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Performance Evaluation and Comparison of SWAT Model-Predicted Potential Trends in Sub-Ping Watershed, Thailand

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Abstract

Evapotranspiration (ET) is an important factor used in hydrological models as well as in the management of irrigation projects and water balance estimations. An essential instrument for the effective management of water resources is the hydrological model. An important factor in linking the energy, water, and carbon cycle in terrestrial ecosystems on a local to a global scale is ET, which creates dynamic interfaces between the ground surface and the lower atmosphere. The performance of the soil and water assessment tool (SWAT) model for the performance evaluation and comparison of potential evapotranspiration (PET) and actual evapotranspiration (AET) of the sub-Ping watershed (SPW) in Thailand. The MapWindow SWAT model was created using spatial and meteorological data. Using soil, topography, land use and land cover (LULC), and meteorological data as input factors, the three existing methods Penman-Monteith (PM), Priestly-Taylor (PT), and Hargreaves (HA) were utilized for the evaluation of PET and AET. The results showed that the predicted average PET values for PM, PT, and HA methods were 1,146.43, 1,124.69, and 1,200.20 mm/year with corresponding standard deviation values of 106.58, 53.27, and 105.90 mm/year, respectively. Furthermore, the average AET values for PM, PT, and HA methods were 652.97, 655.13, and 669.85 mm/year with corresponding standard deviation values of 76.95, 81.28, and 73.24 mm/year, respectively. In conclusion, the analysis indicated that PM and HA methods yielded similar results, while the PT method slightly differs. The study could be beneficial to watershed managers in addressing water-related problems and for sustainable water resource management.

Keywords: SWAT Model; Potential Evapotranspiration; Actual Evapotranspiration; Watershed.

1. Introduction

Sustainable growth and development necessitate efficient management of water resources. The prediction and verification of the major factors of evapotranspiration in the water cycle are important from local to global scales. Accurate evaluation of evapotranspiration (ET) is crucial for hydrological applications, rainfall-runoff models, drought prediction and monitoring, crop water management, and maintaining the water balance of the terrestrial ecosystem. ET includes all processes (transpiration and evaporation) that convert water at the earth's surface to water vapor. ET is one of the fundamental elements in the hydrological cycle, which affects the water yield of the watershed (Harmsen *et al.,* 2009; Dakhlaoui *et al.,* 2020). Although there have been a number of empirical methods for calculating potential evapotranspiration (PET), their applicability in all watersheds is severely limited by regional

conditions (Jung *et al.,* 2016). For assessing actual and projected ET, spatially explicit models and the water-budget computation are two of the most popular techniques (PET and AET). Direct measurement of ET is a complex process that requires expensive equipment to obtain accurate evapotranspiration data (Camp Van *et al.,* 2016; Ochoa *et al.,* 2019).

ET is a term frequently used to describe the climate-driven water demand that is determined by the amount of available surface water and the surrounding air conditions (Dakhlaoui *et al.,* 2020). ET is the collective term for the loss of water from plants' vascular systems during transpiration (TS) as well as evaporation (EV) from soil and exposed water surfaces. The rate of EV is greatly influenced by the amount of energy and water that are present on the surfaces that are evaporating in order to facilitate the diffusion of water vapor into the atmosphere. The maximum rate of ET that happens when there are enough water sources for both plants and soil is known as PET. This is true even if the availability of soil water may limit ET when other environmental factors are taken into account (Anabalón and Sharma, 2017). In order to achieve optimal water usage, decrease waste, and reduce pollution, knowledge of PET and AET is frequently needed for consumers of water after assessing the water requirements of crops and landscaping plants. Both PET and AET represent important concepts of traditional ET used in hydrology (Anabalón and Sharma, 2017). The direct measurement of ET is expensive, difficult, and time-consuming. The SWAT method used in this study is embedded in the HA as a temperature-based method, PT as a radiation-based method, and PM as a combined method for modeling ET and PET. The most common methods for estimating PET and AET are spatially explicit models and water budget estimates.

