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Egypt. J. Agron. **Vol. 47** , No. 3, pp: 565 - 574 (2025)

Egyptian Journal of Agronomy

http://agro.journals.ekb.eg/

Assessing SEBAL Model Performance under Center Pivot Irrigation for Efficient and Accurate Irrigation Management: A Case Study on Sugar Beet Cultivation

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ACCURATE evapotranspiration (ET) estimation is crucial for effective irrigation management, particularly in water-stressed agricultural regions. This study evaluates and compares three ET models, SEBAL, Penman-Monteith, and Priestley-Taylor, in estimating ET for sugar beet (*Beta vulgaris* L.) under center-pivot irrigation. The results of Penman-Monteith generated the highest cumulative ET (875 mm), reflecting its sensitivity to meteorological inputs but risking overestimation in data-limited contexts. SEBAL estimated a moderate ET of 759.6 mm, closely matching expected water demands due to its use of satellite-derived energy balance data. Priestley-Taylor yielded the lowest ET (633.2 mm), underestimating peak water needs, risking water stress and yield reduction. Model accuracy metrics confirmed SEBAL's reliability, with a Mean Absolute Error (MAE) of 0.437 mm/day and Root Mean Square Error (RMSE) of 0.541 mm/day. In comparison, Priestley-Taylor showed higher errors (MAE: 0.721 mm/day, RMSE: 0.856 mm/day). The spatial analysis highlighted SEBAL's ability to detect dynamic ET variations, with peak demands of 4.0–5.0 mm/day during the late midseason. Regression analysis further supported SEBAL's predictive accuracy, achieving an R-squared value of 0.95 when correlating ET with DMP. The SEBAL model, integrated with remote sensing, proves valuable for advancing sustainable water management practices in agriculture.

Keywords: Evapotranspiration (ET), SEBAL Model, Remote Sensing, Precision Irrigation, Agricultural Water Management.

Introduction

Efficient water management is a critical factor in sustainable agriculture, particularly in arid and semi-arid regions where water resources are limited and competition for water is intensifying. In these environments, accurately estimating evapotranspiration (ET), the combined process of water loss from soil evaporation and plant transpiration, is crucial for optimizing irrigation practices (Wanniarachchi & Sarukkalige, 2022; Pereira et al., 2020). ET significantly determines the amount of water crops require during different growth stages (Li et al., 2021; Ahmad et al., 2021). Inaccurate estimates of ET can lead to under-irrigation, resulting in water stress and reduced crop yields, or over-irrigation, which wastes water and can degrade soil quality. As global populations continue to grow and climate change exacerbates water scarcity, improving ET estimation is becoming increasingly crucial for enhancing irrigation efficiency, ensuring food security, and maintaining environmental sustainability (Karthikeyan et al., 2020).

Many regions characterized by low annual precipitation and high evaporative demand face significant challenges in maintaining agricultural productivity (Lian et al., 2021). In such climates, rainfall alone is often insufficient to meet crop water requirements, making irrigation a necessity. High temperatures, prolonged dry seasons, and significant climate variability can lead to increased water demand for crops, thereby placing additional pressure on already limited water supplies. To manage this demand effectively, farmers and agricultural planners need reliable methods to predict water requirements based on accurate ET

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Received: 31/12/2024; Accepted: 18/04/2025
DOI: 10.21608/agro.2025.345755.1597

estimates (Wanniarachchi & Sarukkalige, 2022). Such tools are necessary for water resources to be misallocated, resulting in either crop failure due to water stress or inefficient water use that reduces the overall productivity of farming systems.

Traditional methods for estimating ET rely heavily on ground-based meteorological data collected from weather stations (Amani & Shafizadeh-Moghadam, 2023; Kull et al., 2021; Blankenau et al., 2020; Elbeltagi et al., 2022). These methods use a combination of temperature, humidity, wind speed, and solar radiation to calculate the energy exchange between the atmosphere and the crop surface. While such approaches, such as the Penman-Monteith model, are widely used and well-established, they are often limited by their dependence on localized weather data (Paul et al., 2021; Van et al., 2024). Meteorological stations are only sometimes evenly distributed, especially in large agricultural areas or remote regions, and their measurements may not accurately reflect conditions across an entire field. This spatial and temporal variability presents challenges in applying these models to large-scale farming operations, where water demand may vary significantly across different parts of the field (Pasquel et al., 2022; Peng et al., 2020; Kephe et al., 2021).

