Performance Assessment of PySEBAL Model-Derived Evapotranspiration Using Eddy Covariance Measurements in the Philippines

Alvin John B. Felipe
Institute of Agricultural and Biosystems Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños

Ronaldo B. Saludes
Institute of Agricultural and Biosystems Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños

Rubenito M. Lampayan
Institute of Agricultural and Biosystems Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños

Patrick Lemuel P. Relativo
Institute of Agricultural and Biosystems Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños

https://doi.org/10.5109/7323238

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 10, pp.26-32, 2024-10-17. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

Performance Assessment of PySEBAL model-derived Evapotranspiration Using Eddy Covariance Measurements in the Philippines

Alvin John B. Felipe[1], Ronaldo B. Saludes[1], Rubenito M. Lampayan[1], Patrick Lemuel P. Relativo[1]
[1]Institute of Agricultural and Biosystems Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños
Corresponding author email: abfelipe1@up.edu.ph

Abstract: *Since its introduction, the Surface Energy Balance Algorithm for Land (SEBAL) has been widely used in different applications for environmental, agricultural, and other engineering purposes. This study was conducted to test the applicability of the Python-based SEBAL (PySEBAL) model in estimating actual evapotranspiration using Landsat imagery in the Philippines using eddy covariance ETa data. Despite inherent problems due to cloud contamination which can be associated with the season where the images were taken and the prevailing physical condition of the area, statistical analysis suggests that PySEBAL is acceptable in estimating ETa for homogeneous landscapes which is expected to perform better for non-cloudy areas. Further studies should be conducted to establish its applicability for complex heterogeneous terrains. This study supports the application of remote sensing and surface energy balance models in producing spatiotemporal estimation of actual evapotranspiration (ETa) in the absence of ground-based observations for more effective water resources management.*

Keywords: PySEBAL, Eddy Covariance, Remote Sensing, Landsat, Actual Evapotranspiration

1. INTRODUCTION

Evapotranspiration (ET) is among the important factors in the overall water cycle, particularly for efficient designs of irrigation systems for agricultural water management and water resources planning with great emphasis on water balance since ET is an [1, 2]. Similarly, the importance of flux exchange between the land and the atmosphere for agricultural production systems was reviewed by Ghiat et al. [3]. They assessed the different empirical equations in calculating ET and the direct methods of ET measurements which articulate the significance of ET in water conservation that also influences the energy and consequent food production. ET measurement transcends different disciplines. Irrigation scheduling and water productivity improvement are highly dependent on the ET rate which is the core concept of agricultural water requirement estimation and the need for a more accurate estimation of ET as a subject for future research is needed particularly in terms of the changing climate [4]. Eisenhauer et al., [5] thoroughly define evapotranspiration as the term that describes "plant water use" and is very important for water management, especially for critical areas as ET-based water use curves serve as a significant tool needed for considerable decisions in regulating water supply where such strategy can affect savings in terms of water and monetary terms.

To improve irrigation management, ET has been a great tool for researchers in developing and identifying plant responses to different irrigation methods. Ko and Piccini [6] developed a crop evapotranspiration-based irrigation management strategy to assess the physiological response of corn crops in terms of yield, they found out that the water use efficiency of the crop evapotranspiration-based irrigation scheduling scheme was the highest where the corresponding yield reduction is attributable to the deficiency of delivered irrigation water. Correspondingly status, in their comparative study of different irrigation practices based on the growth and yield of papaya in South Florida, Migliacco et al. [7] found out that among the treatments, the ET-based irrigation method calculated from historical weather data and soil water status which is based on a tensiometer reading, about 65% of irrigation water was conserved compared to scheduled irrigation where the said method only receives 31 to 36% of water yet identified to be the more sustainable method of irrigation that can maintain good physiological characteristics and yield. ET data is also used as an important criterion for suitability mapping studies of high value crops such as dragon fruit [8]

However, ET estimates are still subjected to errors and discrepancies arising from personal to instrumental, and even extrapolation errors. In addition, field measurements such as lysimeters and eddy covariance techniques are expensive to conduct and maintain [9, 10]. ET is inherently difficult to measure and predict, especially in large areas due to the variability in climate, soil, and vegetation properties [11]. This was elaborated by Moqbeli Damane et al. [12] when they estimated the actual ET of a large area in Iran where they mainstreamed the difficulty of measuring ET using traditional methods due to the existing climatic and topographic elements. Particularly when dealing with sparse ground observations and missing data, the lack of proper and complete meteorological observation data is considered to be one of the major limitations of traditional ET measurement techniques which most of the time reproduces erratic estimates.

