Research Article

Evaluation of the Operational Simplified Surface Energy Balance Model for Pastureland Evapotranspiration Mapping and Drought Monitoring in North Central Kentucky

Maheteme Gebremedhin ¹, **Ian Ries**,¹ **Gabriel B. Senay**,² **Martin Matisoff**,¹ **Ibukun Amusan**,³ **Jeremy Sandifer**,¹ and **Buddhi Gyawali**¹

¹College of Agriculture, Communities, and the Environment, Kentucky State University, 400 East Main Street, Frankfort, KY 40601, USA

²United States Geological Survey, Earth Resources Observation and Science Center, North Central Climate Adaptation Science Center, Boulder, CO 80303, USA

³College of Business and Computational Sciences, Kentucky State University, 400 East Main Street, Frankfort, KY 40601, USA

Correspondence should be addressed to Maheteme Gebremedhin; maheteme.gebremedhin@kysu.edu

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The use of remotely sensed evapotranspiration (ET) for field applications in drought monitoring and assessment is gaining momentum, but meeting this need has been hampered by the absence of extensive ground-based measurement stations for ground validation across agricultural zones and natural landscapes. This is particularly crucial for regions more prone to recurring droughts with limited ground monitoring stations. A three-year (2016–2018) flux ET dataset from a pastureland in north central Kentucky was used to validate the Operational Simplified Surface Energy Balance (SSEBop) model at monthly and annual scales. Flux and SSEBop ET track each other in a consistent manner in response to seasonal changes. The mean bias error (MBE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) were 5.47, 21.49 mm mon^{-1} , 30.94%, and 0.87, respectively. The model consistently underestimated ET values during winter months and overestimated them during summer months. SSEBop's monthly ET anomaly maps show spatial ET distribution and its accurate representation. This is particularly important in areas where detailed surface meteorological and hydrological data are limited. Overall, the model estimated monthly ET magnitude satisfactorily and captured it seasonally. The SSEBop's functionality for remote ET estimation and anomaly detection, if properly coupled with ground measurements, can significantly enhance SSEBop's ability to monitor drought occurrence and prevalence quickly and accurately.

1. Introduction

Evapotranspiration (ET), the turbulent transfer of water from the ground (evaporation; E) and plant surfaces (transpiration; T), is a key component of the hydrologic cycle, which is responsible for returning 60–90% of precipitation (P) to the atmosphere [1–3]. Previous studies (e.g., [4–6]) showed that ET exhibits considerable variation in space and time and, as a result, obtaining reliable and accurate measurements continues to present challenges [7]. ET is the second largest component in the terrestrial water

balance ($ET = P - R - S - I$, where P = precipitation, R = runoff, S = soil storage, and I = infiltration) and is the single most important predictor of seasonal crop water consumptive use drought prevalence. ET estimation and drought monitoring are determined by the availability and proliferation of remotely sensed data. Furthermore, the need for improved methods for monitoring and modeling the water cycle has fueled interest in the rapid, widespread use of remote-based ET data.

Traditional land-based ET measurements have largely relied on *in situ* ground observation methods, such as

lysimetry, energy balance, Bowen ratio (FR), eddy covariance (EC), scintillometry, and soil water balance [8–12]. The surface-based EC method for small areas of coverage has proven invaluable in providing direct measurement of turbulent water vapor fluxes between the ground and the atmosphere. For more than two decades, a network of systems [11] has provided the high-quality data needed to validate remotely sensed ET estimates. The EC method directly measures ET based on statistical covariance between vertical water-vapor flux and scalar concentration fluctuations [13]. Scaling up observational ET information is a major challenge of this method because it involves a complex and multidimensional process that varies with landscape, vegetation type, soil moisture, and crop management. It is also affected by underlying environmental factors [14, 15]. In this regard, space-borne ET estimates [16–18] are ideal to circumvent some of the stringent requirements (e.g., sensor placement and calibration) and limitations (smaller footprint) of land-based ET observations [1, 7].

