistency. The AgSAT application, while consistent, significantly underestimated the ET (–0.78 mm), posing risks of insufficient irrigation. At the same time, the substantial overestimation (1.39 mm) produced by Evapotranspiration Calculator (Ukraine) could lead to overwatering, particularly problematic in water-scarce regions and in the soils that are susceptible to secondary salinization and sodification. Thus, EVAPO should be preferred for ET assessment.

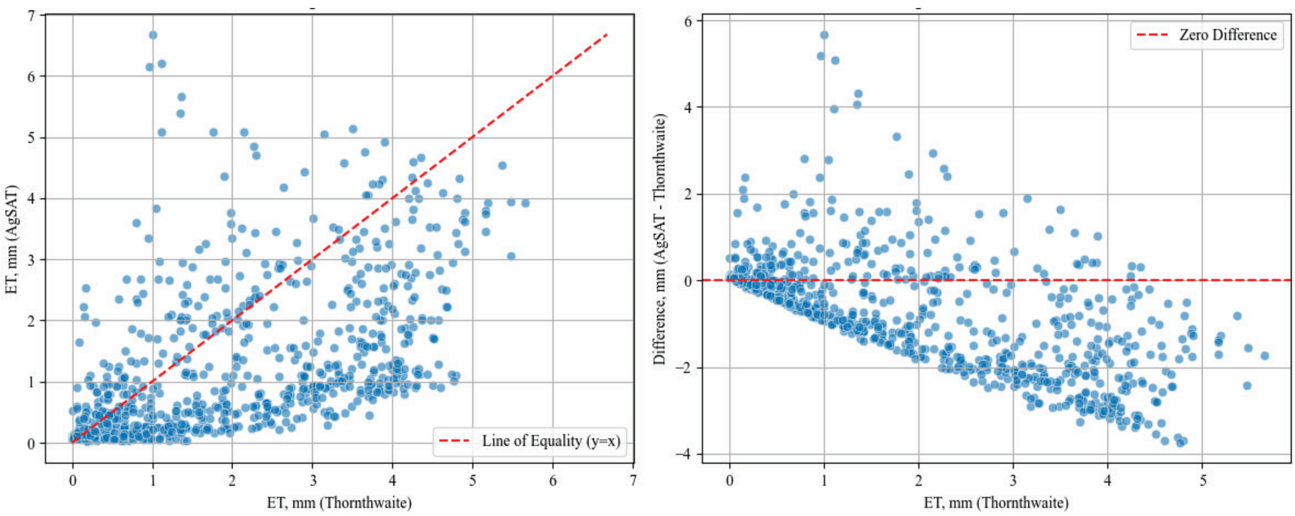

Fig. 5. The scatter and residual plot of different evapotranspiration (ET) methods: AgSAT versus Thornthwaite