For sustainable water management, accurate estimates of ET should be the basis since ET is a major process of water consumption in agricultural areas. More accurate ET estimation methods are of high importance and the utilization of current technological advances is beneficial for agricultural operations such as satellite remote sensing data which offers the capability to predict and monitor climatic and eco- hydrological processes such as the occurrence of drought and forecasts [13]. Additionally, accurate ET measurements in precision agriculture parlance evaluate the performance of efficient water-saving technologies being proposed that will greatly influence the reduction of water losses. Although the use of ground ET measuring devices and climatological approaches were the standard of assessing and calculating ET over different areas.

Satellite-based ET provides practical implications for water managers and policymakers because it shows that estimating actual applied water use amounts can be reasonably accurate if done regularly [14]. This accurate estimation of ET can be attributed to the advancements in satellite and remote sensing technology as elaborated by [15], where they assess and analyze the surface energy balance (SEB) principles assimilated with remotely sensed data from satellite observations which gave way to measure and quantify surface fluxes mostly through the energy exchange between the Sun and the Earth which stands on the fact these exchanges of energy mainly through shortwave-radiation and long-wave radiation is what defines the total energy in climate systems, particularly for soil-plant-atmosphere interaction.

As an application, SEB and remote sensing, are used to estimate the actual evapotranspiration of irrigated fields where SEB-based studies were found to have a spatiotemporal advantage in contrast to water balance studies, which requires information on both the amount and temporal distribution of rainfall and irrigation applied to fields, SEB can estimate the spatial extent of irrigated fields and their water-use patterns without reference to the source of water [16].

The Surface Energy Balance for Land (SEBAL) model is among the long-standing SEB models and has been validated in different countries across the globe. It has subjected to different iterations which include the Python-based SEBAL [17] It is capable of estimating actual evapotranspiration from both observed and remotely sensed data sets and is currently available for several remote sensing products such as Landsat and MODIS. In the Philippines, however, its application has not been widely tested due to the lack of studies about its application in different environments and climatological zones which can also be attributed to the lack of actual and reliable ET measurements. Several studies have been conducted in the past but none of which used established in-situ ET measurements for validation and calibration and often resort to comparison of ET estimates using Penman-Monteith Method. [18, 19].

This study aims to assess the performance of PySEBAL model in capturing actual ET using the lone Eddy Covariance (EC) Flux Tower data in the Philippines to evaluate the possible implications and constraints in utilizing remote sensing-based ET estimates, particularly in agriculture. This study serves to be the first attempt to validate the SEBAL-based ET using ground observations in the country. While it can be said that SEBAL can rely on global validations, it is still imperative to determine its local performance specifically in a tropical agricultural country like the Philippines.

2. METHODOLOGY

2.1. PySEBAL Model

This study makes use of the PySEBAL model which essentially uses the SEBAL framework in a Python environment and is freely available from [CITE]. It is based on the principle of surface energy budget (Fig. 1.)

$$LE = Rn - (H + G) \quad (1)$$

where LE is the latent heat flux where the ET is being derived, and Rn is the net radiation received by the surface. H is the sensible heat, and G is the ground heat flux.

The model makes use of anchor pixels. Cold pixel is designated for relatively covered and wet surface, and hot pixel is for dry and barren land pixels which is automatically selected by the PySEBAL algorithm.

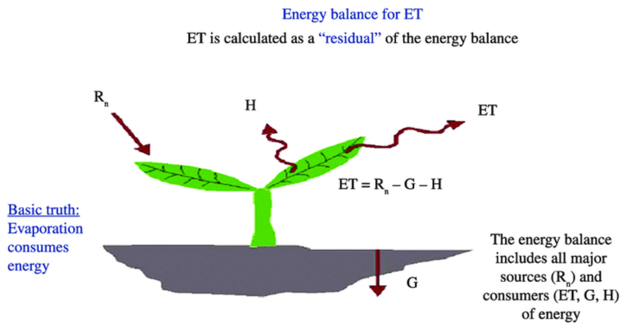

Fig. 1. Surface Energy Balance Components [20].

The model simultaneously solves the different surface flux equations and the corresponding parameters of interest. For a more complete description of the PySEBAL workflow, the reader is referred to [21].

The evaporative fraction (EF) is calculated from the computed Rn, H, and G values using the formula:

$$EF = \frac{R_n - H - G}{R_n - G} \quad (2)$$

Where the numerator simply represents the LE. The daily evaporative fraction is calculated using the advection factor term (AF) which is used to minimize estimation errors for ETa.

$$AF = 1 + 0.985 \times EF \times \{\exp[0.08\,(e_s - e_a)] - 1\} \quad (3)$$

where e_s and e_a are the saturated and actual vapor pressure above the canopy reference height, respectively.