The hydrological modeling in developing countries and tropical regions, the collecting of trustworthy and ongoing meteorological data is a significant challenge (Odusanya *et al.,* 2019). In most investigations, Penman-Monteith (PM), Priestly-Taylor (PT) (using radiation-based), and Hargreaves (HA) (using temperature-based) are the three fundamental methods used to estimate PET (Aouissi *et al.,* 2016). The PM method is regarded as the gold standard, but it requires continuous daily climatic data, including solar radiation, wind speed, relative humidity, and maximum and minimum temperatures, all of which have a significant impact on the ET rate. (Arnold *et al.,* 1998; Aouissi *et al.,* 2016; Banda *et al.,* 2018; Djaman *et al.,* 2019). For the spatiotemporal calculation of the water budget and its precise projections, the use of geographic information systems (GIS) in conjunction with remote sensing technology has been continuously investigated as a substitute to assure efficient and effective management of watersheds. For simple use on a wide scale for spatiotemporal analysis of watersheds, these technologies are frequently coupled with some hydrological models, like soil and water assessment tool (SWAT), among others (Arnold *et al.,* 1998). Users have been motivated to integrate spatial data, GIS, and hydrologic modeling due to the existence of cutting-edge technology and the accessibility of cost-effective free data (Odusanya *et al.,* 2019; Lopez *et al.,*, 2017; Sholagberu *et al.,* 2019).

The SWAT model is a part of the group of distributed, deterministic hydrological models that incorporates PM, PT, and HA techniques for PET estimate. It is a physically-based semi-distributed model that can compute hydrological balance parameters on a daily, monthly, and annual basis within the watershed (Neitsch *et al.,* 2011; Abbas and Mohammad, 2012). Considering the lack of reliable to nonexistent ground-observed climatic data required for accurate daily estimation of PET and AET in many parts of Thailand, an assessment of other alternative methods requiring less climatic data is invaluable to estimate PET and AET that would ensure efficient water resource management for agricultural, hydrological and environmental purposes. However, the selection of appropriate models for ET computations in watersheds remains challenging to watershed managers, especially in data-scarce regions. The current, water resources issue of SPW is likely to worsen and intensify, due to the high concentration of agricultural activities and LULC change in the high land, which natural and environmental resources become a serious issue for the SPW. This affects people living in the Khlong Lan, Phran Kratai, Um Phang, Kosamphi Nakhon, and Muang Kampaeng Phet District in Kampaeng Phet Province, including the Phop Phra and Muang

Tak District in Tak Province, as well as surrounding areas and all living things. Thus, this study aimed to investigate the performance evaluation and comparison of the SWAT model predicted PET and AET trends of watersheds.

2. Materials and methods

2.1 Study area

The watershed studied is in the sub-Ping watershed (SPW). The SPW is in northern Thailand, between latitudes 99°96′09.51″E and 99°55′25.01″E, and longitudes 16°87′25.57″N and 16°36′01.85″N, covering an area of 2,318.60 km². The southwest of SPW is of high elevation surrounded by mountains with a digital elevation model (DEM) ranging between 67 and 1,737 mean sea level (MSL) (Figure 1). A 10×10 m pixel DEM was obtained from the shuttle radar topography mission (SRTM) archive. Each of the SW has a distinct mixture of land use and land cover (LULC), slope, soil data, and 2 automatic weather stations. This makes it possible to study the differences in evapotranspiration and other hydrological characteristics for different LULC, soil, and slope units within the watershed area. During SWAT modeling, the watershed was delineated and discretized into 9 SW and 287 hydrological response units (HRUs).

2.2 Land use and land cover (LULC) of the sub-ping watershed (SPW)

The LULC map of SPW used for SWAT modeling was obtained from Land Development Department in the year 2020. The LULC of SPW were classified into 14 classes: agricultural areas, maize, paddy field, marsh and swamp, evergreen forest, deciduous forest, forest plantation, orchard, pasture, urban or built-over, scrub, other (landfill, laterite pit, sand pit, soil pit, grass, garbage dump, beach, abandoned mine, institutional land, etc.), reservoir, and water (rivers, streams, canals, farm pond, fish farm, etc.), respectively. According to the statistics gathered, the deciduous forest was the biggest LULC in the SPW with 47.75 % or around 1,107.05 km². Following the significant LULC in the SPW depicted, there were an increase in agricultural areas, paddy field, and evergreen forest was 22.19, 10.43, and 7.70 % or around 514.51, 241.73, and 178.50 km², respectively. In contrast, the lowest LULC was pasture about 0.09 % or around 2.02 km² (Figure 2 and Table 1). At this cell size, the resulting grids for the SPW consisted of 2,437 cells (Figure 3).
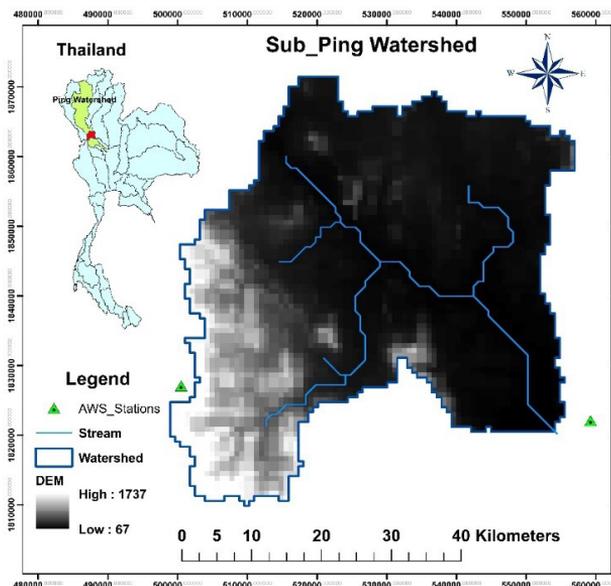