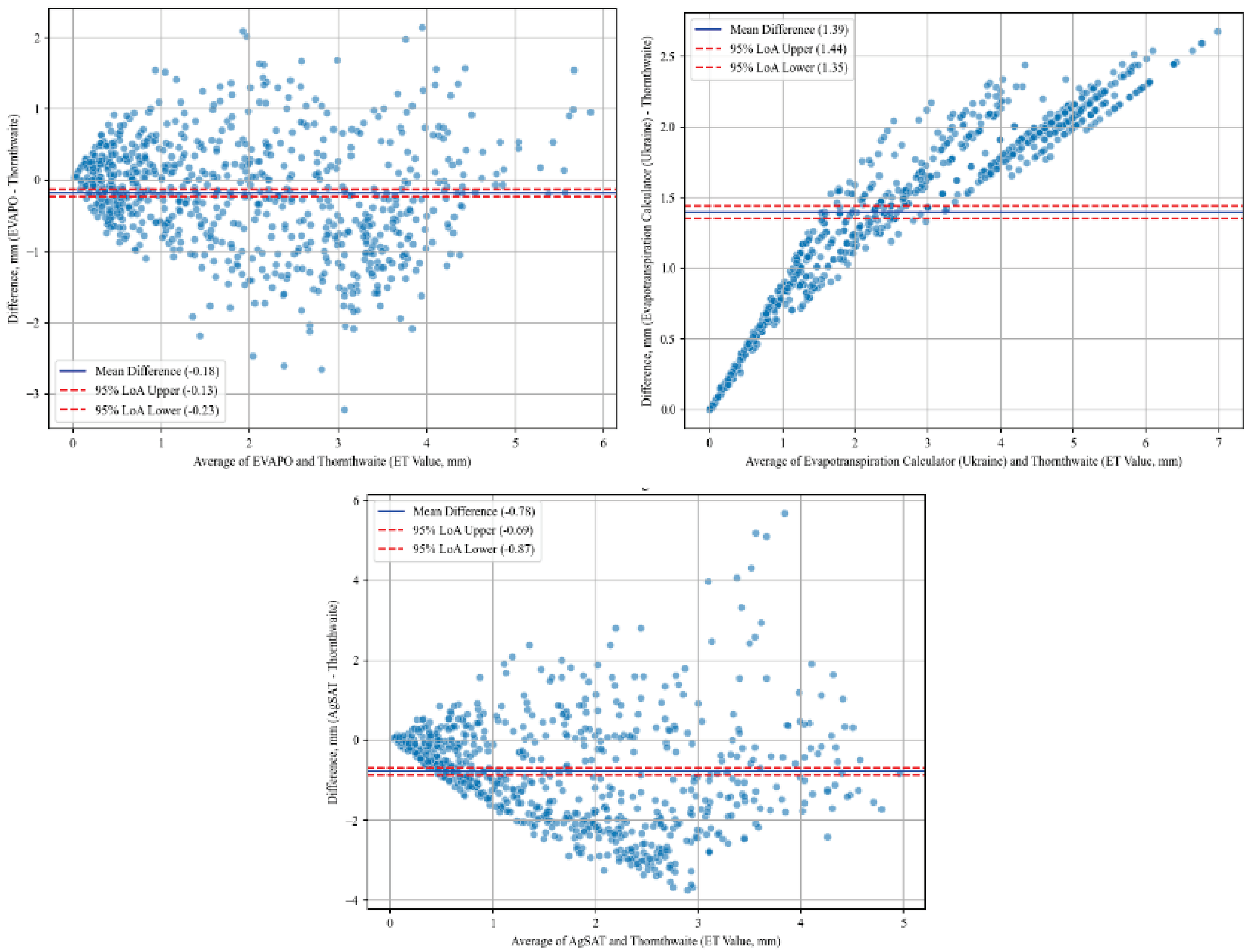

Fig. 6. Bland-Altman plots comparing the AgSAT, EVAPO, and Evapotranspiration Calculator (Ukraine) with the reference Thornthwaite method for evapotranspiration (ET) assessment

The accuracy of the assessment results are provided in Table 1. According to the results of statistical analysis, EVAPO exhibits the smallest bias, closely aligning with Thornthwaite, while Evapotranspiration Calculator (Ukraine) method overestimates and AgSAT underestimates more substantially, with all biases statistically significant given the non-overlapping CIs with zero. The EVAPO application demonstrated superior accuracy, with the lowest RMSE, while both Evapotranspiration Calculator (Ukraine) method and AgSAT showed higher errors. In addition to RMSE, EVAPO's lower MAE highlights its superior agreement with Thornthwaite, while the other methods exhibit larger average deviations. Notwithstanding the fact that Evapotranspiration Calculator (Ukraine) excels other methods in capturing the linear ET trend, its bias may limit practical utility. The EVAPO application shows a solid correlation, while AgSAT's low R-squared indicates weak predictive power compared with Thornthwaite. The EVAPO application's high NSE confirms its effectiveness, while the negative NSE values for both other approaches highlight their inadequacy, as they fail to outperform a simple mean-based prediction.

Table 1
Accuracy assessment (agreement and bias) of the AgSAT, EVAPO, and Evapotranspiration Calculator (Ukraine) compared with the reference Thornthwaite method for evapotranspiration (ET) assessment

Statistical indicator	EVAPO	Evapotranspiration Calculator (Ukraine)	AgSAT
Mean difference, mm	–0.1812	1.3925	–0.7787
95% CI for Mean difference	(–0.2340, –0.1283)	(1.3460, 1.4390)	(–0.8703, –0.6871)
RMSE, mm	0.7782	1.5436	1.5249
MAE, mm	0.6012	1.3925	1.1683
R-squared	0.7366	0.9840	0.2881
Nash-Sutcliffe efficiency (NSE)	0.7170	–0.1135	-0.0867