Then the daily actual evapotranspiration (ETa) is calculated using eq (4).

$$ET_{a24} = \frac{8.64\times 10^7 \times AF \times EF \times (R_{n24} - G_{24})}{\lambda \times \rho_w} \quad (4)$$

where G_{24} is the average daily soil heat flux and R_{n24} is the average daily net radiation, both in (W/m^2).

$$R_{n24} = [(1 - \alpha) \times R_a - 110] \times \tau_{sw} \quad (5)$$

where R_a is the extraterrestrial radiation and τ_{sw} is the daily atmospheric transmissivity [22]

2.2. Location of the Study Area

The location of the of the EC flux tower at IRRI, located at (14° 8′ 27.7″ N; 121° 15′ 54.98″ E) was considered to be the location of the study. Since the Landsat scenes over the location of the EC flux tower will be considered. The EC flux tower was situated on an irrigated lowland rice environment which is shown in Fig. 1.

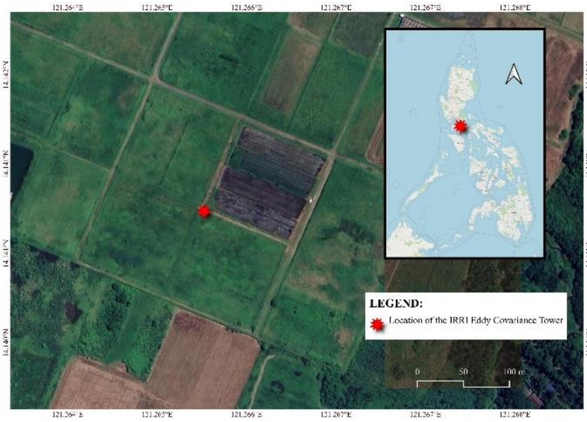

Fig. 2. Location of the IRRI Eddy Covariance Tower

2.3. Data Acquisition

2.3.1. Eddy Covariance Data

The ETa from the EC flux tower was acquired in collaboration with the IRRI. The ETa data encompasses the dates between November 30, 2015 to April 3, 2016 which essentially covers 4 consecutive months.

2.3.2. Landsat Imagery

This study makes use of Landsat 8 datasets acquired from the open-sourced USGS Earth Explorer website [23]

2.3.3. Meteorological Data

This study utilizes the remotely sensed meteorological data derived from the recommended NASA Global Land Data Assimilation System (GLDAS) [24, 25]. The meteorological requirements include air temperature, relative humidity, shortwave radiation, wind speed, and transmissivity.

2.3.4. Digital Elevation Model (DEM) and Soil Data

The 30m- m-resolution DEM was acquired from the publicly available Shuttle Radar Topography Mission (SRTM) dataset.

On the other hand, this study makes us of the HiHydro v2.0 high-resolution global soil hydraulic properties dataset (26).

2.4. Statistical Analysis

The PySEBAL-generated ETa values were compared to the EC data using statistical methods which were considered based on the different studies that assess the capability of the SEBAL model in generating ETa values [27, 28, 29]. The statistical analysis was conducted using the following metrics:

Coefficient of Determination (R^2)

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{meanobs}\right)\left(Y_i^{gen} - Y_i^{meangen}\right)}{\sqrt{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{meanobs})^2}\sqrt{\sum_1^n(Y_i^{gen} - Y_i^{meangen})^2}}\right]^2 \quad (6)$$

Normalized Root Mean Square Error (NRMSE)

$$NRMSE = \frac{RMSE}{Y_{ave}^{obs}} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_1^n\left(Y_i^{obs} - Y_i^{gen}\right)^2}{n}} \quad (8)$$

Mean Bias Error (MBE)

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(\ Y_i^{obs} - Y_i^{gen}) \quad (9)$$

Nash-Sutcliffe Efficiency (NSE)

$$NSE = 1 - \left[\frac{\sum_1^n\left(Y_i^{obs} - Y_i^{gen}\right)^2}{\sum_1^n\left(Y_i^{obs} - Y_i^{meanobs}\right)^2}\right] \quad (10)$$

Mean Relative Error (MRE)

$$MRE = \frac{1}{n}\sum_{i=}^{n}\frac{|Y_i^{obs} - Y_i^{gen}|}{Y_i^{obs}} \quad (11)$$

where Y_i^{obs} and Y_i^{gen} are the EC ETa and PySEBAL-generated ETa, respectively and $Y_i^{meanobs}$ and $Y_i^{meangen}$ pertains to the average value of EC ETa data and the average value of the PySEBAL-generate ETa, respectively.

Kling-Gupta Efficiency (KGE)

$$KGE = 1 - \sqrt{(CC-1)^2 + \left(\frac{cd}{rd}\right)^2 + \left(\frac{cm}{rm} - 1\right)^2} \quad (12)$$

where CC is the pearson coefficient value; rm is the average of the EC ETa values; cm is the average value of PySEBAL-generated ETa; rd is the standard deviation of the EC ETa values; and cd is the standard deviation of the PySEBAL-generated ETa values.