For the past 18 years, simplified surface energy balance (SSEBop) has generated and issued ET maps for the continental United States on a monthly time interval at a 1 km spatial resolution scale. It also provides an efficient and timely data delivery system that is critical for operational decision-making by water resource planners and managers and hydraulic engineers. The model's use and application have successfully reported ET on different scales, i.e., watershed, basin, United States, and global scale [19, 20]. In addition, the model has been used to generate ET_a and anomaly maps over very large extents (the coterminous United States) using low spatial resolution (1 km) MODIS data.

One key attribute of satellite-based ET estimate models is model validation, which is defined as the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model [21]. SSEBop at basin and global scales is a good example of the successful application of satellite-based ET drought monitoring [22]. SSEBop increases our understanding of the global water cycle by mapping seasonal and year-to-year changes in ET across the landscape and providing complete spatial ET coverage, supplying input data aiding simulating irrigation requirements, and assessing trends of ET. Monthly maps of actual and anomaly ET and products are available publicly via the Famine Early Warning System (<https://app.climateengine.org/climateEngine>).

Few studies have evaluated SSEBop across wide geographical areas (see noted exceptions [19]) and less frequently on ecosystem scales. Therefore, the goal of this study was to evaluate the performance of SSEBop in estimating ET from a pasture agroecosystem under the climate and soil conditions of north central Kentucky. Although the SSEBop model has been in use for 18 years, validation studies on its use over varied ecosystems are limited. The objectives of this study were (i) to evaluate SSEBop against EC data and its comparison to reference evapotranspiration (ET_{ref}) as its upper boundary and (ii) to assess the application of SSEBop

for drought monitoring and identifying drought years/seasons using rainfall as a surrogate variable.

2. Materials and Methods

2.1. Site Microclimate. The study site is located at the Harold R. Benson Research and Demonstration Farm, 12 km southwest of the main campus of Kentucky State University, Frankfort, Kentucky (38.11°N, 84.88°W; 242 m above mean sea level). The study period had marked differences in total precipitation among the years, ranging from the lowest (1012 mm·yr⁻¹) in 2016 to 1855 mm·yr⁻¹ in 2018. 2018 was a 150-year record, which gave 697 mm (60%) more rain than the historical (1980–2010) average. Based on the 30-year average of 1159 mm for the region, the observation years can be classified as dry in 2016 (1012 mm), average in 2017 (1219 mm), and wet in 2018 (1855 mm). Air temperature (T_a) from 2016 through 2018 at the site showed no major departure relative to the thirty-year (1981–2010) average of 12.8°C. Averaged over the three years, monthly T_a varied between -1°C in January and 24.2°C in July, with annual averages of 13.5, 13.8, and 13.3°C in 2016, 2017, and 2018, respectively. The only exception was January 2018, which was the coldest month (-5.0°C; Figure 1). The soil at the site is in the well-drained McAfee silt loam soil series, commonly found in a range of 6 to 12 percent slopes, slightly acidic in pH, and moderately drained with high permeability [23].

2.2. Pasture Management. Kentucky's pasture agroecosystem is extensive and largely rain-fed. Approximately 25% (2.5 million acres) of the total 13.4 million land area is used for pasture agroecosystems. The study area at the Harold R. Benson Research and Demonstration Farm (pasture) was seeded in 2005 and consisted of mixed grasses, predominantly fescue (*Festuca arundinacea*), as well as Johnson grass (*Sorghum halepense*), green foxtail (*Setaria viridis*), hemlock (*Conium maculatum*), common chicory (*Cichorium intybus*), and red clover (*Trifolium pratense*). During the observation years, the same mix of grass species was used and meat goats rotationally and intermittently grazed the pasture for a maximum of two weeks beginning in late June through late summer (August). Grazing was allowed until the stub height reached 0.1 m.

