

ESTIMATING EVAPORATION FROM SATELLITE REMOTE SENSING AND METEOROLOGICAL PARAMETERS

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Abstract

Northeastern Thailand is central to agriculture, growing rice and crops. Recently, this region has faced extreme climate conditions, more water in the rainy season, and drought in the dry months, which is a big concern for the Thai government to resolve. Lakes are essential in supporting the local nation in this area to solve the problem. Nong Han Lake is the second biggest nature lake in Thailand. Therefore, information on the hydrologic system is essential for efficient water management. This work focused on estimating the evaporation loss of the water system for Nong Han Lake. The relationship of evaporation with solar radiation (SR) and meteorological parameters was investigated using the linear mixed effect (LME). Evaporation (EVA) data were retrieved from the Thai Meteorological Department (TMD), and meteorological parameters were obtained from the National Centres for Environmental Prediction (NCEP)/the National Centre for Atmospheric Research (NCAR) global reanalysis. SR was downloaded from the Clouds and the Earth's Radiant Energy System (CERES). EVA changes throughout the year, reaching a peak in April compared with December. The model confirms that predicted EVA obtained from meteorological parameters has a high performance for increasing existing ground-based EVA monitoring networks.

Keywords: Evaporation; Meteorological; Parameters; Satellite Remote Sensing

Introduction

EVA is an efficient water loss from the water system, which has been substantial in recent climate change systems. It directly influences lake supplements, daily water use, agriculture plans, the economy, and people's livelihoods. The evaporation process is more significant when considering climate change results: increasing temperatures (T) warn to reduce available surface water via rising

evaporation. During drought, the lake plays a vital role in the agricultural enhancement of Sakon Nakhon province by providing a water supply. Nonetheless, the effect of climate on the hydrological system must be better understood, computed, and measured in water management plans.

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Previous evaporation studies have dealt with an immediate increase in surface water temperature, indicating increased evaporation rates (Woolway *et al.*, 2020). Liu *et al.* (2022) demonstrate that weather conditions result in increasing/decreasing evaporation. EVA is the main element of the water plan for lakes under complex climate programs, implying an indicator of climate change. Therefore, achieving more precise estimates of the evaporation model is necessary to improve effective water resource management strategies and policies.

The pan evaporation method has been broadly employed in running lake water management, installed on land to estimate evaporation. Surveys such as those conducted by (Finch and Calver, 2008); and Majhi *et al.* (2020) are among the widely utilized and consistent approaches for estimating evaporation. However, an evaporation model can be applied in the other part of the lake, where there is a lack of pan evaporation installed. On the other hand, despite their importance for water resource planning and management, we did not find most studies on evaporation models. In this environment, increasing knowledge about the region is fundamental, which indicates evaluating the performance of techniques for estimating extensive lake evaporation. The objectives of this study were to assess the performance of evaporation methods for estimating massive lake evaporation in Nong Han.

Methodology and Validations

Study area

The Nong Han (Lat 17.15 °N, Lon 104.13 °E) is a lake in Sakon Nakhon province, which is in northeast Thailand. The lake area is 125.2 km², the largest natural lake in northeast Thailand (Figure 1). The Phu Phan Mountains originate from the main river, which flows to the southeast into the Mekong River.



Figure 1. Nong Han Lake

Data

The daily average T data, mean, and relative humidity (RH) were achieved every 4 hours from NCEP/NCAR from 2018 to 2022, and all the data

were then interpolated into an hour. SR data were acquired from CERES Satellite data which lasted an average of 8 hours. The EVA data simultaneously was taken from the TMD (Table 1). T and RH obtained from NCEP/NCAR data resolution are 2.5×2.5 and SR data obtained from CERES with a resolution of 2.5×2.5. We averaged SR during the day from sunrise to sunset (8.00 am to 4.00 pm). Figure 2 compares SR from CERES and the ground level at Sakon Nakhon Rajabhat University with R²=0.72, RMSE = 242.97 W/m², and MAE = 237.65 W/m².

Table 1. NCEP data reanalysis datasets were applied to predict EVA.