3. RESULTS AND DISCUSSION

To establish some kind of baseline values on the performance of the model, a preliminary run was conducted over an area within situ ETa observation. However, the acquired EC data only covers approximately 4 months of observations. Given that Landsat has a 16-day overpass interval which only enables it to visit the site about twice every month. Landsat 8 was the only dataset available since the missing values due to the scan-line error of Lansat 7 significantly falls within the location of the study area, it was omitted to reduce possible inaccuracy brought by missing raster values characterized by alternating lines of null values. Landsat 8 images were utilized for this purpose, but it is not completely devoid of any setback. The timeframe was considerably short and since the area is near Mt. Makiling, cloud built-up is evident in almost all images from November to April. While the area is under Type 1 climate, which has a dry season classification from November to April, convective and orographic clouds cover most of the study area. Moreover, the Northeast Monsoon or Amihan is also considered to contribute to cloud development. Its onset covers the November to April period where it brings cold and dry air from Siberia but is still capable of producing rains and therefore clouds which is more apparent in mountainous areas [30]. It was once reported that Amihan causes cloudy skies over Laguna and other provinces. The prevailing easterlies also bring cloudy skies apart from isolated thunderstorms and rain showers [31, 32]. These factors were recognized to have affected the cloud cover in the area as perceptible from the Landsat scenes used in estimating the ETa over the IRRI area (Fig. 2).

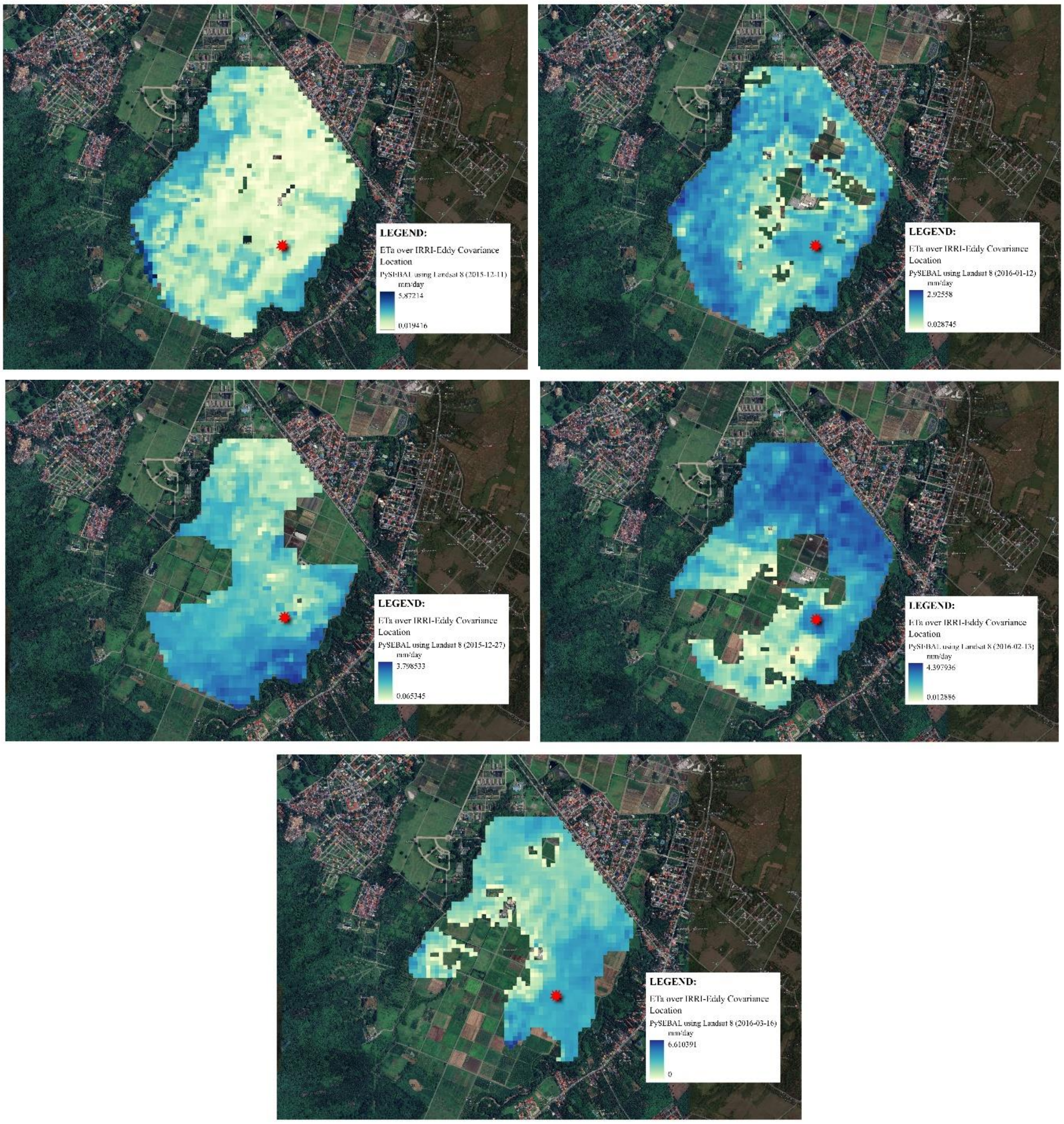

Fig. 3. PySEBAL ETa Map over the EC Flux Tower.