2.3. Latent and Sensible Heat Measurements. Vertical exchange of H₂O vapor, sensible heat, and latent heat were measured using the EC technique. The EC flux tower is located on a pasture with a sufficiently wide and horizontal fetch of at least 200–300 m in the major wind (westerly and southwesterly) direction. The EC tower was instrumented with a fast-response 3D sonic anemometer (WindMaster Pro; Gill Instruments, Lymington, Hampshire, UK) that measures wind speed (m s⁻¹) and sonic air temperature (T_s , °C). The wind sensor is located 2.82 m above the ground level. Water vapor concentration was measured *in situ* using a closed path infrared CO₂/H₂O gas analyzer (LI-7200; LI-COR Inc., Lincoln, NE, USA). The two sensors are installed such that they are within the mixed surface layer, i.e.,

FIGURE 1: Average air temperature ($^{\circ}\text{C}$) (a) and monthly annualized precipitation (mm) (b) at the Harold R. Benson Research and Demonstration Farm for the observation period of 2016–2018. Precipitation records are from the Franklin County Mesonet Weather Data (Lat: $38:12^{\circ}\text{N}$; Lon: -84.88°W , which is located about 670 m from the flux station. Long-term (normal, gray bars) data are from the National Weather Service Capital City Airport, Station no. US W00053841 (Lat: 38.1847°N ; Lon: -84.9033°W) (National Oceanic and Atmospheric Administration, National Environmental Satellite Data and Information Service (NOAA/NCDC)) (<https://gis.ncdc.noaa.gov/maps/ncei/normals/>) [24].

$z_h > 5z_m + d$, where z_h is the measurement height (m), z_m is the surface roughness length (m), and d is the zero plane displacement height (m; the theoretical height above the ground where the logarithmic wind profile vanishes to zero). The measurement height z_h was nearly 9 times the average z_h of the grass canopy height (0.30 m at peak developmental stage).

The turbulent sensible (H) heat flux was computed as follows:

$$H = \rho_a C_p \overline{w' T_s'} \quad (1)$$

where ρ_a is dry air density (kg m^{-3}) and C_p is the specific heat capacity of the air at constant pressure ($1004 \text{ J kg}^{-1} \text{ K}^{-1}$). The overbar indicates the averaging period, in this case 30 min. Similarly, latent heat (LE , W m^{-2}) was calculated as

$$LE = \lambda \overline{w' q'} \quad (2)$$

where λ is the latent heat of vaporization (2.45 MJ kg^{-1}) and q' is the fluctuation about the mean of density of water vapor (kg m^{-3}), ρ_w , in air (1000 kg m^{-3}), and w' and q' are the turbulent vertical wind speed (m/s) and water vapor density (kg m^{-3}), respectively. Overbar indicates the averaging period, which in this case was 30 min. Daily ET (mm/day) was estimated using the following relationship:

$$ET = \frac{LE}{\rho_w \lambda} \quad (3)$$

Daily LE totals were calculated by integrating the 30-minute observations.

The energy balance at a surface can be thought of as accounting of energy gains and losses within a specified time interval (e.g., 30 min, daily, monthly, seasonally, and

annually). We assessed the relative energy balance by plotting the sum of H and LE against the available energy (i.e., $R_n - G$) and the mathematical expression for a complete energy closure assumes

$$y + a(R_n - G) = H + LE + G + \varepsilon, \quad (4)$$

where a and y are the slope and intercept of the linear regression, respectively, and G is ground heat flux. Unit for R_n , G , LE , and H terms is W m^{-2} . The last term, ε , is the error term, which includes both instruments and random errors. G was directly measured using a soil heat plate at a 10-cm depth.