Figure 1. Location of the sub-ping watershed (SPW) with a digital elevation model (DEM), drainage network, and automatic weather stations
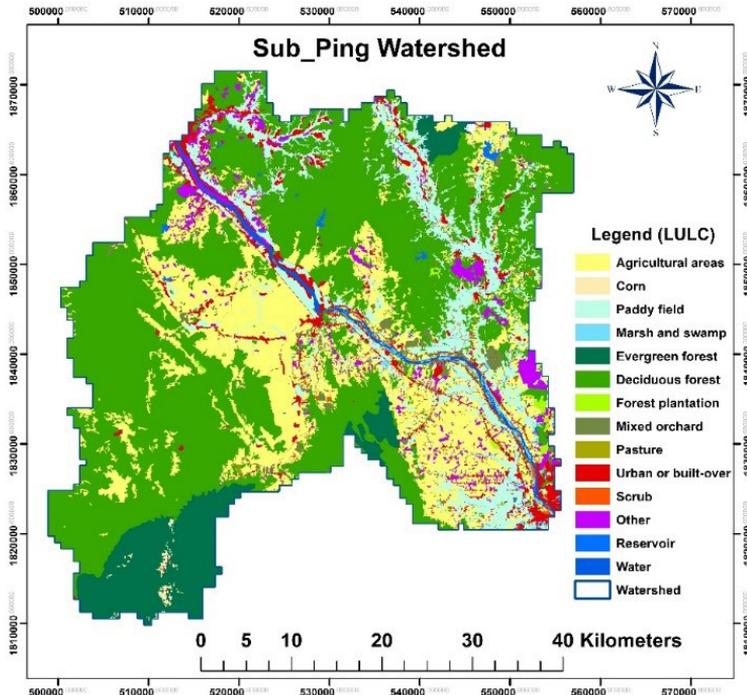
Figure 2. Land use and land cover (LULC) of the sub-ping watershed (SPW) map

Table 1. Land use and land cover (LULC) of the sub-ping watershed (SPW)