As shown in Table 1, shows the results of ETa estimation using PySEBAl compared to the EC observation values. The statistical analysis (Table 2) presents the performance of PySEBAL to capture accurate ETa values which can be said to have been affected by the quality of satellite images.

Table 1. EC and PySEBAL ETa

Landsat Acquisition Date	**ETa (mm/day)**	
	EC	**PySEBAL**
Dec. 11, 2015	3.11	1.61
Dec. 27, 2015	4.06	2.88
Jan. 12, 2016	1.97	1.63
Feb. 13, 2016	4.27	3.21
Mar. 16, 2016	4.09	4.36

Table 2. Statistical Analysis

R^2	RMSE	NRSME	MBE	MRE	NSE	KGE
0.68	0.90	0.28	-0.69	0.20	-0.07	0.67

Although considerable cloud contamination takes place on the image, in terms of R^2 it performs adequately at 0.68 which is higher than the acceptable value of 0.5 for hydrologic studies [33]. The RMSE ranges from 0 to infinity [34] and RMSE values closer to 0 are of high regard. The RMSE value of 0.90 considering the sufficiency and condition of the sample images used is too small to conclude otherwise since there is not enough data to classify outliers. This can be normalized however to bound the range from 0 to 1and for this particular dataset results in NRSME of 0.28 which can be said to be acceptable since it is not greater than 1 [35].

The MBE value on the other hand is negative which implies that PySEBAL overestimates the ETa values [36]. For the MRE, there is no defined rule to interpret the value range, yet a value closer to zero implies a more accurate model. MRE refers to the difference between the actual values and the predicted values in relation to the actual values. Here, the MRE value of 0.20 can be regarded to be acceptable since it is close to zero and falls within the 0 – 0.4 range mentioned by [37].

The negative NSE value of -0.07 on the contrary, implies that the mean of observations is a better indicator than the generated values ETa values of PySEBAL (Patton et al., 2022). This denotes that the generated ETa values were able to capture the variability but failed to produce the mean. It happens when the error in simulating the mean exceeds one standard deviation of the simulated variability [38]. This negative value may have arisen from the number of data available for this comparison. In terms of the KGE, the EC and PySEBAL ETa comparison resulted in a value of 0.68. KGE can be considered as an improvement of the NSE (Pool et al., 2018) but because of their ambiguous relationship and dependence on the observed coefficient of variation, NSE and KGE values cannot be directly compared; thus, NSE should not influence the corresponding KGE interpretation [39]. The KGE ranges from -infinity to 1. A value of 1 denotes a perfect fit between the model predictions and the actual data. Here it can be regarded as acceptable since KGE in this study is positive and above 0.5 which can be said that the variability in simulating ETa was captured by the PySEBAL model [39, 40]. From the results of the statistical analysis, the performance of the PySEBAL model can be considered in the surface energy balance study, particularly in measuring ETa. However, due to the drawbacks in terms of the cloud cover interference on the satellite data which affects the adequacy of the considered images for this initial validation, the use of PySEBAL is for now suggested for homogenous fields such as from the IRRI site where the EC flux tower was located. While there are studies that validate the SEBAL model using the same or relatively few satellite images using other means such as ETc based on FAO 56, ET from pan coefficient method, lysimeter, and other methods [41; 42, 43]. This initial assessment reveals the necessity of having ground observation points to further evaluate and calibrate the model for wider application. It is expected however that by assimilating more cloud-free images, the PySEBAL model could produce sound estimates for planning purposes. Other methods such as the use of drones in carrying out field observations for localized applications should be explored as it will surely eliminate cloud problems. Similarly, assimilation of other satellite imageries should also be explored. All these with the added work in modifying the pySEBAL code to be able to run such datasets as the PySEBAL is currently available on few satellites produces such as MODIS which is has a courser resolution than SEBAL. For this particular application, the main study area is a rice production area which can be considered as homogenous in terms of land cover. The results of this initial assessment support the application of PySEBAL in estimating water productivity parameters. Moreover, even if the SEBAL model is not widely validated in the Philippines using state-of-the-art instruments like the EC flux tower which was only available at IRRI or other in-site data for that matter, the application of the SEBAL model has been accepted and globally validated and have demonstrated acceptable performance under different conditions [44, 45]

4. CONCLUSION

The ETa estimates using the PySEBAL model was assessed using the EC data from IRRI. The statistical analysis supports the applicability of PySEBAL for ETa estimation despite inherent cloud cover contamination issues which limits the availability of Landsat images. Furthermore, it is expected that in clear sky conditions which may be present in other areas in the Philippines, the PySEBAL performance is anticipated to improve particularly in areas with relatively less cloud cover potential due to mechanical lifting of airmass such as in mountainous areas and where convective lifting dominates. However, for wide-scale applications particularly in non-homogenous areas such as rice fields, further studies should be conducted to measure actual evapotranspiration. Further studies with regards to the assimilation of both high temporal and spatial resolution image datasets should also be considered. PySEBAL accepts numerical values or raster images interpolated from actual measurements. The utilization of in-situ ground meteorological data is highly advised if available as it will surely influence the overall performance of the model.