In recent years, remote sensing technologies have emerged as a valuable tool for overcoming these limitations. By providing continuous, large-scale data on crop and environmental conditions, satellite-based remote sensing offers a more comprehensive and scalable solution for monitoring ET (Weiss et al., 2020; Radočaj et al., 2020; Chen et al., 2022; Fuentes-Peñailillo et al., 2024). Satellite data can capture spatial variations in surface temperature, vegetation health, and other factors that influence ET across vast agricultural areas. This capability allows for more precise, field-level ET estimation and enhances the real-time management of water use. Remote sensing-based models, such as the Surface Energy Balance Algorithm for Land (SEBAL), integrate satellite-derived data like surface temperature and the Normalized Difference Vegetation Index (NDVI) to calculate ET without the need for extensive ground-based measurements (Awada et al., 2022; Cheng et al., 2021; Chen et al., 2023). This makes them particularly useful in regions with sparse or unavailable meteorological data.

Despite the clear advantages of remote sensing technologies, the application of such methods for ET estimation still needs to be explored in many agricultural contexts. While several studies have evaluated the performance of traditional ground-based models, such as the Penman-Monteith and Priestley-Taylor models, there is a need for more research comparing these models to satellite-based approaches, particularly in the context of large-scale farming, where SEBAL is often used. Moreover, few studies have systematically validated these models against actual crop growth metrics, such as dry matter production (DMP), which is directly linked to crop yield and water use efficiency (Tang et al., 2023; de Roos et al., 2021; Chevuru et al., 2023; de Roos et al., 2024; Carthy et al., 2024). As a result, there is a critical need for studies that assess the reliability and practicality of remote sensing-based ET models, especially in areas where water scarcity is a growing concern (Bhattarai & Wagle, 2021; Jindo et al., 2021; Derardja et al., 2024; Bretreger et al., 2022).

Addressing this gap in the literature, this study aims to evaluate and compare the performance of three ET models—SEBAL, Penman-Monteith, and Priestley-Taylor—in estimating ET for sugar beet (*Beta vulgaris* L.) cultivation. Sugar beet, a high-water-demand crop, is widely grown in various regions and serves as a valuable test case for assessing the accuracy of evapotranspiration (ET) models. The models are validated against dry matter production (DMP), a key indicator of crop growth and productivity. DMP represents the total biomass a crop produces and is directly related to the water it uses. By comparing the ET estimates from each model with the observed DMP, we can assess how well the models predict water use and its impact on crop growth.

Materials and Methods

Study Area and Crop

The field experiment was conducted on a privately owned farm located in Minya Governorate, Egypt, at the following geographical coordinates: 27°47'17.06"N latitude and 30°29'56.82"E longitude (Figure 1). This area lies within an arid climatic zone, typified by prolonged dry periods, high temperatures, and limited precipitation. During the growing season, which extended from August 2020 to May 2021, the region experienced considerable thermal stress, with an average maximum air temperature of 37.4 °C (SD ±3.7 °C), an average minimum temperature of 20.1 °C (SD ±2.0 °C), and a mean daily temperature of 28.0 °C (SD ±2.8 °C). Relative humidity remained low throughout the season, averaging 27.6% (SD ±2.8%), with maximum and minimum averages recorded at 37.8% (SD ±3.8%) and 15.9% (SD ±1.6%), respectively. Wind speed, measured at a height of 2 meters, averaged 3.3 m/s (SD ±0.3), while cloud cover was consistently minimal, with a seasonal average of 2.5 octas (SD ±0.3). These conditions contributed to elevated evapotranspiration rates, highlighting the importance of effective water management strategies to support crop growth in such environments.

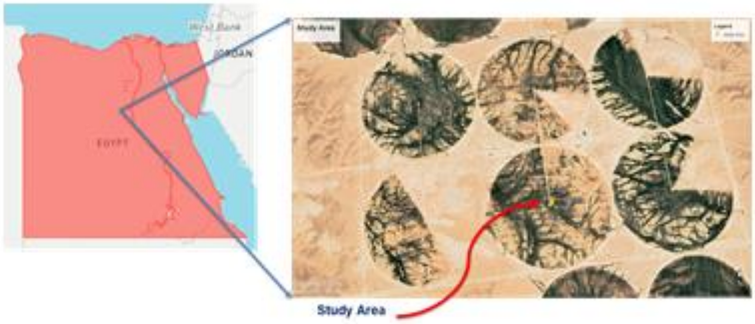

Fig. 1. Map showing the location of the study area in the Minya governorate, Egypt, highlighting the specific agricultural fields where the research was conducted. The right panel provides a detailed view of the study site, which consists of center-pivot irrigation systems used for sugar beet cultivation.

The crop selected for the study was sugar beet (*Beta vulgaris* L.), a strategically important crop for Egypt's sugar industry. The growing period spanned approximately 210 days, aligning with the typical sugar beet production cycle in the region.

Table 1. Overall Average Climatic Conditions at the Experimental Site in Minya Governorate, Egypt. Values represent the overall means of monthly averages ± standard deviations across the entire study period (August 2020 to May 2021).

