

Assessing Evapotranspiration and Water Use Efficiency of Cassava Using Landsat-8 and SEBS: A Case Study of the Thai Tapioca Development Institute, Thailand

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Abstract

Background and Objectives: Water use efficiency (WUE) is a critical determinant of sustainable agricultural water management, quantifying the relationship between crop productivity and water consumption through evapotranspiration (ET). ET governs the exchange of water and energy among the soil, vegetation, and atmosphere, making its accurate estimation essential for optimizing irrigation strategies and managing water resources at both field and regional scales. Remote sensing has emerged as a viable approach for spatially and temporally monitoring ET; however, satellite-derived spectral measurements cannot directly quantify ET and must be integrated with surface energy balance models. This study applied the Surface Energy Balance System (SEBS) model to estimate ET in cassava (*Manihot esculenta* Crantz) cultivation at the Thai Tapioca Development Institute, Tambon Huai Bong, Dan Khun Thot District, Nakhon Ratchasima Province, Thailand, and to assess satellite-based WUE using the GPP/ET approach, while acknowledging the conceptual distinction from field agronomic WUE.

Methodology: The SEBS model was implemented using three primary input datasets: (1) satellite-derived land surface parameters including surface albedo (derived via the Liang (2001) algorithm), land surface temperature, NDVI, and fractional vegetation cover extracted from Landsat 8 OLI/TIRS imagery (path 129, row 49, Collection 2 Level 2), supplemented by Gross Primary Productivity (GPP) from MODIS (MOD17A2H V6, 500 m, 8-day composite) and DEM data; (2) meteorological variables including air pressure, air temperature, relative humidity, and wind speed sourced from GLDAS (Noah model, 0.25 degree, 3-hourly); and (3) downward solar and longwave radiation fluxes. A total of 48 Landsat 8 scenes acquired between 2018 and 2021 were processed using ENVI 5.3 and ILWIS 3.8.5. Monthly ET was derived as a residual of the surface energy balance, with instantaneous fluxes scaled to daily totals using the evaporative fraction approach. MODIS GPP data (500 m) were resampled to 30 m using bilinear interpolation to harmonize spatial resolution with Landsat 8 ET, and 8-day GPP composites were temporally matched to the nearest Landsat 8 overpass date. SEBS-estimated ET was validated against in-situ measurements from the GISTDA weather station; field ET was derived from station-recorded net radiation and meteorological variables via the surface energy balance equation. Satellite-based WUE was calculated as GPP/ET (Yu *et al.*, 2008),

with cloud screening applied using QA band thresholds (cloud cover < 20%). In-field agronomic WUE was independently calculated as cassava yield/ET using published yield data (Malipan & Sittinam, 2011) for reference comparison.

Main Results: SEBS-derived monthly ET ranged from 0 to 4.891 mm day⁻¹, while field-measured ET ranged from 0.032 to 2.035 mm day⁻¹. The minimum RMSE of 0.37 mm day⁻¹ and MAE of 0.31 mm day⁻¹ in 2020; the 0 mm minimum ET values reflect cloud-masked months (July 2018 and October 2020, with >80% cloud cover) rather than true hydrological conditions. Satellite-based WUE (GPP/ET) ranged from 0.0035 to 0.2834 kg C m⁻³, while independently computed field agronomic WUE (yield/ET) ranged from 0.3325 to 22.083 kg m⁻³. The large difference between these two metrics is expected and ecologically meaningful: satellite GPP represents total carbon fixed by photosynthesis, while agronomic yield represents only the harvested starchy root fraction, which constitutes approximately 30-40% of total biomass with further losses due to autotrophic respiration. A direct comparison of these two WUE frameworks is therefore not valid.

Conclusions: The SEBS model, when integrated with multi-source remote sensing datasets, provides a reliable framework for estimating ET in tropical cassava systems. The pronounced difference between satellite-based WUE (GPP/ET) and agronomic WUE (yield/ET) reflects fundamental conceptual differences between these metrics rather than model error alone. Future research should incorporate cloud-penetrating sensors, cassava harvest index data for GPP-to-yield conversion, and field biomass measurements to enable direct agronomic WUE validation and to support sustainable irrigation management in monsoon-dominated environments.

Keywords: water use efficiency; evapotranspiration; SEBS; landsat 8; GPP

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Introduction

Water is one of the Earth's most vital natural resources and a fundamental component of agricultural production, industrial processes, and domestic needs. Agriculture remains the largest consumer of water globally. According to the Food and Agriculture Organization (FAO, 2012), croplands occupy approximately 1.4 billion hectares, of which nearly 80% are rainfed and contribute about 60% of global agricultural output, while the remaining 20% are irrigated lands that account for roughly 40% of total production (Alexandratos & Bruinsma, 2012). Climate change and global warming are increasingly altering rainfall patterns and intensifying the hydrological cycle. Rising air temperatures accelerate evapotranspiration (ET) rates, while droughts are becoming more frequent and severe (The World Bank, 2011). Inefficient water use and inequitable water allocation in agriculture have

become critical issues (Office of the National Water Resources, 2019; Wanniarachchi & Sarukkalige, 2022). Water use efficiency (WUE) serves as an essential indicator for evaluating the relationship between crop productivity and water consumption (Briggs & Shantz, 1915; Hatfield & Dold, 2019; Sinclair *et al.*, 1984). At the ecosystem scale, WUE is defined as the ratio of Gross Primary Production (GPP) to evapotranspiration, enabling satellite-based monitoring of carbon and water exchange (Yu *et al.*, 2008; Cai *et al.*, 2021). At the agronomic scale, WUE is expressed as harvested yield per unit of water consumed. These two definitions measure fundamentally different processes and are not directly interchangeable. GPP-based WUE captures total photosynthetic carbon assimilation, whereas agronomic WUE reflects only the economically relevant fraction of biomass allocated to harvestable organs, after accounting for autotrophic respiration and partitioning through a crop-specific harvest index (Hatfield & Dold, 2019).