| Order	LULC Type	SWAT code	Area (km^2)	% of Watershed
1	Agricultural areas	AGRL	514.51	22.19
2	Maize	CORN	4.38	0.19
3	Deciduous forest	FRSD	1,107.05	47.75
4	Evergreen forest	FRSE	178.50	7.70
5	Forest plantation	FRST	5.66	0.24
6	Marsh and swamp	MASW	11.43	0.49
7	Mixed orchard	MORC	41.26	1.78
8	Other	OTHR	68.80	2.97
9	Paddy field	RICE	241.73	10.43
10	Pasture	PAST	2.02	0.09
11	Reservoir	RESE	9.64	0.42
12	Scrub	SCRU	19.31	0.83
13	Urban or built-over	URBN	87.40	3.77
14	Water	WATR	26.92	1.16
	Total		2,318.60	100.00
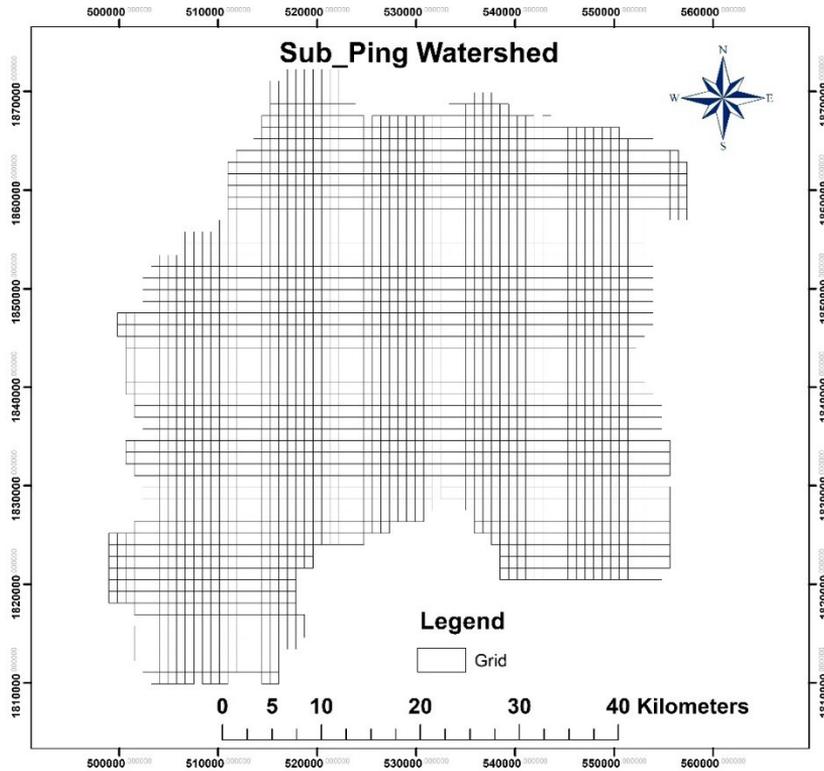
Figure 3. The resulting in grid cells of the sub-ping watershed (SPW) map

2.3 The soil group of the sub-ping watershed (SPW)

The digital soil group for the SPW was obtained from soil data of Thailand in form of soil type and texture, produced by the Land Development Department. The 6-soil group of the SPW area was extracted for use in the SWAT model as one of the input parameters. The soil group map consists of 35.40 % soil-1, 29.63 % soil-14, 25.19 % soil-20, 3.89 % soil-18, 3.11 % soil-4, and 2.78 % soil-10, respectively (Figure 4 and Table 2).

2.4 Weather data of the sub-ping watershed (SPW)

The hydrological balance within the watershed is influenced by a number of meteorological records, including rainfall, maximum and lowest temperatures, solar radiation, and humidity. The weather data was obtained from the Thai Meteorological Department of Thailand, and employed in simulations of AET and PET utilizing the model. A weather generator built inside the SWAT model was used to create additional meteorological data in order to meet the simulation's data requirements.

2.5 Model input data

The watersheds can be preprocessed and divided into SW depending on their topographical characteristics using the MapWindow SWAT platform. Some other processing on the platform includes shape file editing, input parameterization, model running, and calibration. The parameters needed input to run the SWAT model include the topography in form of a DEM rasterized to 10 x 10 m, LULC map, digital soil group map, and meteorological data, as in Table 3. The during GIS process of putting up a model using MapWindow SWAT, all of the maps are analyzed, the watershed and stream networks are defined, and SWAT creates all of the files necessary to execute the model (George and Leon, 2007; Abbas and Mohammad, 2012; Banchongsak *et al.,* 2017).
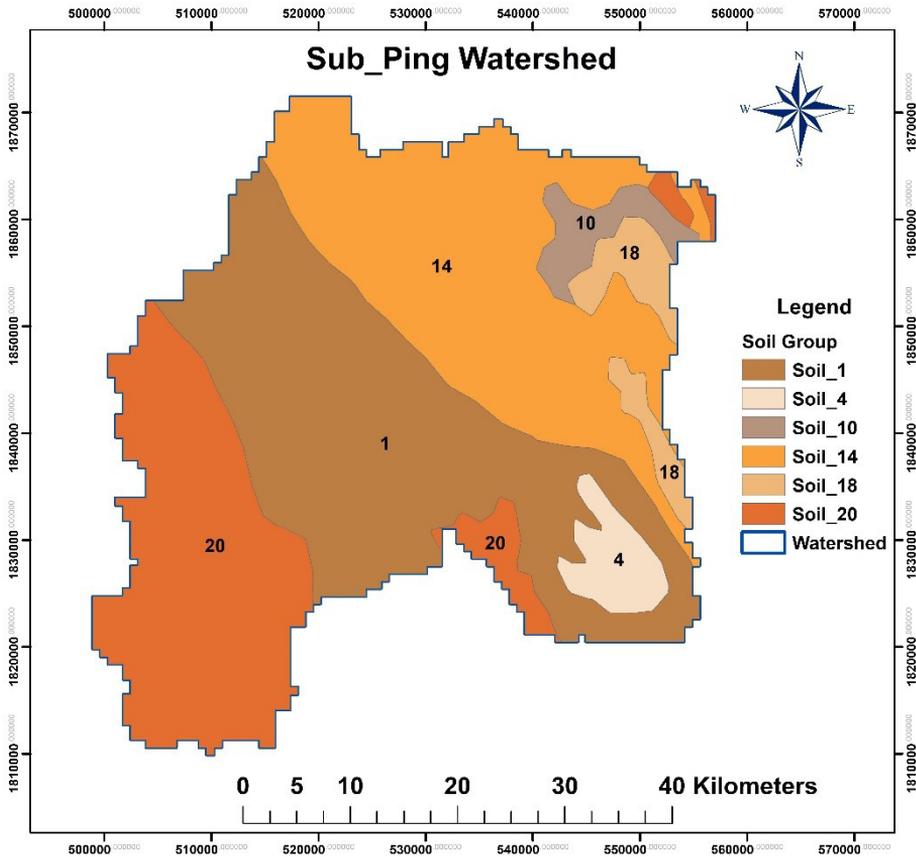
Figure 4. Soil group of the sub-ping watershed (SPW) map