5. ACKNOWLEDGEMENT

The authors would like to express their gratitude to the Department of Science and Technology (DOST)–Engineering Research and Development for Technology (ERDT) for providing substantial funding for this study, and to the International Rice Research Institute (IRRI) for sharing the eddy covariance ETa data which is a core information for this study.

6. REFERENCES

[1] A. Elbeltagi, J. Deng, K. Wang, A. Malik, and Saman Maroufpoor, “Modeling long-term dynamics of crop evapotranspiration using deep learning in a semi-arid environment,” vol. 241, pp. 106334–106334, Nov. 2020, doi: https://doi.org/10.1016/j.agwat.2020.106334.

[2] H. Půčková, J. Kotlík, M. Vávrová, and T. Miyazaki, “Accumulation of water and energy in environment by short rotation coppice,” in Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES), Fukuoka, Japan: Interdisciplinary Graduate School of Engineering Sciences, Kyushu University, Oct. 2017, pp. 75–78.

[3] I. Ghiat, H. R. Mackey, and T. Al-Ansari, “A Review of Evapotranspiration Measurement Models, Techniques and Methods for Open and Closed Agricultural Field Applications,” Water, vol. 13, no. 18, p. 2523, Sep. 2021, doi: https://doi.org/10.3390/w13182523.