Parameter	**Value ± SD**
Average Max Air Temp	37.4 ± 3.7°C
Average Min Air Temp	20.1 ± 2.0°C
Mean Air Temp	28.0 ± 2.8°C
Average Max Relative Humidity	37.8 ± 3.8%
Average Min Relative Humidity	15.9 ± 1.6%
Mean Relative Humidity	27.6 ± 2.8%
Average Wind Speed	3.3 ± 0.3 m/s (at 2 meters height)
Average Cloud Cover	2.5 ± 0.3 octas

Soil and Irrigation Water

The soil at the experimental site was analyzed prior to sugar beet planting. The soil was characterized as sandy loam with the following physical and chemical properties:

Clay (10%), silt (20%), sand (70%), bulk density of 1.45 g/cm³, field capacity (18%), permanent wilting point (8%), organic matter (1.2%), pH of 7.9, and electrical conductivity (EC) of 3.66 dS/m.

The water used for irrigation was analyzed for quality parameters and showed the following characteristics: EC of 1.07 dS/m, pH 7.35, sodium adsorption ratio (SAR) 3.21, and major ions: Ca^{2+} (3.0 meq/L), Mg^{2+} (2.5 meq/L), Na^{+} (5.3 meq/L), K^{+} (0.2 meq/L), Cl^{-} (9.0 meq/L), SO_4^{2-} (1.76meq/L), and HCO_3^{-} (0.24 meq/L). The irrigation water quality was considered suitable for sugar beet cultivation without posing significant salinity or sodicity issues.

Description of the Center Pivot Irrigation System and Actual Irrigation Requirements

The center pivot irrigation system used in the experiment had an arm length of 338 m, irrigating approximately 35.7 hectares (85 feddan). Sprinklers with low-pressure spray nozzles were distributed along the pivot arm, delivering uniform water applications. The pivot operated at a base pressure of approximately 1.8 bar, with an average flow rate of about 100.5 m³/h. The irrigation efficiency (IE) was assumed to be 75%, typical for modern center pivot systems. Actual irrigation requirements (IR) for sugar beet under the center pivot irrigation system were calculated using the equation:

$$IR = \frac{ET_0 \times K_c}{IE}$$

Where:

- IR is the Irrigation Requirement (mm/day)
- ET_0 is the Evapotranspiration estimated by each model (SEBAL, Penman-Monteith, Priestley-Taylor).
- Kc is the Crop coefficient for sugar beet.
- **IE**: Irrigation Efficiency

Satellite Data Acquisition

To monitor the sugar beet fields and estimate ET, Landsat 8 satellite imagery was employed. Landsat 8 was selected for its high spatial resolution (10 m x 10 m), enabling detailed field-level analysis. The satellite data, with a revisit cycle of 16 days, provided consistent monitoring throughout the growing season. Thermal infrared and visible bands were used to compute key indicators such as surface temperature and the Normalized Difference Vegetation Index (NDVI), essential for estimating ET.

Landsat imagery was pre-processed through a series of standard steps to ensure the accuracy and reliability of the remote sensing data used in the study. First, geometric correction was applied to align the images with real-world geographic coordinates, ensuring spatial consistency. This was followed by atmospheric correction, which removed distortions caused by atmospheric conditions such as haze and aerosols, resulting in more accurate surface reflectance values. Lastly, cloud masking was performed to exclude pixels affected by cloud cover, thereby enhancing the precision of evapotranspiration (ET) estimates derived from the imagery.

Field Data Collection

To ensure accurate validation of satellite-based ET models, field data were collected at key phenological stages of sugar beet throughout the growing season, which spanned from September 2020 to May 2021. Biomass sampling for dry matter production (DMP) and soil moisture observations occurred approximately every 30–40 days, aligned with critical growth phases. Sampling took place on the following dates: 15 September 2020 (emergence stage), 15 October 2020 (early vegetative growth), 15 November 2020 (canopy development), 15 December 2020 (full canopy), 15 January 2021 (early root bulking), 15 February 2021 (root development), 15 March 2021 (late growth), 15 April 2021 (maturation), and 15 May 2021 (harvest). At each stage, representative plant samples were collected, oven-dried, and weighed to determine total DMP. Soil moisture content was manually assessed during each field visit using gravimetric sampling methods. This structured sampling approach facilitated the temporal validation of ET estimates produced by the models and supported the analysis of the relationship between evapotranspiration, crop growth, and irrigation needs.