2.4. Penman–Monteith (P - M) Method. Reference evapotranspiration (ET_{ref} , mm/d) measures the rate at which water vapor is released from actively growing vegetation (typically, grass height of vegetation is assumed to be 0.12 m) unlimited by water with a fixed crop surface resistance of 70 s m^{-1} and an albedo of 0.23 [25, 26]. The FAO-56 (Food and Agriculture Organization) Penman–Monteith (P - M) method is currently considered as the standardized method of computing reference ET from an assumed uniform grass reference surface worldwide [26]. The method computes reference evapotranspiration as daily totals (mm day^{-1}) using the following equations:

$$ET_0 = \frac{0.408 \Delta (R_n - G) + \gamma (900 / (T + 273)) u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)},$$

$$\Delta = \frac{0.4098 \times [0.6108 \times \exp((17.27T / (T + 237.3)))]}{(T + 237.3)^2}, \quad (5)$$

where Δ is the slope of the saturation vapor pressure function ($\text{kPa}/^\circ\text{C}$), R_n is the daily average net radiation ($\text{MJ m}^{-2}\text{d}^{-1}$), G is the daily average ground heat flux ($\text{MJ m}^{-2}\text{d}^{-1}$), γ is the psychrometric constant ($\text{kPa}/^\circ\text{C}$), T is the daily average temperature ($^\circ\text{C}$), u_2 is horizontal daily average wind speed (m s^{-1}), e_s is the vapor pressure of the air at saturation (kPa), and e_a is the actual vapor pressure (kPa).

2.5. Operational Simplified Surface Energy (SSEBop) Model. A SSEBop model was used in this study as described by Senay et al. The model uses two data streams acquired from MODIS and Global Data Assimilation Systems (GDAS) which include elevation (z), temperature correction coefficient (c), land surface (T_s) and air (T_a) temperatures, temperature difference (dT), clear sky net radiation (R_n), reference ET (ET_o), aerodynamic resistance (r_{ah}), albedo (α), and Normalized Difference Vegetation Index ($NDVI$) as input variables [22]. The SSEBop directly solves for ET without explicitly resolving the other energy terms. A noteworthy feature of the model is that, for any given pixel being analyzed, the model uses two boundary surface temperature conditions (the hot and cold pixel approach) to scale LST values linearly between 0 and max ET fraction. Such codification would then permit the use of the linearization assumption by taking into account the fact that latent heat (LE) varies according to a linear function of the “hot” and “cold” pixels. Hence, the variable dT is assumed to remain constant from year to year and is typically calculated under clear sky conditions for each pixel and is derived as

$$dT = \frac{R_n * r_{ah}}{p_a * C_p}, \quad (6)$$

where R_n is the daily cloud-free net radiation ($\text{J m}^{-2}\text{s}^{-1} = \text{W}\cdot\text{m}^{-2}$), r_{ah} is aerodynamic resistance to sensible heat transfer from bare and dry surface with constant value of 110 s m^{-1} [22], and p_a and C_p are density of air (kg m^{-3}) and specific heat of air at constant pressure ($1.013\text{ kJ}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$), respectively. In this case, cold temperature pixels ($T_c = C * T_{\max}$) are those from which there is little or no sensible heat flux, while hot temperature pixels ($T_h = T_{\text{cold}} + dT$) are described as those with little or no latent heat flux (T_c). The SSEBop does not solve all energy balance components; rather it sets limited boundary conditions based on clear-sky net radiation balance principles [20, 22] and the only data required are surface temperature (T_s , K), air temperature (T_a , K), and potential ET. With this simplification, the model computes actual evapotranspiration (ET_a) as a fraction of the ET_o ; that is,

$$ET_a = \frac{p_a * C_p}{R_n * r_{ah}} (T_h - T_s) * k * ET_o = ET_f \times k \times ET_o, \quad (7)$$

where k is a scaling coefficient applied for ET_o to achieve a theoretical maximum set for an optimally grown alfalfa. The model uses inputs to produce anomaly maps, calculated as the arithmetic median ET deviation of a target year for measuring drought occurrence, which has a great deal of

interest for geographical areas prone to drying. For a detailed and full description of the model, its application, and performance in estimating ET, please see [22, 27].