Table 2. Soil group of the sub-ping watershed (SPW)

Order	Soil group	Soil texture	Area (km²)	% of Watershed
1	Soil-1	Clay-Loam	820.87	35.40
2	Soil-4	Clay	72.08	3.11
3	Soil-10	Clay-Loam	64.35	2.78
4	Soil-14	Sandy-Clay-Loam	687.11	29.63
5	Soil-18	Sandy-Loam	90.19	3.89
6	Soil-20	Sandy-Loam	584.01	25.19
	Total		2,318.60	100.00

Table 3. The parameters input for the soil and water assessment tool (SWAT) model

Order	Data type	Description	Source/Remark
1	Topography	Digital elevation model (10 x 10 m)	NASA and the Ministry of Economy
2	Land use types	LULC classification (14 classes)	Land Development Department
3	Soil groups	Soil data of Thailand (Soil type and texture)	Land Development Department
4	Meteorology	Daily precipitation, maximum and minimum temperatures, relative humidity, wind, and solar radiation	Thai Meteorological Department

2.6 Model setup

The most important steps in the SWAT model are the division of the watershed into SW, the definition of soil, land use, and weather data. The delineating of the watershed comes first, then data on soil and land use are entered to create the HRUs in SW. The first step in setting up the SWAT model uniformly projects all spatial datasets. Furthermore, the setup entails choosing weather sources from the SWAT database and specifying simulation periods. The MapWindow SWAT model was used to mimic the weather data for a 30-year period. Additionally, a number of techniques are available for the estimation of surface runoff (such as the curve number or Green and Ampt methods), channel water routing (such as the Muskingum method's variable), and PET (such as the MP, PT, and HA methods).

2.7 The soil and water assessment tool (SWAT) model description

The SWAT model is a continuous, long-term, semi-distributed, conceptual river watershed scale model with spatially distributed parameters developed to predict the effects of land management practices in large, complex watersheds on the hydrology, sediment, and contaminant transport in agricultural watersheds under varying soils, land use, and management conditions (Arnold *et al.* 1998; Neitch *et al.* 2010; Krysanova and White, 2015; Banchongsak, 2022; Banchongsak *et al.* 2022). The SWAT makes different predictions for soil and plant evaporation. SWAT calculates the actual ET using PET. The PET is a measure of how much water could evaporate and transpire if soil water were unrestricted. The relationship between PET and leaf area index is used to assess potential soil water evaporation. Using exponential functions of soil depth and water content, the actual soil evaporation is approximated. The amount of water in the soil can serve as a limiter for plant transpiration, which is estimated as a linear function of PET, leaf area index, and root depth (Arnold *et al.,*1998). The hydrologic cycle as simulated by SWAT is based on the water balance, as in Equation 1.