Evapotranspiration (ET) Models

Three ET models—SEBAL (Surface Energy Balance Algorithm for Land), Penman-Monteith, and Priestley-Taylor—were used to estimate daily ET in the sugar beet fields. The following is the detailed information for each model:

1. SEBAL (Surface Energy Balance Algorithm for Land)

SEBAL estimates ET using satellite-derived inputs, including surface temperature, NDVI, and albedo. SEBAL calculates ET by solving the surface energy balance equation (Chen et al., 2023):

$$ET = \frac{R_n - G - H}{\lambda}$$

Where:

$R_n \ is \ the \ net \ radiation \ (W/m^2)$

$G \ is \ the \ soil \ heat \ flux \ (W/m^2)$

$H \ is \ the \ sensible \ heat \ flux \ (W/m^2)$

$\lambda \ is \ the \ latent \ heat \ of \ vaporization \ (MJ/kg)$

SEBAL requires minimal ground-based data, mainly relying on satellite inputs. Thermal infrared data from Landsat were used to estimate surface temperature, while NDVI provided information on vegetation health. The model was applied on each Landsat acquisition date, and daily ET values were interpolated for the periods between satellite overpasses.

2. Penman-Monteith Model

The Penman-Monteith model is a physically based method that calculates ET by combining energy balance and aerodynamic principles. The FAO-56 Penman-Monteith equation was used (Abeysiriwardana et al., 2022):

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

Where:

R_n is the net radiation ($\mathrm{MJ/m^2}$ / day),

G is the soil heat flux ($\mathrm{MJ/m^2}$ / day),

u_2 is the wind speed at 2 meters hight $(\mathrm{m/s})$,

T is the mean daily air temperature ($^\circ\mathrm{C}$),

$e_s - e_a$ is the vapor pressure deficit (kPa),

Δ is the slope of the saturation vapor pressure curve $(\mathrm{kPa}/\ ^\circ\mathrm{C})$,

γ is the psychrometric constant $(\mathrm{kPa}/\ ^\circ\mathrm{C})$.

Meteorological data, including solar radiation, temperature, humidity, and wind speed, were collected from a weather station situated near the study area. These data were used to calculate daily ET values using the Penman-Monteith model, which served as a reference for comparison with SEBAL and Priestley-Taylor.

3. Priestley-Taylor Model

The Priestley-Taylor model simplifies the Penman-Monteith equation by assuming a negligible aerodynamic component, making it ideal for humid environments. The model estimates ET as a fraction of available energy (Su & Singh, 2023):

$$ET = \alpha \frac{\Delta(R_n - G)}{\Delta + \gamma}$$

Where α is the Priestley-Taylor coefficient, typically set to 1.26 for well-watered conditions. This model requires fewer input parameters than Penman-Monteith, relying mainly on net radiation, soil heat flux, and temperature. The values of R_n and G were estimated from the Landsat satellite data and supplemented with field-based measurements.

Data Analysis and Model Evaluation

The performance of the three ET models was assessed by comparing their daily ET estimates. Statistical metrics were employed to evaluate model accuracy:

- Mean Absolute Error (MAE): Quantified the average absolute error between predicted ET values and the reference data (Penman-Monteith).
- Root Mean Square Error (RMSE): Measures the standard deviation of prediction errors, with greater weight given to more significant deviations.
- R-squared (R^2): Evaluated the correlation between ET estimates and dry matter production

(DMP), providing insight into how well each model explained variability in crop growth.

Estimating Dry Matter Production (DMP)

The dry matter production (DMP) of sugar beet was estimated through periodic biomass sampling conducted at multiple stages of crop growth, including early vegetative stages, mid-season, and just before harvest. Biomass samples were collected from randomly selected 1 m^2 plots distributed across the field, with the sampling designed to capture spatial variability. All above-ground plant material (leaves, stems, and roots) within the plots was harvested at each sampling interval. The harvested biomass was then dried in an oven at 70°C until a constant weight was reached, ensuring moisture removal and leaving only the dry matter. The dry weight was measured using a precision balance, and the DMP was calculated by extrapolating the average dry weight per square meter to the total field area, resulting in the DMP expressed in kg/ha.

This final dry matter estimation was conducted at the end of the growing season to assess the total crop yield. The DMP data collected throughout the season were used to validate the ET models (SEBAL, Penman-Monteith, and Priestley-Taylor) by comparing the ET predictions with the observed crop growth. Regression analysis was performed to evaluate the correlation between ET estimates and DMP. R-squared (R^2) values were calculated to assess the models' ability to predict biomass production based on water use. This methodology provided accurate, field-based observations of crop growth, which were critical for assessing the performance of the ET models in optimizing irrigation practices.