Parameter Unit	Temporal	Resolution Sources
EVA (mm)	Daily	TMD
SR (W/m ²)	Daily	CERES
T (°C)	Every 4 h.	NCEP/NCAR
RH (%)	Every 4 h.	NCEP/NCAR

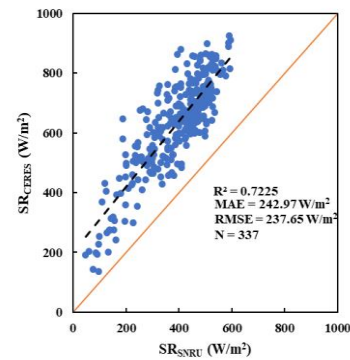


Figure 2. Comparison of SR from CERES and ground based at Sakon Nakhon Rajabhat University

Equations for evaporation

Evaporation models with climatic variables were developed using the LME. Climate variables impact local daily evaporation. This work separated data into two datasets: the first set is used for the run model (80%), and the second for the test model (20%). The LME is utilized to estimate evaporation (Althoff *et al.*, 2019). All those factors were counted for precision at discrete times. Evaporation equations for estimation based on meteorology conditions. Then, the LME was used to 3 factors in Equation (1).

$$\text{EVA} = (\beta_0 + \mu_0) + (\beta_1 + \mu_1) \text{SR} + (\beta_2 + \mu_2) \text{T} + (\beta_3 + \mu_3) \text{RH} + \varepsilon_r \quad (1)$$

Where EVA are in a site, β_0 is the fixed intercept, and μ_0 is the random intercept, respectively. T (°C), and RH (%) are the factors at the site; β_1 - β_3 are the fixed and μ_1 - μ_3 are random slopes, and ε_r is the

Table 3. The fixed effect of three models was utilized to calculate EVA collected in 2018-2022

Model	β_0	$\beta_{1(SR)}$	$\beta_{2(T)}$	$\beta_{3(RH)}$	RMSE	MBE	R ²
Model 1	-0.20	0.02***			0.39	0.29	0.54
Model 2	-4.06***	0.02***	0.16***		0.08	0.07	0.93
Model 3	-4.08***	0.02***	0.16***	0.00	0.04	0.04	0.96

***Parameter is significant at the $\alpha = 0.001$ level**Parameter is significant at the $\alpha = 0.01$ level*Parameter is significant at the $\alpha = 0.05$ level

residual error. SR is only one parameter giving maximum correlation to evaporation which remained for the last simulations. Four equations were developed to predict evaporation based on climatic parameters.

The coefficient of determination (R²), mean bias error (MBE), and root mean square error (RMSE) were applied to evaluate the performance of the model. The mean error implies underestimating or overestimating the value obtained from the model. The root of the mean square error improves more substantial weight to the mistakes of a more extensive scale.

Results and Discussion

Descriptive statistics

The EVA in Sakon Nakhon was obtained from January 2018 to December 2022, and the mean of EVA, SR, T, and RH are shown in Table 2. Seasonal factors are classified as follows: the dry season includes November-April; the rainy season includes May to October. The dry season had a higher EVA (4.22 mm) than the rainy season (4.14 mm). Mean climate factors include SR, T, and RH, which are 210.83 W/m², 26.52°C, and 85.13%, respectively.

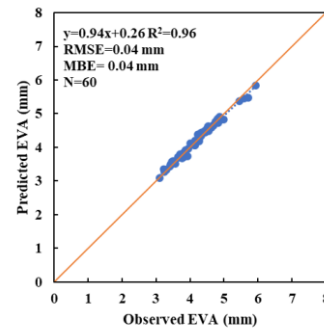
Table 2. Mean EVA (mm) and climate conditions

Season	EVA (mm)	SR (W/m ²)	T (°C)	RH (%)
Dry	4.22	646.31	25.71	73.05
Rainy	4.14	618.18	27.33	91.22
Annual	4.18	632.25	26.52	82.13

Evaporation model

The LME was used for monthly SR, T, and RH data. LME was applied to all parameters. LME applied to the first Model as a standard to evaluate the enhancement. The significant level of each Model was tested at $\alpha = 0.001$, 0.01, and 0.05. Table 3 demonstrates 3 LME models. The best Model is shown in the 3rd row with R²=0.96 and RMSE = 0.04 mm. The results achieved from using the 3rd Model are presented in Figure 3. As shown in Figure 3, R² significantly rises by 78%, and RMSE declines by 0.86% compared with the

standard Model. Therefore, all factors are essential for estimating daily EVA. The fixed intercept (β_0) and the slopes ($\beta_1 \sim \beta_3$) of the LME model are established in Table 3. Table 3 demonstrates SR and T are significant at the $\alpha = 0.001$ level. High R² was found in the 3 Model; nonetheless, RH are insignificant at the $\alpha = 0.05$ level. β values indicate the change in the parameters that would increase the EVA.