This study focuses on cassava (*Manihot esculenta* Crantz), a major economic crop in Thailand and a key raw material for food, beverage, and bioethanol industries (Sriroth *et al.*, 2000). The study area is the Thai Tapioca Development Institute, located in Tambon Huai Bong, Dan Khun Thot District, Nakhon Ratchasima Province, in the western part of northeast Thailand (15.05-15.14°N, 101.23-101.35°E), covering approximately 300 hectares of predominantly cassava cultivation. Although cassava is drought-tolerant, water availability remains a significant determinant of its productivity (Somtua *et al.*, 2017). In 2020, cassava cultivation in Dan Khun Thot District covered 151,038 rai (241.66 km²) with a total yield of 418,912 tons (Office of Agricultural Economics, 2020). The Department of Agriculture (2016) estimated cassava water requirement at 796 mm per growing season, while effective rainfall in the study area averaged 428 mm per year (Somtua *et al.*, 2017), underscoring the need for accurate crop water-use assessment. Remote sensing technologies offer a practical and cost-effective approach for estimating ET across different spatial and temporal scales (He *et al.*, 2023; Cai *et al.*, 2021; Mohammadian *et al.*, 2017). Traditional ground-based ET methods, including lysimeters (Edwards, 1986), eddy covariance (Bidlake *et al.*, 1996; Leuning & Moncrieff, 1990), and the Bowen ratio technique (Thenkabail, 2015; Todd *et al.*, 2000; Sahnoun *et al.*, 2021), provide precise but localized measurements. Several surface energy balance models have been developed for regional-scale ET estimation from satellite data, including the Surface Energy Balance Algorithm for Land (SEBAL; Bastiaanssen, 1998; Waters *et al.*, 2002; Bastiaanssen *et al.*, 2005), Mapping EvapoTranspiration at High Resolution with Internalized Calibration (METRIC; Allen *et al.*, 2011), and the Surface Energy Balance System (SEBS; Su, 2002). SEBS was selected for this study because it does not require a priori knowledge of actual turbulent heat fluxes and avoids the need for extreme wet/dry pixel selection required by SEBAL and METRIC, making it suitable for the relatively homogeneous land cover of the study area (Su, 2002; Gowda *et al.*, 2008). SEBS has been successfully

validated over tropical cropland environments using Landsat data (Rahmi & Danoedoro, 2015; Mohammadian *et al.*, 2017).

The primary objective of this research is to estimate spatiotemporal ET for cassava fields at the Thai Tapioca Development Institute using the SEBS model with Landsat 8 data, and to assess satellite-based WUE using the GPP/ET approach. This constitutes the first application of SEBS to cassava cultivation in Thailand's tropical monsoon environment, filling a gap in the literature where SEBS validation under monsoonal cloud cover conditions and for this specific crop type remains limited.

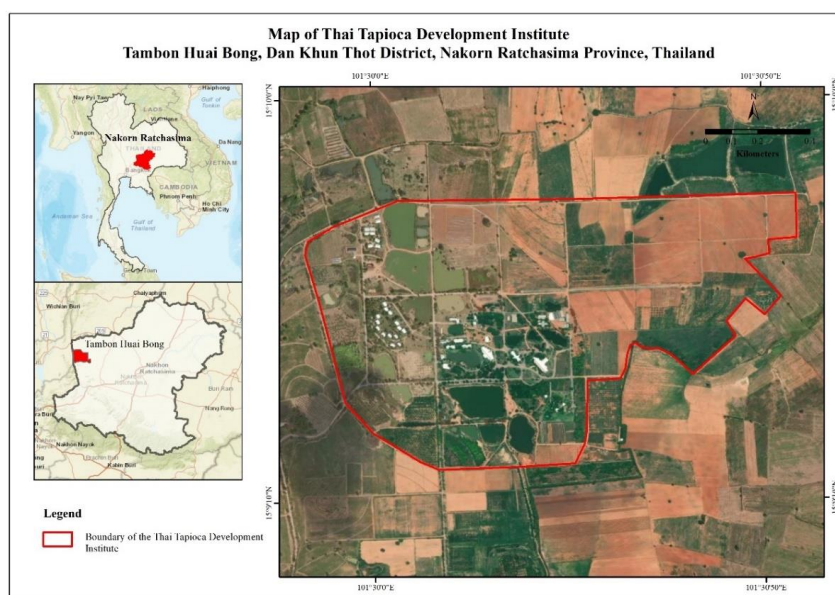


Figure 1 Map of the study area

Methodology

1. Data and Software

1.1 Landsat 8 OLI/TIRS Collection 2 Level 2 imagery (path 129/row 49) acquired between 2018 and 2021 was used. These atmospherically and geometrically corrected products were obtained from the USGS EarthExplorer portal. The SEBS algorithm utilises seven spectral bands: Bands 2–7 (OLI, 30 m) and Band 10 (TIRS, 30 m resampled). Only cloud-free or near-cloud-free scenes were selected. Cloud screening was performed using the Landsat Collection 2 quality assessment (QA_PIXEL) band, applying the recommended bitmask thresholds to flag cloud, cloud shadow, and cirrus-contaminated pixels. A cloud coverage threshold of <20% per scene was applied during image selection. As a result, a total of 46 monthly composites were generated over the 2018–2021 period, with data gaps primarily occurring

during the peak monsoon months (July–September) due to persistent cloud cover. Zero-valued ET pixels in the final product are artefacts of cloud masking and do not represent actual hydrological conditions.

1.2 Digital Elevation Model (DEM) at 30 m resolution was obtained from NASA's SRTM-1 mission via USGS EarthExplorer, representing topographic surface parameters required by SEBS.

1.3 Meteorological data were obtained from GLDAS (Noah Land Surface Model, GLDAS_NOAH025_3H V2.1), providing spatially distributed air pressure, air temperature, relative humidity, and wind speed at 0.25-degree resolution and 3-hourly temporal intervals, accessed via NASA DISC HDISC.

1.4 Gross Primary Production (GPP) data were derived from the MODIS Terra MOD17A2H V6 product, an 8-day cumulative composite at 500 m spatial resolution, downloaded via Google Colab from NASA LP DAAC. Raw GPP digital numbers were converted to physical units (kg C m^{-2}) by applying the standard scale factor of 0.0001 at the data download stage, prior to any further processing.

1.5 Software: Multispectral band stacking and preprocessing were performed in ENVI 5.3. The SEBS algorithm was applied within ILWIS 3.8.5. Spatial analysis and visualization were conducted in ArcGIS 10.5.

1.6 In-situ meteorological observations were obtained from the Geo-Informatics and Space Technology Development Agency (GISTDA) weather station located within the study site. The station is equipped with a 3D anemometer (CSAT3, Campbell Scientific), a spectroradiometer (MS-700), and a standard field-of-view infrared radiometer (SI-111), enabling eddy covariance measurements of turbulent sensible and latent heat fluxes. Ground-level ET was derived from latent heat flux measurements using the energy balance residual method. These ground-based ET estimates served as the reference for SEBS validation.