Results and Discussion

1. Comparison of ET Models

Figure 2 presents the cumulative evapotranspiration (ET) values estimated by the three models—SEBAL, Penman-Monteith, and Priestley-Taylor—over the entire period of sugar beet cultivation. This figure highlights the key differences in how each model estimates total water use, which have important implications for irrigation management. The Penman-Monteith model consistently estimates the highest cumulative ET, reaching approximately 875 mm by the end of the growing season. This suggests that Penman-Monteith considers the sugar beet crop to have the highest water demand. The high cumulative ET values reflect the model's sensitivity to daily meteorological inputs, such as temperature, humidity, and wind speed. While this sensitivity enables the calculation of detailed daily ET estimates, it may lead to an overestimation of total water demand in the long term. This could result in excessive irrigation if these estimates are applied without adjustment, potentially leading to water waste and inefficiency.

On the other hand, SEBAL produces a more moderate cumulative ET estimate of 759.6 mm. This result aligns more closely with expected crop water requirements based on typical sugar beet growth patterns. SEBAL's cumulative ET curve indicates that the model strikes a balance between sensitivity to daily weather conditions and an overall realistic assessment of crop water use. Its reliance on satellite-derived data and the surface energy balance method enables a more accurate representation of real-time crop water needs, making SEBAL particularly effective in regions where detailed meteorological data may be limited or inconsistent.

The Priestley-Taylor model, in contrast, consistently estimates the lowest cumulative ET, with a final value of 633.2 mm. While this model is often used due to its simplicity and ease of application, it tends to underestimate the crop's water requirements, particularly during periods of high demand, such as peak growth stages. The cumulative ET curve for Priestley-Taylor rises more slowly compared to the other models, indicating a conservative approach to estimating water demand. This underestimation poses a risk of under-irrigation, which can lead to water stress and negatively impact crop productivity, particularly in regions with limited water availability.

Overall, Figure 2 illustrates the significant variability among the three models in estimating cumulative ET, with important implications for irrigation scheduling and water management strategies. The Penman-Monteith method, while providing detailed estimates, may lead to over-irrigation, particularly in regions where water efficiency is crucial. Priestley-Taylor, although simple, risks underestimating the crop's water needs, potentially leading to water shortages during crucial growth phases. SEBAL emerges as the most balanced model, providing accurate and realistic water-use estimates, making it an optimal choice for managing irrigation in sugar beet cultivation. Its ability to provide moderate yet precise cumulative ET estimates ensures that crops receive sufficient water without over-application, promoting both crop health and water conservation.

This analysis reinforces the importance of selecting the appropriate ET model based on regional water availability, crop type, and irrigation goals. SEBAL's moderate cumulative ET estimates make it particularly well-suited for precision irrigation systems, ensuring that water is applied efficiently while avoiding both water stress and wastage.

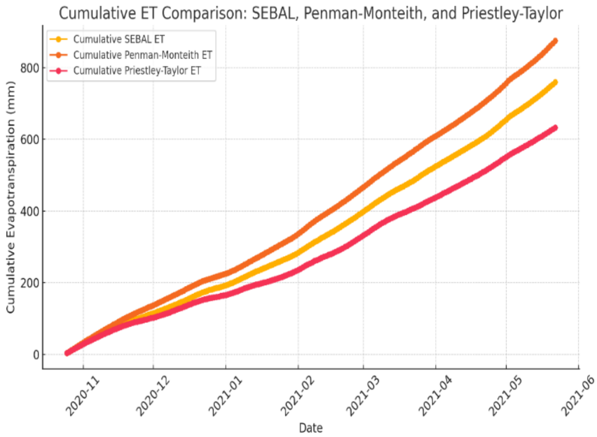

Fig. 2. Cumulative evapotranspiration (ET) values for SEBAL, Penman-Monteith, and Priestley-Taylor over the growing season.

Moreover, Penman-Monteith, recognized as the reference ET model due to its extensive use in agricultural water management, predicted the highest mean ET values (Figure 3). The variability in daily ET estimates, ranging from 1.7 mm/day to 7.7 mm/day, highlights the sensitivity of the Penman-Monteith method to detailed meteorological inputs. Although Penman-Monteith remains accurate under ideal conditions, its reliance on comprehensive meteorological data makes it more prone to overestimation in data-limited environments. This overestimation could result in excessive irrigation, leading to water waste.

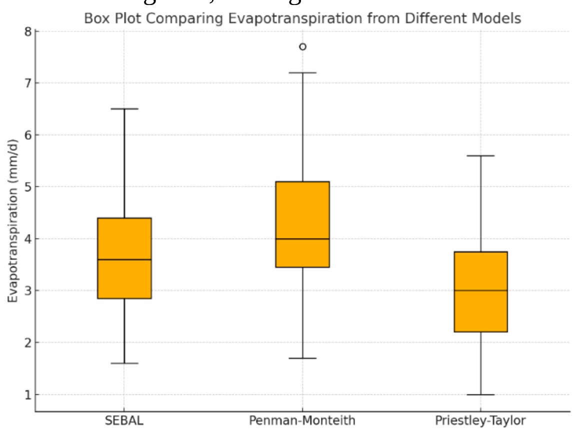

Fig. 3. Box plot comparing the mean evapotranspiration (ET) values from SEBAL, Penman-Monteith, and Priestley-Taylor, illustrating variability and range of estimates.