[4] "Evapotranspiration and agriculture-A review-Indian Journals," www.indianjournals.com. https://www.indianjournals.com/ijor.aspx?target=ijor:ar&volume=40&issue=1&article=001 (accessed Aug. 19, 2021).
[5] D. E. Eisenhauer, D. L. Martin, D. M. Heeren, and G. Hoffman, Irrigation Systems Management. American Society of Agricultural and Biological Engineers (ASABE), 2021. Available: doi: 10.13031/ISM.2021
[6] J. Ko, "Simulation for Irrigation Management of Corn in South Texas," Korean Journal of Crop Science, vol. 53, no. 2, pp. 161–170, 2008.
[7] K. W. Migliaccio, B. Schaffer, J. H. Crane, and F. S. Davies, "Plant response to evapotranspiration and soil water sensor irrigation scheduling methods for papaya production in south Florida," Agricultural Water Management, vol. 97, no. 10, pp. 1452–1460, Oct. 2010, doi: https://doi.org/10.1016/j.agwat.2010.04.012.
[8] None Armdin A. Valmoria, J. E. Bala, and M. Letecia, "Suitability Mapping for White-fleshed (Hylocereus undatus) and Red-fleshed (Hylocereus costaricensis) Dragon fruit Farming in Butuan City Using Multi-Criteria Decision Analysis and GIS," Proceedings of international exchange and innovation conference on engineering & sciences, IEICES, vol. 9, pp. 168–174, Oct. 2023, doi: https://doi.org/10.5109/7157968.
[9] A. Kumari et al., "Estimation of Actual Evapotranspiration and Crop Coefficient of Transplanted Puddled Rice Using a Modified Non-Weighing Paddy Lysimeter," Agronomy, vol. 12, no. 11, p. 2850, Nov. 2022, doi: https://doi.org/10.3390/agronomy12112850.
[10] T. Pütz, J. Fank, and M. Flury, "Lysimeters in Vadose Zone Research," Vadose Zone Journal, vol. 17, no. 1, p. 180035, 2018, doi: https://doi.org/10.2136/vzj2018.02.0035.
[11] K. Zhang, J. S. Kimball, and S. W. Running, "A review of remote sensing based actual evapotranspiration estimation," WIREs Water, vol. 3, no. 6, pp. 834–853, Jul. 2016, doi: https://doi.org/10.1002/wat2.1168.
[12] M. M. Damane, H. S. Nejad, and M. Kafash, "Evaluation of SEBAL algorithm for actual evapotranspiration estimating by using Landsat 8 images in multiple land use landscape (Case study: Freeman area)," Journal of Climate Research, vol. 1401, no. 51, pp. 182–165, 2022.
[13] S. Wanniarachchi and R. Sarukkalige, "A Review on Evapotranspiration Estimation in Agricultural Water Management: Past, Present, and Future," Hydrology, vol. 9, no. 7, p. 123, Jul. 2022, doi: https://doi.org/10.3390/hydrology9070123.
[14] P. Droogers, W. W. Immerzeel, and I. J. Lorite, "Estimating actual irrigation application by remotely sensed evapotranspiration observations," Agricultural Water Management, vol. 97, no. 9, pp. 1351–1359, Sep. 2010, doi: https://doi.org/10.1016/j.agwat.2010.03.017.
[15] Y.-A. Liou and S. Kar, "Evapotranspiration Estimation with Remote Sensing and Various Surface Energy Balance Algorithms—A Review," Energies, vol. 7, no. 5, pp. 2821–2849, Apr. 2014, doi: https://doi.org/10.3390/en7052821.
[16]G. Senay, M. Budde, J. Verdin, and A. Melesse, "A Coupled Remote Sensing and Simplified Surface Energy Balance Approach to Estimate Actual Evapotranspiration from Irrigated Fields," Sensors, vol. 7, no. 6, pp. 979–1000, Jun. 2007, doi: https://doi.org/10.3390/s7060979.
[17] T. Hessels, J. Van Opstal, P. Trambauer, W.G. Bastiaanssen, M. Faouzi, Y. Mohamed, and A. Er-Raji, "PySEBAL Version 3.3.7, 2017.
[18] M. M. Hafeez, Y. Chemin, V. De, and B. A. M. Bouman, "Estimation of crop water deficit through remote sensing in Central Luzon, Philippines," Oct. 2003, doi: https://doi.org/10.1109/igarss.2002.1026772.
[19] M. Hafeez, Y. Chemin, N. Van De Giesen, and B. A. M. Bouman, "Field evapotranspiration estimation in central Luzon, Philippines, using different sensors: Landsat 7 ETM+, Terra MODIS and ASTER," in ISPRS/CIG conference , International Journal of Photogrammetry and Remote Sensing.
[20] R. Waters, R. Allen, W. Bastiaanssen, M. Tasumi, and R. Trezza, Sebal. Surface energy balance algorithms for land. Idaho implementation. Advanced Training and Users Manual. Idaho, USA, 2002.
[21]M. Mul, P. Karimi, H. M. Coerver, and S. Pareeth, Water Productivity and Water Accounting Methodology Manual. Project report. IHE Delft Institute for Water Education, The Netherlands and the International Water Management Institute, Sri Lanka., 2020.
[22] J. Xue, K. M. Bali, S. Light, T. Hessels, and I. Kisekka, "Evaluation of remote sensing-based evapotranspiration models against surface renewal in almonds, tomatoes and maize," Agricultural Water Management, vol. 238, p. 106228, Aug. 2020, doi: https://doi.org/10.1016/j.agwat.2020.106228.
[23] USGS - U.S. Geological Survey, "EarthExplorer," Usgs.gov, 2023. https://earthexplorer.usgs.gov/
[24] H. Beaudoing and M. Rodell, "GLDAS Noah Land Surface Model L4 3 hourly 0.25 x 0.25 degree V2.1," Goddard Earth Sciences Data and Information Services Center (GES DISC), Greenbelt, Maryland, USA. Available: 10.5067/E7TYRXPJKWOQ
[25] M. Rodell, E. B. McWilliams, J. S. Famiglietti, H. K. Beaudoing, and J. Nigro, "Estimating evapotranspiration using an observation based terrestrial water budget," Hydrological Processes, vol. 25, no. 26, pp. 4082–4092, Dec. 2011, doi: https://doi.org/10.1002/hyp.8369.
[26] G. W. H. SIimons, R. Koster, and P. Droogers, "HiHydroSoil v2.0 - A high resolution soil map of global hydraulic properties. FutureWater Report 213.," 2020.
[27] X. Zhou, S. Bi, Y. Yang, F. Tian, and D. Ren, "Comparison of ET estimations by the three-temperature model, SEBAL model and eddy covariance observations," Journal of Hydrology, vol. 519, pp. 769–776, Nov. 2014, doi: https://doi.org/10.1016/j.jhydrol.2014.08.004.
[28] J. Xue, K. M. Bali, S. Light, T. Hessels, and I. Kisekka, "Evaluation of remote sensing-based evapotranspiration models against surface renewal in almonds, tomatoes and maize," Agricultural Water Management, vol. 238, p. 106228, Aug. 2020, doi: https://doi.org/10.1016/j.agwat.2020.106228.

[29] Y. Ma, S. Sun, C. Li, J. Zhao, Z. Li, and C. Jia, "Estimation of regional actual evapotranspiration based on the improved SEBAL model," Journal of Hydrology, vol. 619, pp. 129283–129283, Feb. 2023, doi: https://doi.org/10.1016/j.jhydrol.2023.129283.