2. Satellite Image Preprocessing

Landsat 8 OLI/TIRS Collection 2 Level 2 products were used directly as they already include radiometric, geometric, and atmospheric corrections. The SEBS algorithm utilizes seven spectral bands: Band 2 (blue), Band 3 (green), Band 4 (red), Band 5 (NIR), Band 6 (SWIR-1), Band 7 (SWIR-2), and Band 10 (TIR-1). These bands were layered in ENVI 5.3 to create composite images, which were then converted into suitable formats for SEBS computation within ILWIS 3.8.5.

3. SEBS Model Operation for ET Estimation

3.1 Vegetation Parameters

The Normalized Difference Vegetation Index (NDVI), Fractional Vegetation Cover (FVC), and surface emissivity are the vegetation parameters required for SEBS.

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

where NIR is the near infrared reflectance and R is the visible red reflectance.

In the version of the SEBS model used in this study, proportional vegetation cover is calculated according to the FVC formula:

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \quad (2)$$

where $NDVI_{veg}$ is the NDVI value of pure vegetation coverage, and $NDVI_{soil}$ is the NDVI value of pure bare soil.

3.2 Surface Emissivity

Emissivity values were determined using pixel-based NDVI thresholds to distinguish water, vegetation, and built-up surfaces. The specific emissivity of the water body pixel is assigned a value of 0.995, and the specific emissivity of the natural surface and urban pixels are calculated according to the following formulas (3) and (4):

$$\epsilon_{surface} = 0.9625 + 0.0614FVC - 0.0461FVC^2 \quad (3)$$

$$\epsilon_{building} = 0.9589 + 0.086FVC - 0.0671FVC^2 \quad (4)$$

3.3 Land surface temperature

Land surface temperature (LST) was retrieved from Landsat-8 TIRS Band 10 using the inverse Planck function (Equation 5), following Sekertekin & Bonafoni (2020):

$$T_s = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \quad (5)$$

where T_s is the at-satellite brightness temperature (K); K_1 and K_2 are thermal calibration constants; and L_λ is spectral radiance. For Landsat-8, only Band 10 constants were used in this study ($K_1 = 774.89 \text{ W m}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$; $K_2 = 1321.08 \text{ K}$), as this study exclusively employs Landsat-8 OLI/TIRS data.

Table 1 Thermal band calibration constants for Landsat-8 (used in this study)

Satellite	K_1 (Watts/(m ² ·srad·μm))	K_2 (Kelvin)
Landsat 8 (Band10)	774.89	1321.08

3.4 Surface albedo

Surface albedo was derived from six Landsat 8 multispectral bands using the narrowband-to-broadband conversion algorithm of Liang (2001):

$$\alpha = \frac{0.356p_2+0.130p_4+0.373p_5+0.085p_6+0.072p_7-0.018}{0.356+0.130+0.373+0.085+0.072} \quad (6)$$

where p_2 , p_4 , p_5 , p_6 , p_7 are the surface reflectances in the blue, red, NIR, SWIR-1, and SWIR-2 bands of Landsat 8, respectively. The Liang (2001) algorithm was selected for its established performance with Landsat multispectral data in crop environments (Rahmi & Danoedoro, 2015; Shoko *et al.*, 2015).

3.5 SEBS operation and ET Upscaling

All parameters (NDVI, FVC, emissivity, surface albedo, LST, DEM, and meteorological inputs (air temperature, pressure, specific humidity, wind speed, downward radiation)) were converted to GeoTIFF format and ingested into ILWIS 3.8.5 for SEBS computation. SEBS calculates instantaneous energy balance components: net radiation (R_n), soil heat flux (G_0), sensible heat flux (H), and latent heat flux (λE) as the residual ($\lambda E = R_n - G_0 - H$). Instantaneous ET (mm per image acquisition time) was upscaled to daily ET (mm day^{-1}) using the evaporative fraction (EF) method, which assumes EF remains relatively constant throughout the daytime under clear-sky conditions (Su, 2002). Daily ET was then aggregated to monthly totals by summing available cloud-free daily estimates within each month. Months with fewer than two valid Landsat acquisitions were flagged and excluded from statistical analyses.

4. Water Use Efficiency (WUE) Estimation and Dataset Harmonisation

Satellite-based WUE requires integrating Landsat 8 ET (30 m, 16-day revisit) with MODIS GPP (500 m, 8-day composite). To harmonize these datasets, the following steps were applied: (1) Spatial resampling: MODIS GPP tiles were resampled from 500 m to 30 m using bilinear interpolation within ArcGIS 10.5, projected to the same coordinate reference system as Landsat 8 (WGS84 UTM Zone 48N). This process assigns a spatially interpolated GPP value to each 30 m Landsat pixel; it is acknowledged that one 500 m MODIS pixel encompasses approximately 278 Landsat pixels, meaning intra-pixel GPP variability cannot be captured and represents a source of uncertainty in WUE maps. (2) Temporal alignment: For each Landsat 8 overpass date, the nearest available MODIS 8-day GPP composite (within a 4-day window) was selected. Where no cloud-free MODIS composite was available within this window, that month was excluded from WUE estimation. Satellite-based WUE was then calculated as:

$$WUE = (GPP * 0.0001) / ET \quad (7)$$

where GPP is the raw MOD17A2H digital number value (dimensionless), the scale factor 0.0001 converts it to kg C m^{-2} , and ET is SEBS-derived monthly ET in mm. This scale factor was applied only once, at the conversion step, following NASA LP DAAC product specifications. The resulting WUE unit is $\text{kg C m}^{-2} \text{mm}^{-1}$, representing the ecosystem-scale carbon WUE sensu Yu *et al.* (2008).