2. Quantifying Model Differences

To assess the accuracy of the models, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were calculated using Penman-Monteith as the benchmark model. SEBAL performed better, with an MAE of 0.437 mm/day and an RMSE of 0.541 mm/day (Figure 4), indicating that SEBAL's ET estimates closely aligned with those of the Penman-Monteith method, with minimal deviations. The low error values confirm SEBAL's robustness in predicting ET under various conditions, making it suitable for use in well-instrumented and data-scarce environments. In contrast, Priestley-Taylor showed higher error values, with an MAE of 0.721 mm/day and an RMSE of 0.856 mm/day. This indicates that Priestley-Taylor's ET estimates deviate significantly from Penman-Monteith's, particularly during peak growth phases when the crop's water demand is high. The higher RMSE for Priestley-Taylor reflects more significant prediction errors, which could result in under-irrigation, leading to decreased crop productivity. The performance of SEBAL, as indicated by its lower MAE and RMSE, confirms its utility in improving water-use efficiency and minimizing errors in irrigation scheduling.

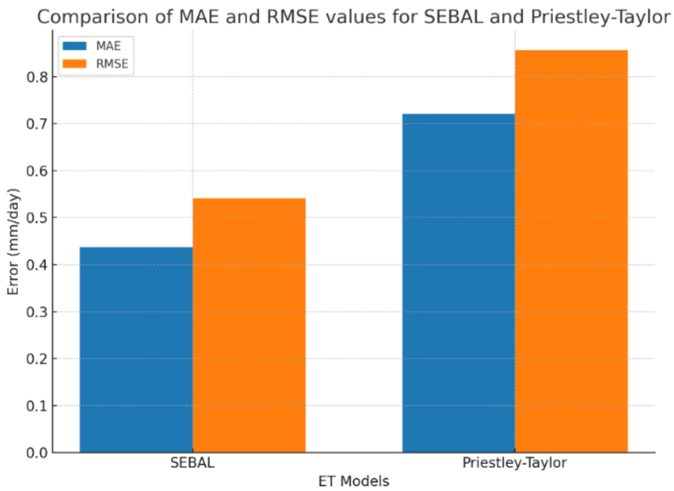

Fig. 4. Bar plot comparing MAE and RMSE values for SEBAL and Priestley-Taylor relative to Penman-Monteith.

3. Spatial Distribution of Evapotranspiration Using SEBAL Model

Figure 5 illustrates the spatial distribution of evapotranspiration (ET) across the distinct growth stages of sugar beet, derived from the SEBAL model. The selected dates—10/11/2020 and 12/12/2020 (Early Growth Stage); 13/01/2021 and 14/02/2021 (Mid-Season); 18/03/2021 and 19/04/2021 (Late Mid-Season); and 05/05/2021 and 21/05/2021 (Late Season)—represent critical phases in the crop's development, from establishment to maturity.

During the early growth stage, ET values were relatively low, averaging approximately 1.0–1.5 mm/day on October 11, 2020, and December 12, 2020. This reflects the crop's lower water requirements during the establishment phase when the plants are still small. As the growth transitions into the mid-season, ET values increase substantially, averaging around 2.5–3.0 mm/day on January 13, 2021, and 3.0–4.0 mm/day on February 14, 2021. This rise corresponds to the crop's vegetative growth period, during which water demand is at its highest to support biomass accumulation.