2.6. Monthly SSEBop Anomaly. To develop ET-modeled anomaly maps for the site and surrounding regions for each area considered in the study, the following steps were followed: (i) monthly averages were calculated; (ii) individual monthly anomaly of respective years was then calculated as percent difference of each year from the previous 18 years' average value using

$$ET_m = \left(\frac{(ET_a - ET_L)}{ET_L} \right) \times 100, \quad (8)$$

where ET_m is the respective monthly percent anomaly, ET_a is the monthly climatology parameter, and ET_L is the long-term ET average.

2.7. Statistical Measures of Model Fitness. As part of the validation and accuracy test, we used several statistical metrics to evaluate the SSEBop model fitness, or lack thereof, to the observed ET. A simple regression model of the form $y_i = ax_i + b$, where y_i is model ET_o , x_i are measured (ET_m) values, and b is an intercept, was used to assess model fitness. The monthly and yearly estimates of SSEBop ET modeled values were quantitatively evaluated by percent bias (PBIAS), root mean square (RMSE), and coefficient of determination (R^2), which were defined as

$$\begin{aligned} \text{RMSE} &= \sqrt{\frac{1}{N} \sum_{i=1}^N (ET_{m,i} - ET_{e,i})^2}, \\ \text{PBIAS} &= \frac{\sum_{i=1}^N (ET_{m,i} - ET_{e,i})}{\sum_{i=1}^N ET_{m,i}} \times 100, \end{aligned} \quad (9)$$

$$R^2 = \left[\frac{\sum_{i=1}^N (ET_{m,i} - \overline{ET_m}) - (\overline{ET_{e,i}} - \overline{ET_e})}{\sqrt{\sum_{i=1}^N (ET_{m,i} - \overline{ET_m})^2 \sum_{i=1}^N (e - \overline{ET_e})^2}} \right]^2,$$

where N is the number of observations and ET_o and ET_m are observed (measured) and modeled ET, respectively. Smaller RMSE values indicate the closeness of model fit to the observed ET. Positive PBIAS values indicate a bias toward underestimation and negative values indicate a bias toward overestimation. R^2 values range from 0 to 1, with values near 1 indicating better fit (or stronger power of the input variable).

3. Results

3.1. Description of Daily, Monthly, and Annual ET Values. Table 1 shows descriptive statistics of measured (EC), remotely SSEBop estimated, and reference evapotranspiration ($P-M$) over a period of three years. Daily measured ET ranged between 0.026 and $5.39\text{ mm}\cdot\text{day}^{-1}$ and averaged 1.88 , 1.63 , and $1.49\text{ mm}\cdot\text{day}^{-1}$ in 2016, 2017, and 2018, respectively (Table 1 and Figure 2). Measured monthly rates

TABLE 1: Descriptive monthly statistics of evapotranspiration (mean $\pm$ SEM, range, minimum (min), maximum (max), and sum of ET measured (EC, eddy covariance), simplified surface energy balance (SSEBop) model, and reference Penman–Monteith ($P-M$) evapotranspiration) for 2016, 2017, and 2018.

		Mean $\pm$ SEM*	Range	Min	Max	Sum
2016	EC	57.37 $\pm$ 12.21	111.83	5.24	117.07	688.46
	SSEBop	55.30 $\pm$ 15.75	131.00	0.00	131.00	663.50
	$P-M$	102.0 $\pm$ 9.44	104.54	45.87	150.41	1223.95
2017	EC	49.67 $\pm$ 10.94	99.16	2.53	101.69	596.00
	SSEBop	55.54 $\pm$ 15.03	128.40	0.00	128.40	666.45
	$P-M$	109.08 $\pm$ 13.34	176.80	47.01	176.80	1308.97
2018	EC	45.52 $\pm$ 10.90	98.39	3.21	101.60	546.18
	SSEBop	57.42 $\pm$ 15.09	129.0	0.00	129.00	689.00
	$P-M$	89.77 $\pm$ 12.55	134.08	11.21	145.29	1077.28

*SEM = standard error of the mean.