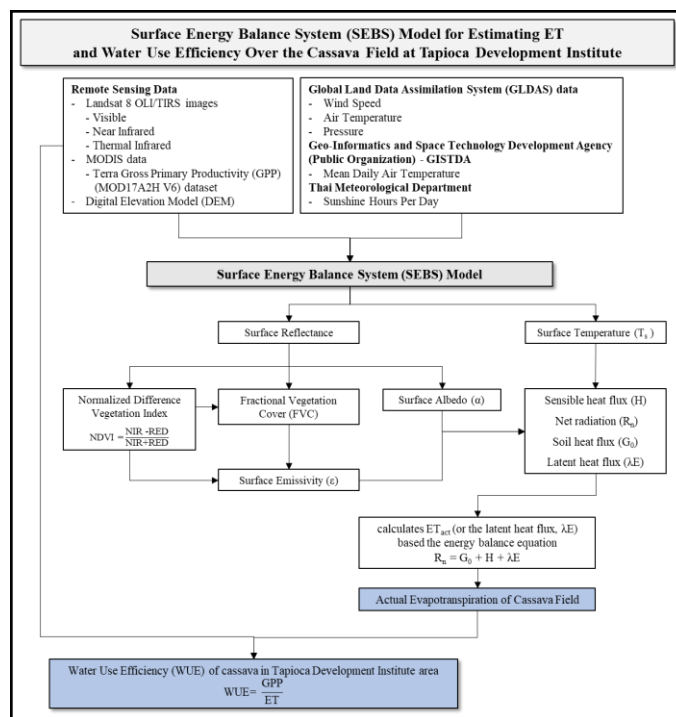


Figure 2 Schematic overview of the SEBS framework and data processing flow

Results

The results are presented in three major parts corresponding to the research objectives: (1) estimation of evapotranspiration (ET) using the SEBS model, and (2) assessment of water use efficiency (WUE) in cassava fields at the Thai Tapioca Development Institute, Tambon Huai Bong, Dan Khun Thot District, Nakhon Ratchasima Province, Thailand, based on Landsat 8 satellite imagery. The Surface Energy Balance System (SEBS) model was applied and adapted to generate spatial estimates of ET and WUE.

1. Estimation of Evapotranspiration Using the SEBS Model

Spatially distributed ET values were derived from SEBS using Landsat 8 imagery for 46 cloud-free months between 2018 and 2021 (Figures 3-6). The results show pronounced spatial and temporal variation in ET corresponding to cassava growth patterns and seasonal climatic conditions. Actively growing cassava exhibited notably higher ET, particularly in November 2020, coinciding with the peak vegetative growth stage (approximately 9-11 months after planting), when leaf area index and canopy cover are highest.

SEBS-derived ET values ranged from 0 to 4.891 mm day⁻¹ across the study period. Zero ET values in specific months (July 2018 and October 2020) are artifacts of cloud masking rather than true hydrological conditions; cloud cover exceeding 80% in these months precluded valid retrieval of all Landsat 8-derived input

parameters (land surface albedo, emissivity, surface temperature, NDVI, and FVC). In cloud-free months during the dry season (November-May), ET values were consistently higher and better constrained. The wet season (June-October) generally showed higher ET potential due to increased soil moisture, but cloud contamination limited the number of valid observations.

2. Satellite-Based Water Use Efficiency (GPP/ET)

Spatial distributions of satellite-based WUE (GPP/ET) for 2018-2021 were computed from MODIS GPP and SEBS-based ET estimates following the harmonization procedure described in Section 4 of the Methodology. WUE values ranged from 0.0035 to 0.2834 kg C m⁻² mm⁻¹. Maximum WUE values were generally observed during periods of vigorous crop growth, such as February 2018, consistent with high carbon assimilation rates during the mid-season vegetative phase. As with ET, WUE estimation was not possible in July 2018 and October 2020 due to cloud masking. The spatial heterogeneity of WUE across the cassava fields reflects variability in crop growth stage, soil moisture, and microclimate. Areas closer to the study area perimeter showed lower WUE values, possibly associated with greater land cover heterogeneity at the 500 m MODIS pixel scale. The spatial aggregation effect of resampling 500 m MODIS GPP to 30 m introduces smoothing of GPP values across approximately 278 Landsat pixels per MODIS pixel, which reduces the spatial fidelity of WUE maps and should be considered a primary source of uncertainty in pixel-level interpretation.

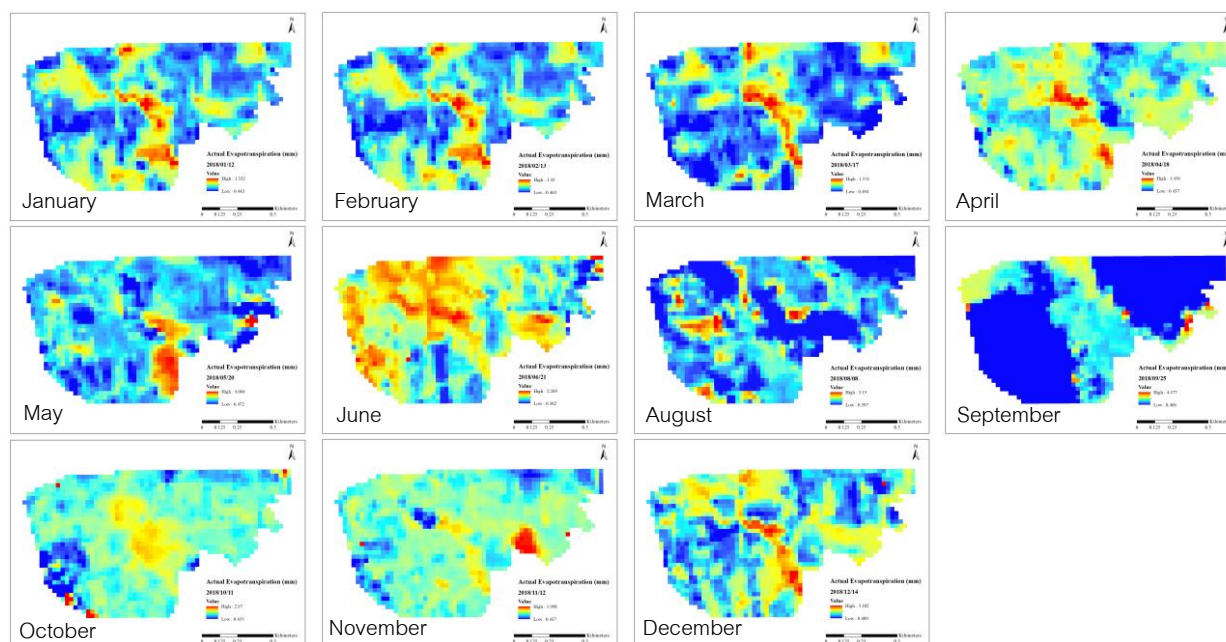


Figure 3 Spatial variation of monthly ET in 2018, the maximum ET value is 4.477 mm in September