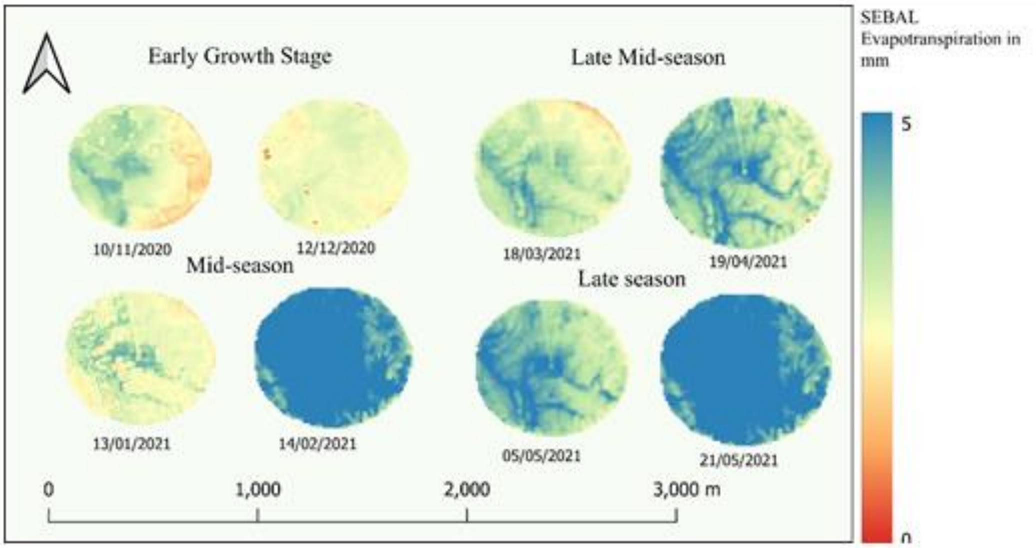

Fig. 5. Spatial Distribution of Evapotranspiration (ET) Across Sugar Beet Growth Stages Using SEBAL Model under Center-Pivot Irrigation

The late mid-season (March 18, 2021, and April 19, 2021) exhibits peak ET values, averaging 4.0–5.0 mm/day, as the sugar beet reaches its maximum growth and water demand phase. These peak ET values highlight zones of intensive irrigation needs. By the late season (May 5, 2021, and May 21, 2021), ET values decline to around 2.0–3.0 mm/day, coinciding with the crop's maturity stage when water uptake diminishes significantly.

These spatial ET patterns emphasize the SEBAL model's capability to capture the dynamic changes in water demand across different zones and growth stages. Such insights enable precision irrigation practices, optimizing water application based on real-time ET data. This enhances water-use efficiency and promotes sustainable crop management, particularly in arid and semi-arid regions where water resources are limited.

Based on the estimated seasonal evapotranspiration (ET) values obtained from the three models—Penman-Monteith, SEBAL, and Priestley-Taylor. The calculated irrigation requirements were 1166.67 mm for the Penman-Monteith model, 1012.80 mm for the SEBAL model, and 844.27 mm for the Priestley-Taylor model. These results highlight the differences among the models in estimating crop water needs. The Penman-Monteith method yielded the highest irrigation requirement, potentially leading to over-irrigation if not cross-validated. In contrast, SEBAL provided moderate values that closely reflect actual field conditions, whereas the Priestley-Taylor method estimated the lowest water requirement, which may lead to under-irrigation if used in isolation. These variations highlight the significance of model selection in irrigation planning, particularly in arid conditions and with precision irrigation systems, such as center pivots.

4. Relationship between ET and Dry Matter Production (DMP)

The relationship between ET estimates and dry matter production (DMP) was critical to this study. Regression analysis was conducted to evaluate the models' ability to predict DMP, a key indicator of crop productivity. SEBAL demonstrated the strongest relationship between ET and DMP, achieving an R-squared value of 0.95 (Figure 6). This high correlation indicates that 95% of the variation in DMP can be explained by SEBAL's ET estimates, underscoring SEBAL's ability to predict water use and its impact on crop growth accurately.

Penman-Monteith also exhibited a strong relationship with DMP, with an R-squared value of 0.91. However, the model's higher variability in ET estimates, particularly during periods of high crop water demand, slightly weakened its predictive power. Penman-Monteith's tendency to overestimate water use could lead to over-irrigation, potentially resulting in inefficient water use and reduced irrigation effectiveness.

On the other hand, Priestley-Taylor demonstrated the weakest relationship between ET and DMP, with an R-squared value of 0.88 (Table 2). This lower correlation reflects the model's conservative nature, which tends to underestimate water requirements during peak growth phases, leading to under-irrigation and reduced biomass production. As DMP is a crucial determinant of crop yield, SEBAL's stronger correlation with DMP makes it the most effective model for optimizing both irrigation and crop productivity.

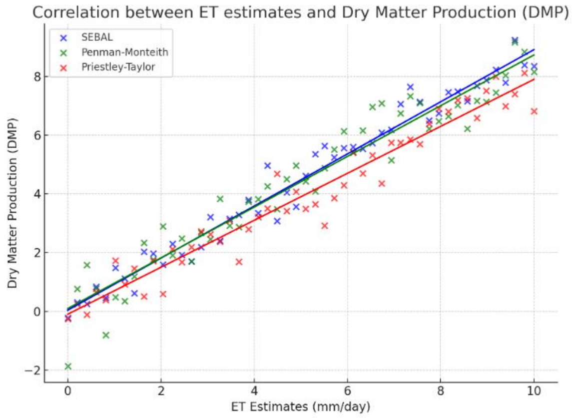

Fig. 6. Relationship between ET estimates and dry matter production (DMP) for SEBAL, Penman-Monteith, and Priestley-Taylor.