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad (1)$$

Where SW_t is the final soil water content (mm H$_2$O), SW_0 is the initial soil water content (mm H$_2$O), t is the time (days), R_{day} is the amount of precipitation on the day (mm H$_2$O), Q_{surf} is the amount of surface runoff on the day (mm H$_2$O), E_a is the amount of evapotranspiration on the day (mm H$_2$O), W_{seep} is the amount of percolation and bypass flow exiting the soil profile bottom on the day (mm H$_2$O), Q_{gw} is the amount of return flow on the day i (mm H$_2$O).

The SWAT model can use various equations for PET calculation, and this study used all three calculations available within SWAT: Penman–Monteith (Monteith, 1965), Priestley–Taylor (Priestley and Taylor, 1972), and Hargreaves (Hargreaves *et al.,*1985). Once the total PET is determined, the AET must be calculated. The SWAT model first evaporates any rainfall that is intercepted by the plant canopy. Next, the SWAT calculates the maximum amount of transpiration and the maximum amount of sublimation/soil evaporation. The actual amount of sublimation and evaporation from the soil is then calculated (Neitsch *et al.* 2011).

2.8 Potential evapotranspiration (PET) of the Penman-Monteith (PM) method

The PM method combines components that account for the energy needed to sustain evaporation, the strength of the mechanism required to remove water vapor, aerodynamic, and surface resistance terms (Monteith, 1965), as in Equation 2.

$$\lambda E = \frac{\Delta \cdot (H_{net} - G) + \rho_{air} \cdot C_p \cdot [e_z^0 - e_z]/r_a}{\Delta + \gamma \cdot (1 + r_c / r_c)} \quad (2)$$

Where λE is the latent heat flux density (MJ/m^2/d), E is the depth rate evaporation (mm/d), Δ is the slope of the saturation vapor pressure-temperature curve, de/dT (kPa/^{o}C), H_{net} the net radiation (MJ/m^2/d), G is the heat flux density to the ground (MJ/m^2/d), ρ_{air} is the air density (kg/m^3), C_p is the specific heat at constant pressure (MJ/kg/^{o}C), e_z^0 is the saturation vapor pressure of air at height z (kPa), e_z is the water vapor pressure of air at height z (kPa), γ is the psychometric constant (kPa/^{o}C), r_c is the plant canopy resistance (s/m), and r_a is the diffusion resistance of the air layer (aerodynamic resistance) (s/m).

2.9 Potential evapotranspiration (PET) of the Priestly-Taylor (PT) method

Priestley and Taylor (1972) developed a simplified version of the combination for use when surface areas are wet. The aerodynamic component was removed and the energy component was multiplied by a coefficient, $\propto_{pet}$ = 1.28, when the general surroundings are wet or under humid conditions, as in Equation 3.

$$\lambda E_0 = = \propto_{pet} \cdot \frac{\Delta}{\Delta + \gamma} \cdot (H_{net} - G) \qquad (3)$$

Where λE_0 is the PET (mm/d), γ is the psychometric constant (kPa/^{o}C), H_{net} the net radiation (MJ/m^2/d), G is the heat flux density to the ground (MJ/m^2/d).

2.10 Potential evapotranspiration (PET) of the Hargreaves (HA) method

The HA method estimates PET using only maximum and minimum temperatures. Several improvements were made to the original equation and the form used in SWAT was published in 1985 (Hargreaves and Samani, 1982, 1985), as in Equation 4.

$$\lambda E_0 = 0.0023 \cdot H_0 \cdot (T_{mx} - T_{mn})^{0.5} \cdot (T_{av} + 17.8) \quad (4)$$

Where λE_0 is the PET (mm/d), H_0 is extra-terrestrial radiation (MJ/m^2/d^1), T_{mx} is the maximum air temperature for the given day (^{o}C), T_{mn} is the minimum air temperature for the given day (^{o}C), and T_{av} is the mean air temperature for a given day (^{o}C).