The statistical analysis of evapotranspiration (ET) estimates across the methods – EVAPO, Evapotranspiration Calculator (Ukraine), and AgSAT – compared with the reference Thornthwaite method, incorporated normality assessments and non-parametric tests to ensure robust conclusions. The Shapiro-Wilk test, applied to assess the overall normality of combined ET values, yielded a statistic of 0.9130 with a P-value of <0.0001, decisively rejecting the null hypothesis of normality ($P < 0.05$). This indicates that the ET data are not normally distributed, necessitating a non-parametric approach. Consequently, the Friedman test, a suitable alternative to ANOVA for repeated measures, was conducted, resulting in a statistic of 1241.9708 and a P-value of <0.0001. This highly significant outcome ($P < 0.05$) confirms substantial differences among the ET estimation methods. To further elucidate these differences, multiple comparisons with the Bonferroni correction were performed for paired tests, revealing highly significant differences ($P < 0.001$) across all the method pairs. This suggests that none of the alternative methods – EVAPO, Evapotranspiration Calculator, or AgSAT – exhibits sufficiently close correspondence to Thornthwaite to serve as a reliable substitute. The consistent statistical divergence underscores the distinct methodological underpinnings of each approach, supporting their uniqueness rather than interchangeability.

In conjunction with the Bland-Altman and performance metric analyses, these findings refine the interpretation. The EVAPO application, despite showing the smallest mean difference (–0.1812 mm), lowest

RMSE (0.7782 mm), and highest NSE (0.7170), still differs significantly from Thornthwaite, precluding its use as a direct replacement. Similarly, the Evapotranspiration Calculator's (Ukraine) overestimation (mean difference = 1.3925 mm) and the AgSAT's underestimation (mean difference = –0.7787 mm), despite their respective strengths in R-squared (0.9840 and 0.2881), are statistically distinct. Thus, while EVAPO remains the closest in performance to Thornthwaite, the significant differences highlighted by the Friedman test and Bonferroni-corrected comparisons emphasize the need for method-specific adjustments or complementary use rather than substitution. This reinforces the individuality of each method and the importance of context-specific validation in relation to Thornthwaite in ET assessment applications.

Discussion

Accurate assessment of evapotranspiration is essential for effective agricultural water management, as it directly affects the efficiency of irrigation scheduling, water resource allocation, and crop yield optimization. Precise ET estimation helps prevent both over- and underirrigation, thereby conserving water, reducing costs, and supporting sustainable environmentally friendly agriculture, especially in regions facing water scarcity or climate variability (Anderson & French, 2019; Lavrenko et al., 2019). Traditional methods for estimating ET, such as tabular crop coefficients and empirical models, often struggle with the diversity of crops, irrigation techniques, and local environmental conditions, leading to inaccuracies that can impact farm productivity and resource use (Ratshiedana et al., 2025). Advances in remote sensing, unmanned aerial vehicles (UAVs), and machine learning now enable high-resolution, site-specific ET measurements and forecasts, improving the precision of water management decisions. These technologies allow for real-time or near-real-time monitoring and forecasting, which is crucial for adapting to changing weather patterns and optimizing irrigation in precision agriculture (Granata et al., 2024). Integrating direct measurements, such as those from lysimeters or eddy covariance systems, with advanced modeling approaches further enhances the reliability of ET estimates, especially when models are calibrated and validated for local conditions (Ratshiedana et al., 2025). Ultimately, accurate ET assessment underpins the sustainable use of water in agriculture, supports food security, and helps mitigate the impacts of drought and climate change.

Automated tools for estimating evapotranspiration have seen significant advances in accuracy, particularly with the integration of machine learning (ML), artificial intelligence (AI), and remote sensing technologies. State-of-the-art ML models, such as ensemble learners and neural networks, consistently outperform traditional empirical and process-based methods, achieving high coefficients of determination (R^2 often above 0.97) and low root mean square errors (RMSE as low as 0.13–0.67 mm/day), even with limited meteorological inputs or in data-scarce regions (Granata, 2019; Aly et al., 2023; Bijlwan et al., 2024). Hybrid AI models that combine optimization algorithms with neuro-fuzzy systems further enhance accuracy, especially when incorporating remote sensing indices like soil wetness deficit (Hadadi et al., 2022). Automated platforms like geeSEBAL, which leverage cloud computing and satellite data, demonstrate robust performance across diverse climates, with average daily ET estimation errors around 0.67 mm/day compared with ground truth, and show low sensitivity to meteorological input variability (Laipelt et al., 2021). Novel deep learning architectures, such as attention-based convolutional capsules, have achieved up to 128% improvement in accuracy over traditional models, maintaining performance across varied landscapes and seasons (Armstrong et al., 2022). Comparative studies confirm that ML approaches, particularly Random Forest and AutoML frameworks, provide reliable ET estimates with minimal bias and strong spatial agreement with established remote sensing products, though some underestimation and consequent risks of underwatering and crop losses may occur (Ravindran et al., 2022; Sun et al., 2025). Overall, automation tools using advanced ML and remote sensing offer highly accurate, scalable, and practical solutions for ET estimation, supporting improved water management and agricultural decision-making.