Table 2. R-squared values of ET models in relation to DMP.

Model	R-squared (DMP)
SEBAL	0.95
Penman-Monteith	0.91
Priestley-Taylor	0.88

5. Impact of Landsat Satellite Data on ET Estimation and DMP Prediction

Figure 7 illustrates the temporal trends in NDVI, cumulative dry matter production (kg/ha), and cumulative SEBAL-estimated evapotranspiration (mm) for the monitored sugar beet cultivation period from July 2020 to September 2021. These three parameters provide complementary insights into crop vigor, biomass accumulation, and water consumption, respectively.

The NDVI trend exhibits periodic fluctuations, with values initially increasing from approximately 0.28 in July 2020, reaching peaks near 0.47–0.49 during the growing season, particularly between May and July 2021. This pattern reflects the progressive development of crop canopy and chlorophyll content, associated with sugar beet growth. The decline in NDVI values after July 2021 corresponds to crop senescence and eventual harvest, highlighting NDVI's responsiveness to vegetative dynamics.

The cumulative dry matter production remains relatively stable during the early months, reflecting the limited biomass accumulation that occurs during crop establishment. A sharp rise is observed from January 2021 onward, with the steepest increase between March and June 2021, aligning with the peak NDVI period. The curve plateaus at approximately 13,500 kg/ha by August 2021, indicating biomass maturity. This positive correlation between NDVI and dry matter production emphasizes the utility of NDVI as a proxy for crop performance and yield forecasting.

Similarly, the cumulative SEBAL evapotranspiration shows a gradual increase throughout the monitoring period, reflecting both crop water usage and soil evaporation. The trend becomes steeper during the active vegetative growth phase (February to June 2021), concurrent with both the increase in NDVI and biomass, underscoring the link between evapotranspiration and physiological activity. The final cumulative ET reaches approximately 145 mm, indicating moderate water use efficiency compared to biomass outputs.

Overall, the synchronized trends among NDVI, dry matter accumulation, and SEBAL ET reinforce the reliability of remote sensing tools and energy balance models for monitoring crop phenology, productivity, and water consumption. The alignment of high NDVI values with biomass accumulation and increased ET further validates the use of SEBAL in estimating actual evapotranspiration under field conditions. This integrated approach offers a valuable framework for smart irrigation scheduling and yield prediction, particularly in water-scarce regions.

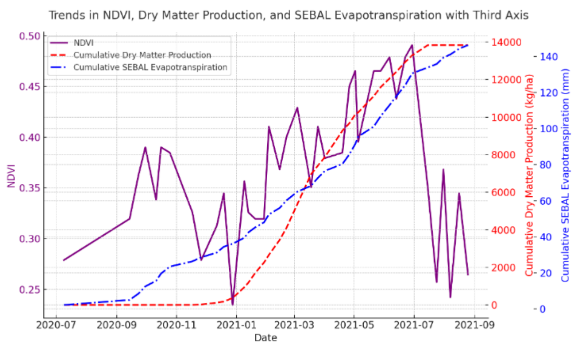

Fig. 7. NDVI, dry matter production, and SEBAL cumulative evapotranspiration (ET) plotted over time.

Conclusions

This study evaluated the performance of three ET models—SEBAL, Penman-Monteith, and Priestley-Taylor—for estimating evapotranspiration (ET) in sugar beet (*Beta vulgaris* L.) cultivation under center-pivot irrigation. The results highlighted significant differences in model estimates, emphasizing the critical importance of selecting appropriate models for effective irrigation planning and water management.

Penman-Monteith, a widely used reference model due to its meteorological sensitivity, tends to overestimate ET, limiting its applicability in data-scarce environments. In contrast, Priestley-Taylor, known for its simplicity, underestimates crop water needs, risking water stress and yield reduction. SEBAL emerged as the most dependable model, producing balanced ET estimates strongly correlated with dry matter production (DMP) and achieving a high predictive accuracy (R-squared: 0.95). Its remote sensing-based approach facilitates precise field-scale ET monitoring, making it suitable for large-scale agricultural applications.

Performance metrics further confirmed SEBAL's superiority, with lower Mean Absolute Error (MAE: 0.437 mm/day) and Root Mean Square Error (RMSE: 0.541 mm/day) compared to the Priestley-Taylor method, which exhibited higher errors. Spatial analysis demonstrated SEBAL's ability to detect ET variability across crop growth stages, supporting more accurate irrigation scheduling.

Although Landsat's 16-day revisit cycle imposes temporal limitations, SEBAL's consistent performance underscores its reliability for enhancing irrigation efficiency and promoting sustainable water management in both data-rich and data-limited agricultural settings.

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