2.11 Potential evapotranspiration (PET) model simulation scenarios

Using daily precipitation statistics and the default SWAT parameters, the soil conservation services - curve number (SCS-CN) approach was used to estimate surface runoff. Based on information on the research area's land use and soil, these parameters were established. The watershed was initially separated into SW and then into hydrologic response units, or the HRUs,

in order to take into consideration, the variations in soil, land use, topography, and meteorological data, among other factors (Gassman *et al.,* 2007). Simulations were run utilizing the three ways to gauge how well the PET techniques included in the SWAT model performed. Based on recorded daily temperature data. The PET was computed using all three available methods in SWAT based on observed daily temperature data. The HA approach was chosen because, in contrast to other methods like PT and PM, it just requires temperature data. The Muskingum method was used to direct the combined runoff from each sub-watershed to the main watershed outlet through the network of rivers. The rainfall distribution was calculated using a first-order Markov chain skewed normal. The outcomes were examined using descriptive techniques, like percentages, averages, standard deviations, etc. The model was then calibrated and validated using statistical techniques, including NSE and R^2 criteria for the accuracy of the findings (Adeogun *et al.,* 2014; Adeogun *et al.,* 2015). The analysis included repeated analysis of variance (ANOVA) to evaluate the three approaches, as well as the XLSTAT program, which executes all descriptive tools.

3. Results and discussion

3.1 Statistical analysis for the predicted potential evapotranspiration (PET)

Using the SWAT model, a quantitative analysis of the simulated dataset acquired from the 30-year simulation period was conducted. The results are shown in Table 4. The correlation between the observed (data from the Thai Meteorological Department) and simulated (data from the model) datasets yielded 0.83 and 0.87, respectively, for calibration and validation using NSE and approximately 0.82 for both calibration and validation when R^2 was used. These values of NSE and R^2 indicated a good model performance in simulating PET and AET for the watershed under consideration. The relationship among the PM, PT, and HA approaches is illustrated

in Figure 5 by showing the expected annual PET average. The HA approach was found to have a higher predictive value in the year 1991 and continued with close proximity to the PM method. The predictions from the three methods are closer to one another with similar patterns. However, the PT method predicted the least prediction until 2017 through 2020 when it predicted almost similar to the other two methods results.

3.2 Analysis of covariance for the simulated average values

The statistical summary for all the methods considered in this study is presented in Table 5. Contrary to the PT approach, it was concluded that the standard deviation values for the PM and HA procedures differ rather little from one another. Analysis of the results showed that the PM, PT, and HA models produced average PET values of 1,146.43, 1,124.69, and 1,200.20 mm/year, respectively.

Table 4. Simulated average values of the potential evapotranspiration (PET) and ET for the three methods

Year	Penman-Monteith (PM)		Priestley-Taylor (PT)		Hargreaves (HA)	
	PET (mm)	ET (mm)	PET (mm)	ET (mm)	PET (mm)	ET (mm)
1991	1,383.95	583.32	1,156.58	537.24	1,583.15	585.10
1992	1,034.33	711.76	1,083.91	709.79	1,178.04	715.62
1993	1,033.15	647.66	1,081.21	627.08	1,220.40	653.09
1994	1,045.66	688.38	1,111.66	700.46	1,122.44	691.61
1995	1,160.00	754.69	1,062.67	753.14	1,049.21	751.99
1996	1,042.91	688.24	1,117.18	691.53	1,155.32	684.75
1997	1,256.98	664.58	1,115.95	673.60	1,190.40	679.47
1998	941.93	706.44	1,054.98	693.98	1,103.61	730.83
1999	1,047.85	619.47	1,017.63	614.02	1,169.83	637.58
2000	1,089.04	735.29	1,114.67	726.09	1,192.85	735.18
2001	1,268.47	719.16	1,070.73	702.13	1,155.04	721.65
2002	1,236.33	757.08	1,119.58	764.73	1,101.61	742.91
2003	1,265.32	755.06	1,079.52	765.44	1,056.10	743.63
2004	1,009.21	736.75	1,102.48	744.72	1,106.54	714.70
2005	1,158.96	626.21	1,129.11	604.45	1,297.37	648.30
2006	1,138.15	647.36	1,157.90	668.75	1,208.13	665.15
2007	1,338.96	448.60	1,321.41	449.39	1,426.21	455.99
2008	1,172.59	480.27	1,132.64	482.23	1,304.47	513.51
2009	1,154.01	557.43	1,134.95	570.50	1,254.03	567.25
2010	1,168.80	634.63	1,168.93	644.72	1,249.13	656.16
2011	1,130.77	699.50	1,157.77	712.05	1,240.87	717.91
2012	1,095.33	550.48	1,073.02	559.03	1,231.90	570.77
2013	1,098.24	616.95	1,161.02	647.02	1,188.14	641.22
2014	1,101.43	604.71	1,138.37	627.93	1,196.66	621.10
2015	1,324.21	615.83	1,117.98	640.49	1,218.05	638.92
2016	1,067.18	724.87	1,151.46	735.98	1,150.86	729.20
2017	1,110.07	684.84	1,153.14	715.11	1,149.22	680.38
2018	1,269.25	647.44	1,153.31	556.73	1,238.10	734.09
2019	1,161.04	663.51	1,169.90	635.73	1,133.14	720.26
2020	1,088.81	618.59	1,131.07	699.80	1,135.05	747.25

Remark: "Potential evapotranspiration (PET)" is the evaporation from an extended surface of plants or crops and is always well-supplied with water.