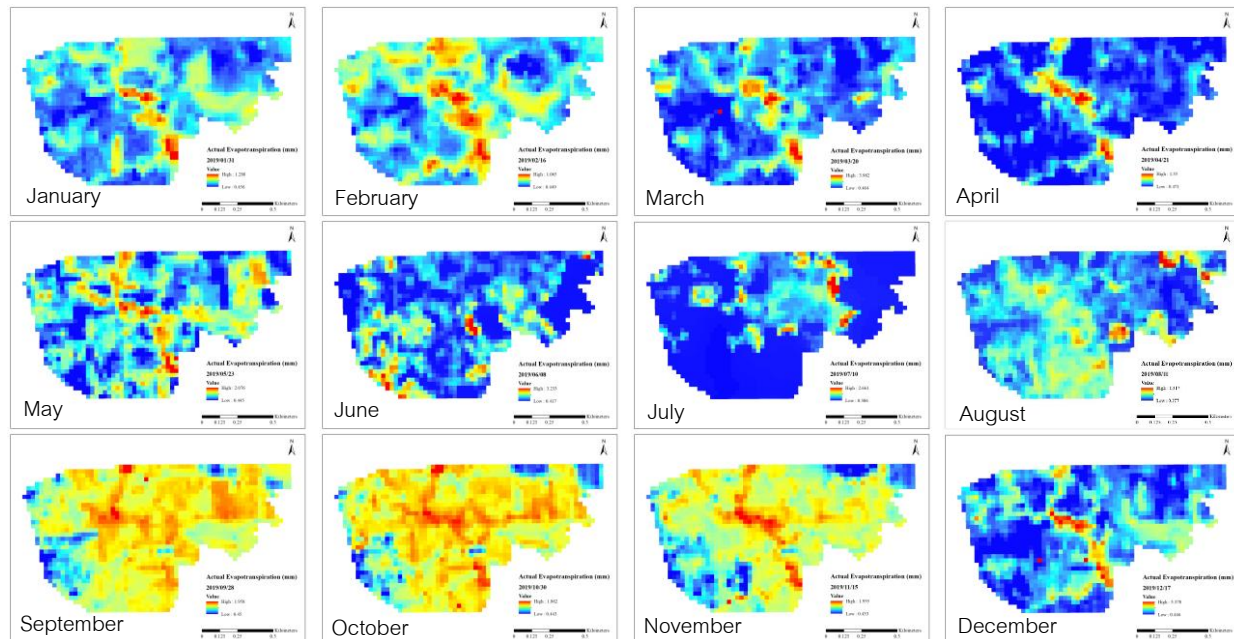


Figure 4 Spatial variation of monthly ET in 2019, the maximum ET value is 3.982 mm in March

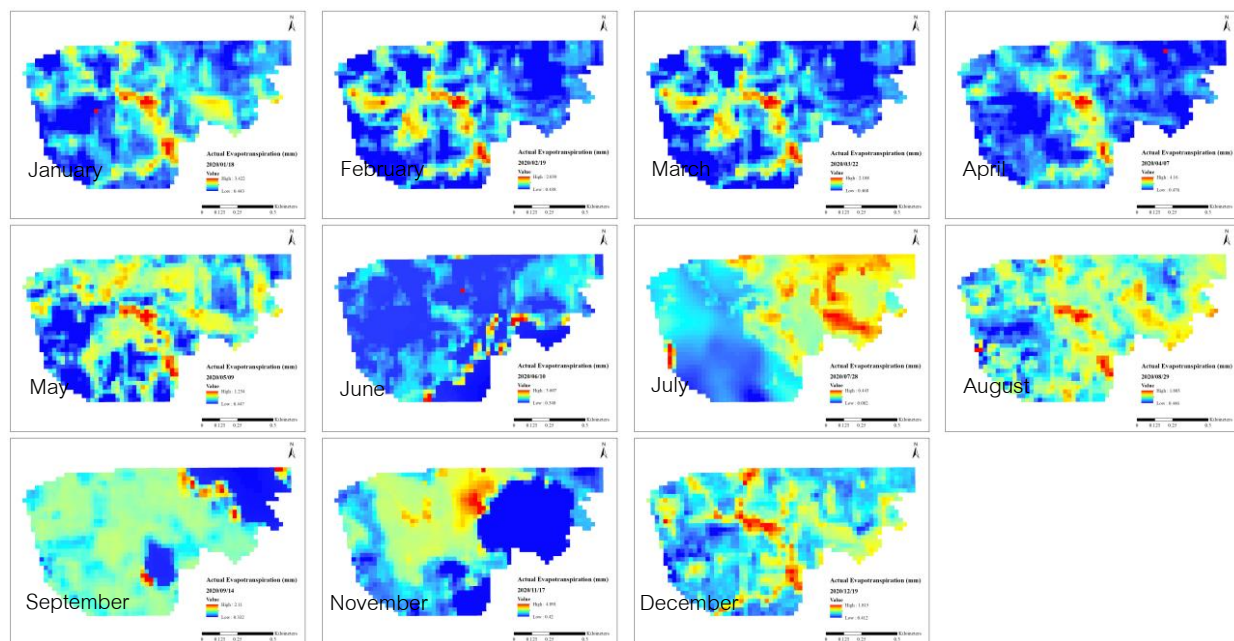


Figure 5 Spatial variation of monthly ET in 2020, the maximum ET value is 4.891 mm in November