**Figure 3. Scatterplots of EVA obtained from observation and prediction**

Seasonal Variation

The most significant LME subset was shown the differences between the two seasons. Tables 4-5 reveal the findings of all subset LME for dry and rainy seasons, respectively, and the best potential model is the 3rd model. SR, T, and RH are contained in the model. This best model describes significant improvements in the LME, notably for the rainy season. The R² increases from 0.92 to 0.99, and the RMSE drops by 83.33% (0.06 to 0.01 mm). In seasonal, best models also contain all parameters. Conversely, some components decrease under the significance level test. A possible explanation might be a slight variation throughout this season.

All β -values presented differing results, such as SR, T and RH providing a positive for both seasons except β_0 . This result is consistent with that of Findell *et al.* (2019), who found rising temperature increases EVA. Additionally, all parameters were significant in the dry season. A positive relationship was found between EVA, SR, and T in all seasons.

Table 4. The fixed effect of 3 models was employed to calculate EVA in the dry season from 2018-2022

Model	β_0	$\beta_{1(SR)}$	$\beta_{2(T)}$	$\beta_{3(RH)}$	RMSE	MBE	R ²
Model 1	-4.31*	0.04***			0.12	0.10	0.87
Model 2	-4.65***	0.02**	0.18***		0.04	0.03	0.97
Model 3	-7.26***	0.03***	0.16***	0.02**	0.03	0.02	0.98

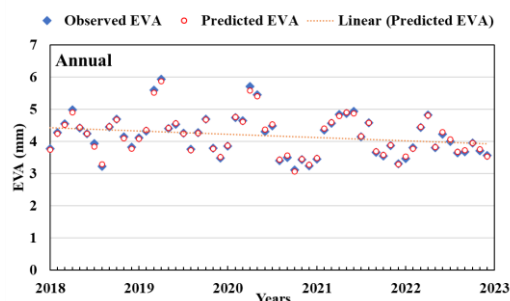
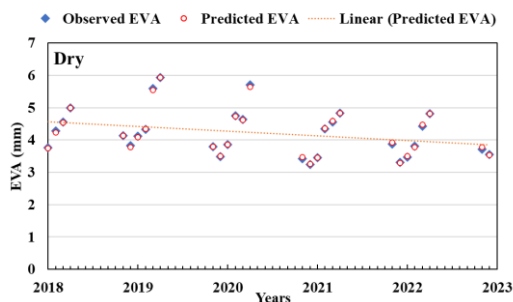
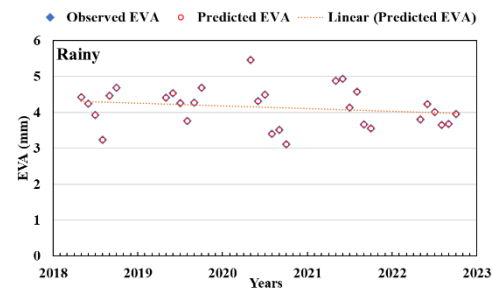
***Parameter is significant at the $\alpha = 0.001$ level**Parameter is significant at the $\alpha = 0.01$ level*Parameter is significant at the $\alpha = 0.05$ level**Table 5. The fixed effect of 3 models was utilized to calculate EVA in the rainy season from 2018-2022**

Model	β_0	$\beta_{1(SR)}$	$\beta_{2(T)}$	$\beta_{3(RH)}$	RMSE	MBE	R ²
Model 1	0.58	0.02***			0.07	0.06	0.92
Model 2	-2.37	0.02***	0.11		0.02	0.02	0.98
Model 3	0.41	0.02***	0.16*	0.04	0.01	0.01	0.99

***Parameter is significant at the $\alpha = 0.001$ level**Parameter is significant at the $\alpha = 0.01$ level*Parameter is significant at the $\alpha = 0.05$ level

EVA predictions

Sakon Nakhon has faced a drought problem in the past ten years. The monthly average of predicted EVA values from 2018 to 2022 are presented in Figure 4-6. In 2019, it gave high EVA values compared with 2022. Notably, observed and expected EVA show a similar tendency. EVA values from observations and predictions show an insignificant decrease in Sakon Nakhon from 2018 to 2022. A possible explanation might be that meteorological conditions such as low SR, and low T impact EVA.

**Figure 4. The monthly average EVA data between observed and predicted from 2018-2022****Figure 5. The monthly average EVA data between observed and predicted in dry season from 2018-2022****Figure 6. The monthly average EVA data between observed and predicted in the rainy season from 2018-2022**

Conclusions

Estimating EVA based on meteorological data was investigated in 2018-2022. Our study shows that predicted EVA achieved from the Model with meteorological parameters has a high performance for increasing current ground-based EVA observing networks. Furthermore, regarding the EVA observing networks, this technique will give necessary data related to drought to EVA and their effect on the climate change crisis.

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