[30] A. Juan, "Amihan and Habagat: Diving seasons in the Philippines explained," Diver Bliss, 2023. https://www.diverbliss.com/amihan-and-habagat-monsoon-seasons-%20philippines/

[31] L. T. Abello, "Shear line, 'amihan' to bring rains across Luzon," Manila Bulletin, 2023. https://mb.com.ph/2023/11/14/shear-line-amihan-to-bring-rains-across-luzon

[32] E. DE VERA-RUIZ, "Ph may have cyclone-free weekend but light rains still possible due to 'Amihan,'" Manila Bulletin, 2024. https://mb.com.ph/2024/3/7/ph-may-%20have-cyclone-free-weekend-but-light-rains-still-possible-due-to-amihan

[33] C. L. Singson, L. A. Alejo, O. F. Balderama, and J. L. F. Bareng, "Modeling climate change impact on the inflow of the Magat reservoir using the Soil and Water Assessment Tool (SWAT) model for dam management," Journal of Water and Climate Change, Feb. 2023, doi: https://doi.org/10.2166/wcc.2023.240.

[34] A. Ritter and R. Muñoz-Carpena, "Performance evaluation of hydrological models: Statistical significance for reducing subjectivity in goodness-of-fit assessments," Journal of Hydrology, vol. 480, pp. 33–45, Feb. 2013, doi: https://doi.org/10.1016/j.jhydrol.2012.12.004.

[35] M. Atiquzzaman and J. Kandasamy, "Prediction of hydrological time-series using extreme learning machine," Journal of Hydroinformatics, vol. 18, no. 2, pp. 345–353, Oct. 2015, doi: https://doi.org/10.2166/hydro.2015.020.

[36] A. Correndo, L. Morro Rosso, R. Schwalbert, C. Hernandez, L. Bastos, D. Holzworth, and I. Ciampitti, "metrica: Prediction performance metrics", R package version, 1(3), 2022.

[37] L. S. Pereira, P. Paredes, and N. Jovanovic, "Soil water balance models for determining crop water and irrigation requirements and irrigation scheduling focusing on the FAO56 method and the dual Kc approach," Agricultural Water Management, vol. 241, p. 106357, Nov. 2020, doi: https://doi.org/10.1016/j.agwat.2020.106357.

[38] H. V. Gupta and H. Kling, "On typical range, sensitivity, and normalization of Mean Squared Error and Nash-Sutcliffe Efficiency type metrics," Water Resources Research, vol. 47, no. 10, Oct. 2011, doi: https://doi.org/10.1029/2011wr010962.

[39] W. J. M. Knoben, J. E. Freer, and R. A. Woods, "Technical note: Inherent benchmark or not? Comparing Nash-Sutcliffe and Kling-Gupta efficiency scores," Hydrology and Earth System Sciences Discussions, pp. 1–7, Jul. 2019, doi: https://doi.org/10.5194/hess-2019-327.

[40] J. Brombacher, I. R. de O. Silva, J. Degen, and H. Pelgrum, "A novel evapotranspiration based irrigation quantification method using the hydrological similar pixels algorithm," Agricultural Water Management, vol. 267, p. 107602, Jun. 2022, doi: https://doi.org/10.1016/j.agwat.2022.107602.

[41] Muhammad Naufil Zahid, S. Ahmad, Junaid Aziz Khan, Muhammad Dilshad Arshad, Muhammad Azmat, and Muhammad Ukasha, "Evapotranspiration estimation using a satellite-based surface energy balance: a case study of Upper Bari Doab, Pakistan," Environmental earth sciences, vol. 82, no. 24, Nov. 2023, doi: https://doi.org/10.1007/s12665-023-11284-5.

[42] N. Shamloo, Mohammad Taghi Sattari, Halit Apaydin, Khalil Valizadeh Kamran, and R. Prasad, "Evapotranspiration estimation using SEBAL algorithm integrated with remote sensing and experimental methods," vol. 14, no. 11, pp. 1638–1658, Aug. 2021, doi: https://doi.org/10.1080/17538947.2021.1962996.

[43] R. Singh and G. Senay, "Comparison of Four Different Energy Balance Models for Estimating Evapotranspiration in the Midwestern United States," Water, vol. 8, no. 1, p. 9, Dec. 2015, doi: https://doi.org/10.3390/w8010009.

[44] Wim G.M. Bastiaanssen, E.J.M. Noordman, H. Pelgrum, G. Davids, B. Thoreson, and R. J. Allen, "SEBAL Model with Remotely Sensed Data to Improve Water-Resources Management under Actual Field Conditions," Journal of Irrigation and Drainage Engineering-asce, vol. 131, no. 1, pp. 85–93, Feb. 2005, doi: https://doi.org/10.1061/(asce)0733-9437(2005)131:1(85).

[45] Ayan Santos Fleischmann et al., "Patterns and drivers of evapotranspiration in South American wetlands," Nature communications, vol. 14, no. 1, Oct. 2023, doi: https://doi.org/10.1038/s41467-023-42467-0.