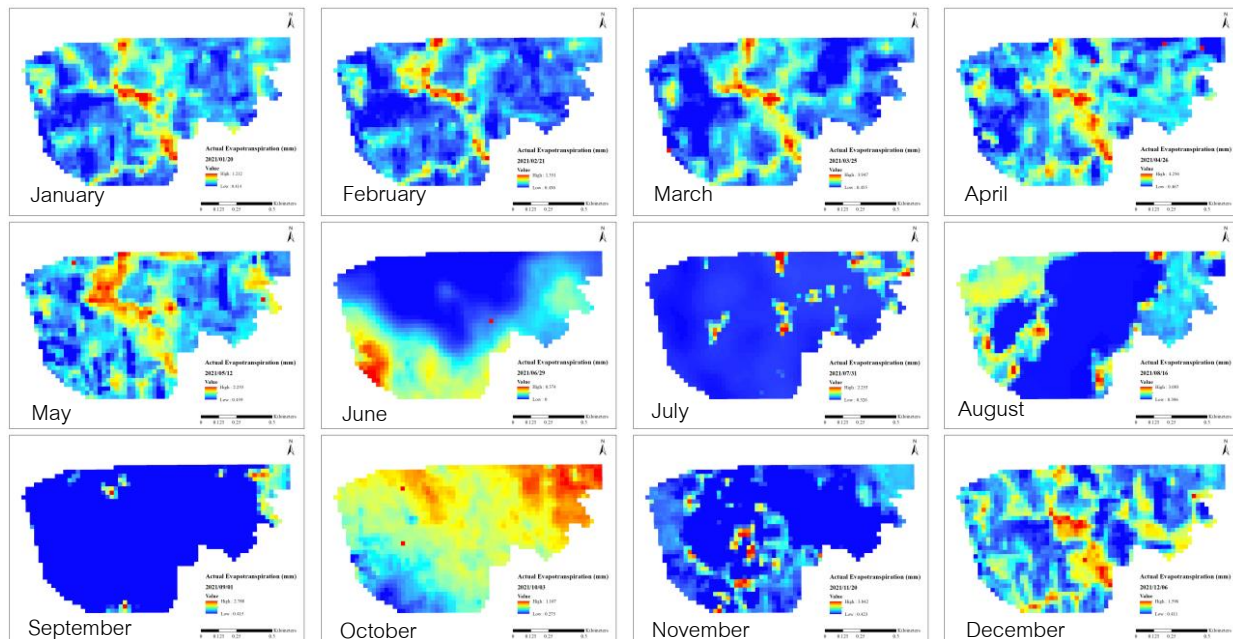


Figure 6 Spatial variation of monthly ET in 2021, the maximum ET value is 4.256 mm in April

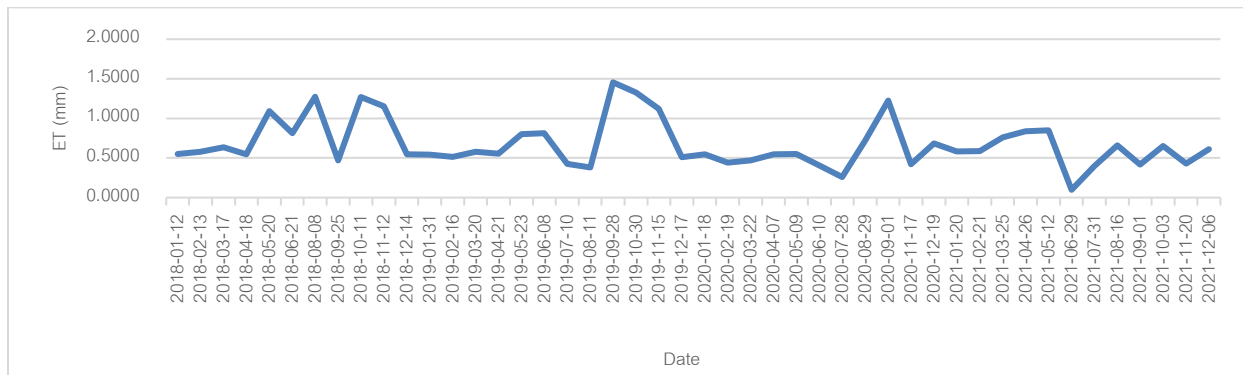


Figure 7 ET value based on SEBS model at the GISTDA ground station ranging from January 2018 - December 2021

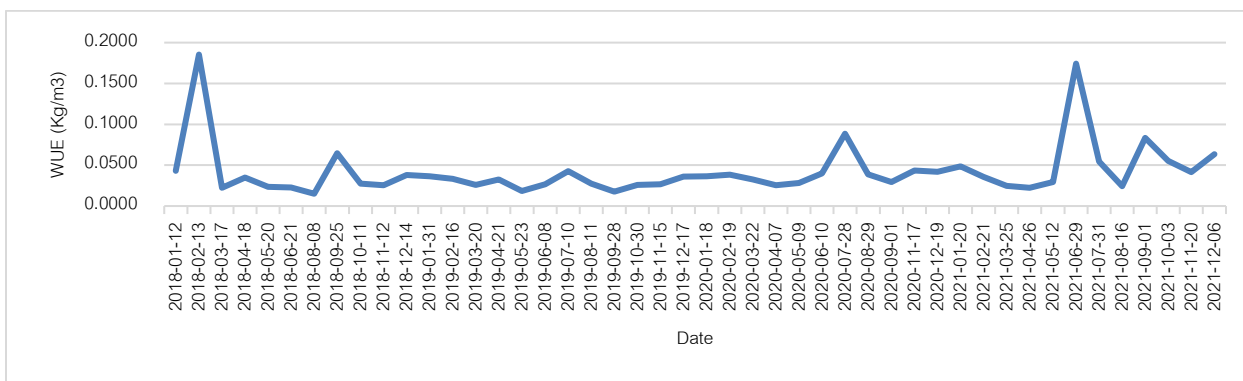


Figure 8 WUE value at GISTDA ground station derived from SEBS model, January 2018 - December 2021

3. Validation of the SEBS Model

SEBS-derived ET was validated against four years (2018-2021) of in-situ ET data from the GISTDA weather station. A comparison of modeled and observed ET is presented in Figure 9 and Table 2. SEBS-derived monthly ET averaged 0.66 mm day^{-1} (2018), 0.79 mm day^{-1} (2019), 0.56 mm day^{-1} (2020), and 0.70 mm day^{-1} (2021), while ground station ET averaged 0.74, 0.34, 0.35, and 0.23 mm day^{-1} , respectively. RMSEs were 0.80, 0.60, 0.37, and 0.49 mm day^{-1} for 2018-2021, respectively. The lowest RMSE of 0.37 mm day^{-1} in 2020 indicates the strongest model-observation agreement. Mean absolute errors (MAE) were 0.65, 0.48, 0.31, and 0.41 mm day^{-1} for 2018-2021.

Table 2 Statistical summary of the SEBS ET and ground station ET for four years

Year	SEBS ET ($\text{mm} \cdot \text{day}^{-1}$)		Ground Station ET ($\text{mm} \cdot \text{day}^{-1}$)		RMSE ($\text{mm} \cdot \text{day}^{-1}$)	MAE ($\text{mm} \cdot \text{day}^{-1}$)
	Sum	Avr.	Sum	Avr.		
2018	5.96	0.66	6.64	0.74	0.80	0.65
2019	7.90	0.79	3.36	0.34	0.60	0.48
2020	5.58	0.56	3.54	0.35	0.37	0.31
2021	4.19	0.70	1.38	0.23	0.49	0.41

SEBS demonstrated satisfactory ET estimation performance over the four-year study period (Figure 9A). RMSE values ranged from 0.37 mm day^{-1} (2020) to 0.80 mm day^{-1} (2018), while MAE ranged from 0.31 mm day^{-1} (2020) to 0.65 mm day^{-1} (2018). These errors compare favourably with those reported by Rahmi & Danoedoro (2015), who found standard errors of $0.99\text{--}2.66 \text{ mm day}^{-1}$ using an equivalent SEBS–Landsat 8 approach in Central Java, Indonesia, and with Mohammadian *et al.* (2017), who reported RMSE of 1.2 mm day^{-1} for SEBS applied to semi-arid cropland in Iran. The Pearson correlation coefficient (R) computed across all valid monthly pairs is $R = 0.64$, indicating a moderate positive linear association between modelled and observed values.