averaged 57.37 ± 12.21 , 49.67 ± 10.94 , and 45.52 ± 10.90 mm-month⁻¹ (mean $\pm$ SEM) varying between 5.2 and 117, 2.5 and 102, and 3.2 and 102 mm-month⁻¹ in 2016, 2017, and 2018, respectively. Annual measured cumulative ET were 688, 596, and 546 mm-yr⁻¹ in 2016, 2017, and 2018, respectively, with corresponding annual precipitations of 1012, 1220, and 1856 mm, respectively. The resulting ET/ P ratios for the three years were 0.68, 0.49, and 0.29 for 2016, 2017, and 2018, respectively, depicting a relatively dry year (2016) and an abnormally wet year (2018). Estimated monthly SSEBop ranged between 0.0 and 131, 0.0 and 128.4, and 0.0 and 129 mm mon⁻¹ in 2016, 2017, and 2018, respectively, with monthly average values of 55.29 ± 15.75 , 55.54 ± 15.03 , and 57.42 ± 15.09 (mean $\pm$ SEM) for 2016, 2017, and 2018, respectively. Estimated annualized totals of SSEBop were 664, 666, and 689 mm-year⁻¹ in 2016, 2017, and 2018, respectively. Reference evapotranspiration based on the physical Penman–Monteith ($P-M$) equation revealed much wider ranges: between 0.16 and 6.7 mm-day⁻¹ (3.2 ± 0.08 mm-day⁻¹; mean $\pm$ SEM), 0.3 and 8.4 mm-day⁻¹ (3.6 ± 0.09 mm-day⁻¹), and 0.2 and 6.4 mm-day⁻¹ (2.9 ± 0.08 mm-day⁻¹) in 2016, 2017, and 2018, respectively (Figure 2, top).

Estimates of monthly satellite-derived ET by SSEBop ranged from 0 to 131 mm-month⁻¹ (Table 1) and averaged 56.1 ± 15.3 mm-year⁻¹ across the observation period. The SSEBop model overestimated the actual ET (50.1 ± 15.3 mm) by nearly 5.5 mm (12%). Similarly, SSEBop's yearly ET sums were 663, 666, and 689 mm-year⁻¹ for 2016, 2017, and 2018, respectively (average: 673 mm-year⁻¹). Summed across the three years, the SSEBop model overestimated ET by 192 mm over the measured ET (EC method). In each year, the median measured ET (EC) increased between January and June and declined thereafter with slight variation from year to year (Figure 2, bottom). Median (EC) evapotranspiration flux ranged between 0.3 (January) and 4.3 mm-day⁻¹ (June).

3.2. Assessment of SSEBop Performance. To evaluate the accuracy of the modeled ET estimates at monthly scale, performance indices including coefficient of correlation (R^2), root mean square error (RMSE) and mean absolute error (MAE), and percent bias (PBIAS) were used (Table 2). Broadly, SSEBop showed a tendency to overestimate

monthly ET flux, exhibiting BIAS, RMSE, MAPE, MRE, and R^2 of 5.47, 21.5, 30.9, 10.5, and 0.87, respectively.

Although the model (SSEBop) consistently tracked measured ET_m, with higher than measured flux values, moderate mismatches existed on monthly scales (Figure 3). Differences between the modeled and measured values were greatly pronounced (under- or overestimated) at two critical phases of the ET cycle during the peak ET summer months and winter months but there was a satisfactory agreement during fall and spring months. As expected, both measured and modeled values followed the natural seasonal pattern of ET, consistent with the cooling (winter, low ET) and warming (summer, high ET). Obviously, the model exhibited a level of bias, but it did track the expected ET trend as a whole. The RMSE test set was within 150.64, 100, and 100 mm of the measured ET for 2016, 2017, and 2018, respectively. Substantial variations existed among months (within a year) and among years between $P-M$ and flux: BIAS = 49.5, RMES = 56.7, MAPE = 95.5, MRE = 94.9, R^2 , and CV = 0.39. As shown in Figure 3, SSEBop tended to overestimate ET particularly during the summer months.