Another automation approach for ET estimation lays in the direction of the automation of calculations and agrometeorological data derivation for these calculations within the framework of cloud-based cross-platform or mobile applications. This approach has made ET data more accessible and actionable for water managers, farmers, and stakeholders. Cloud services like ETWatch Cloud encapsulate complex ET modeling algorithms such as web APIs, enabling users to generate regional ET data efficiently and at scale via web browsers or integrated development environments. This supports water management and hydrological applications by leveraging remote sensing data and scalable computing resources (Wu et al., 2021). Additionally, mobile applications have been developed to provide real-time ET calculations directly to users in the field, utilizing GPS to access and interpolate data from nearby weather stations and automatically applying standardized methods such as the FAO Penman-Monteith equation for both reference and crop-specific ET values (Bueno-Delgado et al., 2017). These tools not only automate the calculation process but also improve user experience by offering intuitive interfaces, data storage, and editing capabilities, thereby facilitating timely and precise irrigation decisions and resource management.

The studied mobile applications EVAPO and AgSAT are some of the best examples of the automated ET calculation approach. They are well-known for their relatively reasonable accuracy and ease of use (Júnior et al., 2019), but there is a lack of studies to draw reliable conclusions about their performance in different climate zones, as well as in the conditions of current rapid climate change. Evapotranspiration Calculator (Ukraine) has an advantage over the other automation applications for ET estimation because of its cross-platform cloud-based nature and multilingual interface. Also, it provides clear reference to the methodology of ET estimation, which is also true for EVAPO but not for AgSAT (Lykhovyd et al., 2024). The main drawback of Evapotranspiration Calculator is that it was developed to estimate the evapotranspiration rates only in Ukraine and only for warm period of the year.

Preliminary studies demonstrated acceptable precision and conformity of the analyzed applications with established methodologies. However, comprehensive long-term assessments of their accuracy under semiarid climatic conditions have yet to be conducted. The present study elucidated the respective advantages and disadvantages of each application, unequivocally indicating that all automated methods of evapotranspiration (ET) estimation require substantial refinement prior to their practical deployment. This refinement is critical for optimizing irrigation water management and enhancing overall efficiency. It is evident that none of the current automation approaches are entirely flawless, though EVAPO exhibits the greatest potential. Subsequent research will explore how the results are affected by the advanced features within AgSAT and Evapotranspiration Calculator, which in this study were configured with default parameters.

Conclusions

The findings of this study underscore the distinct variations among the automated evapotranspiration (ET) estimation tools – EVAPO, AgSAT, and Evapotranspiration Calculator (Ukraine) – compared with the reference Thornthwaite methodology. Among these, EVAPO demonstrated the closest alignment with Thornthwaite, as evidenced by its minimal mean difference and robust statistical performance metrics. Conversely, AgSAT exhibited a consistent underestimation of ET, while Evapotranspiration Calculator (Ukraine) showed a pronounced overestimation, both of which pose significant risks in semiarid climates. These biases could lead to underwatering or overwatering, respectively, with deleterious consequences for crop health and soil integrity.

Despite EVAPO's relatively favorable correspondence, the statistical analysis, including the Friedman test and Bonferroni-corrected multiple comparisons, revealed highly significant differences ($P < 0.001$) across all the methods, precluding the unqualified recommendation of any tool as a direct replacement for Thornthwaite. The initial assumption of employing ANOVA was invalidated by the Shapiro-Wilk test's rejection of normality ($P < 0.0001$), further supporting the non-parametric approach. Consequently, even EVAPO requires prior refinement and calibration to enhance its reliability for ET estimation and irrigation scheduling. In conclusion, while each automated tool offers unique advantages, their limitations necessitate tailored adjustments to ensure effective integration into the digitalized management of irrigated agriculture.

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