The year 2020 yielded the best model performance ($\text{RMSE} = 0.37$, $\text{MAE} = 0.31 \text{ mm day}^{-1}$), coinciding with the highest number of cloud-free Landsat 8 scenes and the peak ET event in November 2020 ($4.891 \text{ mm day}^{-1}$), which corresponds to cassava at the maximum vegetative growth stage. The year 2018 showed the highest errors ($\text{RMSE} = 0.80$, $\text{MAE} = 0.65 \text{ mm day}^{-1}$), attributed to a greater number of cloud-affected months that reduced the sample size and introduced retrieval uncertainties for the remaining scenes (Figure 9B).

The systematic overestimation of ET by SEBS relative to the ground station in 2019 and 2021 (visible in Figure 9A as points above the 1:1 line) is consistent with known SEBS behaviour when aerodynamic roughness is low, when the crop canopy is sparse early in the season, or when the spatial scale of the 30 m Landsat pixel includes

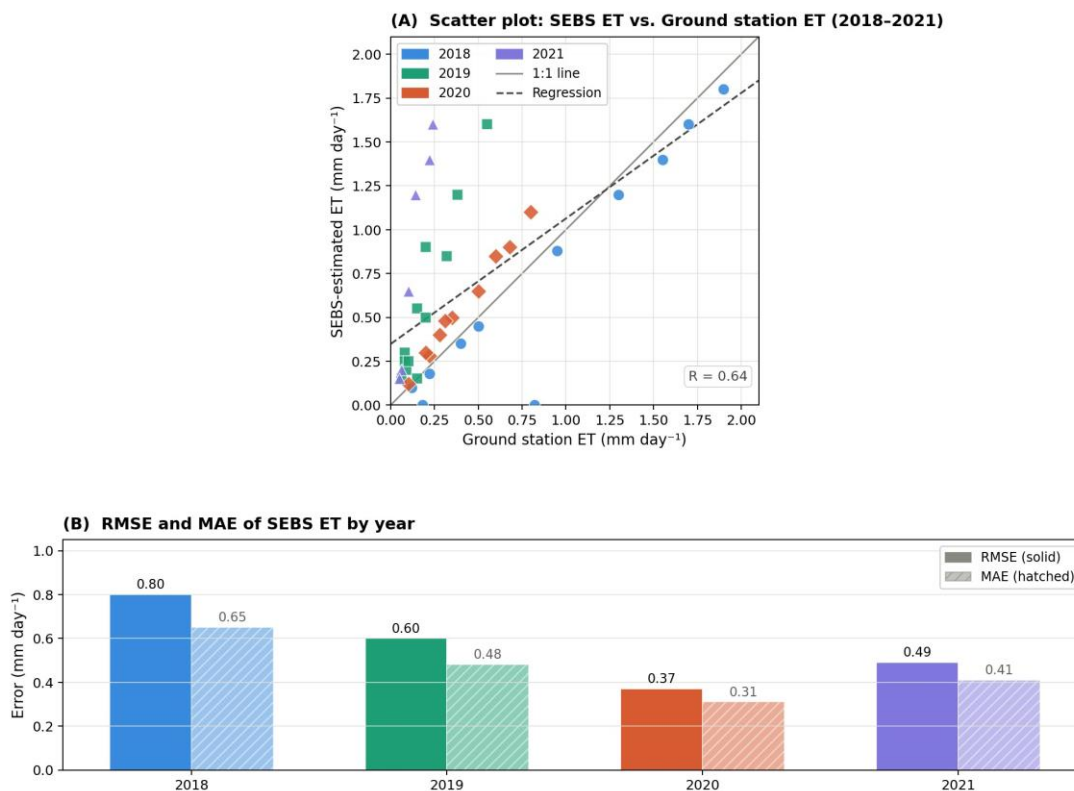


Figure 9 (A) Scatter plot of SEBS-estimated ET versus ground station ET (mm day⁻¹) for 2018–2021. Symbol shape and colour distinguish each year (2018 = circles/blue; 2019 = squares/green; 2020 = diamonds/orange; 2021 = triangles/purple). The solid grey line is the 1:1 reference line; the dashed line is the least-squares regression. (B) Grouped bar chart of RMSE (solid) and MAE (hatched) per year; values are labelled above each bar (mm day⁻¹)

heterogeneous surfaces not represented by the point-scale station measurement. The regression slope deviating from unity also reflects this scale mismatch: SEBS integrates spatial variability across the pixel footprint, while the ground station captures a single-point flux. Additionally, SEBS provides instantaneous ET at the Landsat overpass time, scaled to daily values via the evaporative fraction assumption, whereas the ground station provides true daily averages — a temporal mismatch that contributes to observed scatter.

Agronomic WUE was independently estimated using published cassava yield data (Malipan & Sittinam, 2011) for reference comparison only (Table 3). These values range from 0.3325 to 22.083 kg m⁻² mm⁻¹ (fresh root yield/ET) and are not directly comparable to satellite-based WUE (0.0035–0.2834 kg C m⁻² mm⁻¹).