As expected, the performance of the $P-M$ physical model at this pasture site was not as good as the performance of the SSEBop model at estimating monthly ET (Table 2). Figure 4 shows the scatter plots between SSEBop and measured ET values with the 95% confidence intervals ($R^2 = 0.90$). Regression analysis indicated that the slope of the regression line did not statistically differ ($P < 0.0001$) from 0, suggesting good performances of the remote SSEBop model in estimating ET. Underpredictions suggested that the SSEBop model provided relatively conservative (lower ranges) estimates during the winter. This consistent pattern (i.e., overestimates at the high ET end and underestimates at low ET) may be associated with the inability of the model to fully capture ET fluxes from slowly growing grass during the winter months. Although the underestimation in winter could be offset by overestimation in other seasons (particularly during the summer growing season), the annual ET models values tended to be clustered around 673 mm-year⁻¹ versus the measured value of 609 mm-year⁻¹.

3.3. ET Anomaly Maps. Figure 5 presents annual ET (estimated) monthly anomaly maps for the period between 2016

(a)

(b)

FIGURE 2: (a) Daily rates (mm day⁻¹) of measured (black) evapotranspiration flux (EC) and reference Penman–Monteith (*P-M*) evapotranspiration. (b) Median daily measured evapotranspiration rate (mm day⁻¹) for each month by year. Boxes bounding the inner quartiles and whiskers indicate 50% and 95% of the median values of ET. A: 2016. B: 2017. C: 2018.

TABLE 2: Performance indices used to compare estimated monthly ET (SSEBop) and Penman–Monteith ($P-M$) against flux measured ET.

	BIAS	RMSE	MAPE	MRE	R^2
SSEBop	5.47	21.49	30.94	10.48	0.87
$P-M$	49.55	56.76	95.51	94.90	0.60

FIGURE 3: Monthly total (mm month^{-1}) estimated by SSEBop (black) and measured ET (blue) during 2016–2018.

FIGURE 4: Monthly (mm/month) evapotranspiration (ET; x-axis) plotted against estimated ET by the SSEBop (y-axis) at pasture flux tower location site during 2016–2018. Model performances are assessed using coefficient of determination (R^2). Also shown are the 1 : 1 (dashed line), regression line (solid line), and 95% CI (blue lines).

and 2018. ET anomalies over our measurement area and surrounding regions are shown on a monthly scale. Although severe drought did not occur during the observation years, the anomaly maps show mild drought conditions in 2016 compared to the wetter 2018. The above average precipitation during 2018 resulted in a strong ET positive anomalies (especially in July and August), but the monthly maps depict

water deficiency from the drought in 2016 when the rainfall deficit was relatively large (i.e., 2017 and 2018; Figures 6 and 5).

4. Discussion

In this study, we evaluated SSEBop's ET monthly estimates against observed data (from an eddy covariance flux station) over a pastureland site in north central Kentucky. Overall, the SSEBop monthly estimates were highly correlated and tracked well with seasonal data. We found month-to-month bias ($\sim 5 \text{ mm/month}$) that led to a pattern of overestimation in the warmer months or underestimation in the cooler months. Such bias could likely impact the magnitude of the estimated ET. On the other hand, a high correlation (e.g., low R^2) between modeled and true concentrations is indicative of a high degree of association. We found that while the model captures the temporal variability of ET, month-to-month differences were evident. Notable was the fact that SSEBop quantitative ET estimates tend to underestimate ET during cooler months. This probably could be attributed to strong cloud attenuation effects of the main winter rainy months. Such underestimation of ET_a occurs when the ET fraction ($ET_f = ET_a / kET_o$) is small [19]. Noted differences between the observed and estimated values during the wet and dry months may stem from the key assumption the model makes in that differences in land surface temperature (LST) over a homogeneous landscape are primarily due to differences in vegetation and functional differences in water use. The model also ignores the contribution of albedo (canopy reflectance) and ground heat flux as part of the ET estimation.

The close correspondence between SSEBop estimates demonstrates the promise of satellite-sensed ET approaches to remotely monitor crop water use and drought conditions at plot scales in contrasting precipitation years. The SSEBop model ET estimates have previously been validated using networked eddy covariance data flux station at watershed and regional scales, mainly in western United States [19] and to a lesser degree in the southeastern US.

Whereas space-based estimates, such as the MODIS and SSEBop, are the most promising with regard to spatial and temporal resolution of ET products, retrieval quality is strongly tied to the algorithm's ability to detect and screen cloud interference, reduce the attenuation and scattering effects arising from cloud shadow [27], and hence improve the values of the interpolated pixels [28]. These and the next generation of future advances in retrieval procedures will enhance space-based realistic descriptions of the spatial distribution of ET.

This contrasting anomaly indicates the dependency of ET on precipitation and on soil moisture availability. In the past, SSEBop anomaly maps showed and clearly captured two major drought events that engulfed much of the southeastern United States during the 2007 and 2012 extreme droughts. Drought, as a consequence of soil moisture deficiency, causes an increase in ET anomalies by reducing evaporative (latent heat) fluxes. One of the advantages of estimating ET remotely is to be able to provide anomaly maps for decision-makers in response to emergencies, such

FIGURE 5: Spatial distribution of the remotely sensed actual ET (ET_a) and anomalies at the eddy covariance site and surrounding counties from 2016 to 2018. This map includes the 17-county area known as the “Bluegrass” region of Kentucky and they have similar vegetative features, featuring large pastureland and other agricultural lands. The counties are Anderson, Bourbon, Boyle, Clark, Estill, Fayette, Franklin, Garrard, Harrison, Jessamine, Lincoln, Madison, Mercer, Nicholas, Powell, Scott, and Woodford. The area represents 11,070 km². Significantly lower than average ET (dry conditions) is identified with orange color. Higher than average ET is identified with green color. Maps showing ET anomalies are shown on the left side of each panel. Anomaly is computed as a deviation between average values of ET of any given year from the historical mean (2000 to 2017).

FIGURE 6: Monthly ET anomaly (defined here as $P-ET$) during 2016–2018, where P is precipitation. The monthly $P-ET$ variation is controlled by precipitation exhibiting positive ($P > ET$) and deficit ($P < ET$). Precipitation data were obtained from the nearby (<2 miles) Kentucky Mesonet weather station.

as drought and flooding, and thereby improve response capacity.

5. Conclusion

For this study, we examined and evaluated the performance of SSEBop model using direct, *in situ* ET eddy flux measurements at a managed pastureland in north central Kentucky between 2016 and 2018. The model was chosen because it provides data products at spatial and temporal scales suitable for comparison with ET data. SSEBop over- and underestimated ET with a mean difference of $5 \text{ mm} \cdot \text{month}^{-1}$ averaged over the three years (2016–2018). The comparison between direct flux ET measurement and modeled ET allowed seasonal characterization of EC trends at this managed pasture site. Seasonality was captured well; however, the model underestimated ET during winter months and overestimated it during summer months. These data showed the following:

- (i) SSEBop anomaly maps provide relevant drought information that can be used by various practitioners, and it offers tools for managing and

mitigating drought, which helps guide mitigation strategies.

- (ii) The model's poor performance may not necessarily indicate the model's inaccuracy. One possible explanation for this is mismatched data on spatial scales on 1 point (100 m fetch area) versus 1000 m fetch area.
- (iii) The SSEBop at the pasture site demonstrated the model's efficacy, which enforces its value as a reliable proxy for precipitation and a valuable indicator of ET anomalies on a month-to-month scale; however, the model's validation in areas characterized by contrasting seasonal and year-to-year precipitation requires further testing and additional research.

This study supports the model's use as proxy variable for precipitation and as a viable method for monitoring and assessing ground moisture status (i.e., drought). The SSEBop model is less complex than other remote-based ET products (e.g., METRIC and MODIS) and it provides sufficient information for reliably assessing and monitoring droughts on shorter time scales (e.g., daily to monthly). [29].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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