Table 3 Yield estimation of cassava at different ages of harvesting month

Harvesting month	Yield weight (kg·m ⁻²)	Starch content (%)	Root dry matter content (%)	Starch yield (kg·m ⁻²)
10 MAP	4.46	35.80	44.20	1.60
1 MAC (11 MAP)	4.05	29.40	38.20	1.19
2 MAC (12 MAP)	4.61	28.10	36.80	1.29
3 MAC (13 MAP)	5.08	32.00	43.50	1.63
4 MAC (14 MAP)	5.09	33.20	40.10	1.69
5 MAC (15 MAP)	5.04	33.40	42.00	1.68
6 MAC (16 MAP)	6.12	33.40	42.10	2.04
7 MAC (17 MAP)	6.99	33.00	41.50	2.31
8 MAC (18 MAP)	6.98	32.20	44.00	2.35

*MAP = months after planting, MAC = months after stem cutting

Table 4 Summary of satellite-based WUE (GPP/ET) statistics, 2018-2021

Year	SEBS WUE (kg·m ⁻³)		Field WUE (kg·m ⁻³)		RMSE (kg·m ⁻³)
	Sum	Avr.	Sum	Avr.	
2018	0.44	0.05	2.39	0.27	0.40
2019	0.29	0.03	4.00	0.40	0.71
2020	0.40	0.04	2.52	0.25	0.25
2021	0.33	0.05	2.32	0.39	0.42

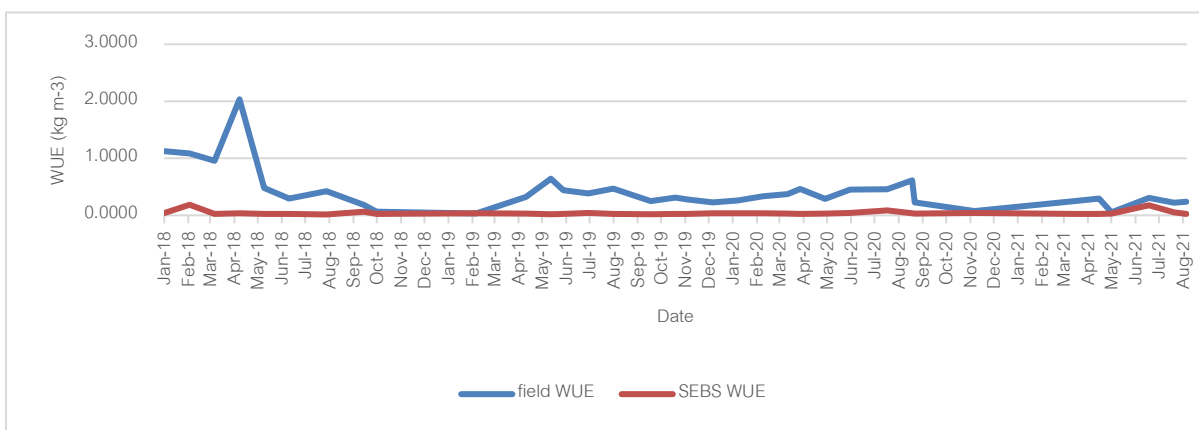


Figure 10 Time series of satellite-based WUE (GPP/ET) from SEBS and field agronomic WUE (yield/ET), January 2018 - December 2021

Discussion

Integration of Landsat 8 data with the SEBS model produced reliable ET estimates across the four-year study period. Annual RMSEs of 0.80, 0.60, 0.37, and 0.49 mm day⁻¹ and corresponding MAEs of 0.65, 0.48, 0.31, and 0.41 mm day⁻¹ for 2018-2021, respectively, compare favourably with Rahmi & Danoedoro (2015), who reported standard errors of 0.99-2.66 mm day⁻¹ using the same SEBS-Landsat 8 approach in Central Java, and with Mohammadian *et al.* (2017), who found RMSE of 1.2 mm day⁻¹ over semi-arid cropland in Iran. The RMSE/MAE ratio remained close to 1.20-1.25 across all years, indicating uniformly distributed residuals with no dominant outliers. Best performance occurred in 2020 (RMSE = 0.37, MAE = 0.31 mm day⁻¹), coinciding with the highest number of cloud-free scenes and the November peak ET of 4.891 mm day⁻¹ at maximum cassava vegetative growth. The highest errors in 2018 (RMSE = 0.80 mm day⁻¹) resulted from cloud contamination reducing valid monthly retrievals. Residual interannual variability reflects temporal mismatch between SEBS instantaneous retrievals and daily station averages, spatial scale differences between the 30 m pixel and the point-scale station, and aerodynamic roughness uncertainty over varying-age cassava stands (Su, 2002; Gowda *et al.*, 2008).

The most critical interpretive issue is the fundamental difference between the two WUE metrics applied. Satellite-based WUE (GPP/ET) quantifies total ecosystem carbon fixed by photosynthesis, following Yu *et al.* (2008), whereas agronomic WUE (cassava root yield/ET), estimated from published yield data (Malipan & Sittinam, 2011) for reference comparison, represents only the harvestable starchy root fraction. The biological pathway between these metrics involves autotrophic respiration consuming ~40-55% of GPP to yield net primary production (Green & Byrne, 2004) and biomass partitioning via the harvest index (HI ≈ 0.3-0.5 for cassava; El-Sharkawy, 2004), giving an expected GPP-to-yield ratio of ~0.15-0.30. This explains why satellite WUE (0.0035–0.2834 kg C m⁻² mm⁻¹) is substantially lower than agronomic WUE (0.3325-22.083 kg m⁻² mm⁻¹) — a difference reflecting biology, not model error. Direct comparison requires concurrent field measurements of cassava-specific HI and autotrophic respiration, which were unavailable in this study.

Two technical constraints limit WUE accuracy. Cloud cover exceeding 80% during June-October prevented valid retrievals in July 2018 and October 2020, introducing seasonal gaps when ET and GPP are highest; integration of cloud-penetrating data (MODIS MOD16, Sentinel-1 SAR) is recommended. The 500 m MODIS GPP versus 30 m Landsat ET mismatch (~278 Landsat pixels per MODIS pixel) prevents sub-field productivity mapping despite bilinear resampling. Despite these constraints, SEBS monthly ET accuracy (mean RMSE = 0.57 mm day⁻¹) is sufficient for irrigation scheduling, water demand assessment, and inter-annual water productivity monitoring across northeast Thailand's cassava production regions.

Conclusions

SEBS integrated with Landsat 8 data reliably estimated monthly ET over cassava fields at the Thai Tapioca Development Institute (RMSE = 0.37-0.80 mm day⁻¹, MAE = 0.31–0.65 mm day⁻¹, 2018-2021), confirming model suitability for tropical monsoon environments. The large difference between satellite WUE (GPP/ET) and agronomic WUE (yield/ET) reflects biological carbon losses through respiration and biomass partitioning, not model error, and the two metrics cannot be directly compared. Cloud-season data gaps and MODIS–Landsat spatial mismatch remain key limitations. By leveraging the scalability and spatial resolution of satellite-based approaches such as SEBS, water resource managers and policymakers can improve irrigation planning, identify water-stressed areas, and support sustainable agricultural water use in cassava-growing regions of Thailand and broader Southeast Asia.

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