"Evapotranspiration (ET)" is a combination of evaporation (from land and water surfaces) and transpiration (from plants or crops)

"Evaporation (EV)" is the movement of water directly to the air from sources such as soil and water bodies.

"Transpiration (TS)" is the movement of water from root systems, through a plant, and exits into the air as water vapor.

3.3 Statistical analysis for actual evapotranspiration (AET)

The anticipated yearly average of actual evapotranspiration is shown in Figure 6. Table 6 provides a quantitative breakdown of the SWAT model outputs. In many scenarios, it is acceptable to formally state that AET is estimated from PET. Since it depends on PET, water loss from the watershed area does not always precede potential. When the ET value is lower than the PET value, vegetation cannot draw water from the soil. The average AET values from the PM, PT, and HA models

were 652.97, 655.13, and 669.85 mm/year, respectively. Earls and Dixon (2008) used the PM, PT, and HA PET methods together with varied meteorological input data (simulated and real data) to estimate and analyze the accuracy of PET. The study highlighted no significant differences in the predicted PET of modeled and real meteorological data for a given PET calculation method. Furthermore, studies have shown that AET and PET are controlled by several hydro-meteorological parameters, such as wind, soil moisture, temperature, relative humidity, etc. in warmer and drier seasons (Xu and Singh, 2005).
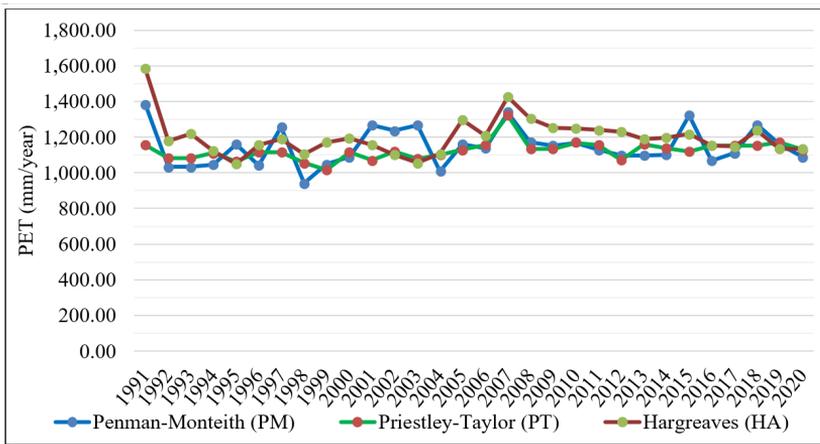

Figure 5. Predicted annual average of potential evapotranspiration (PET)

Table 5. Quantitative summary of the potential evapotranspiration (PET)

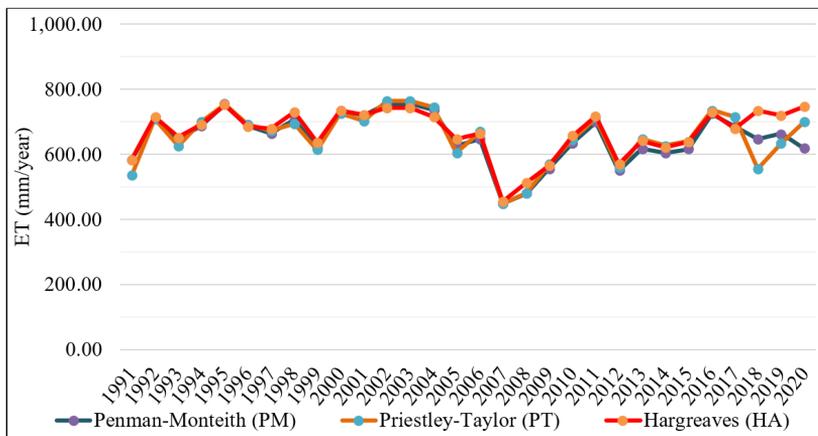| Order	Observations	Variable	Maximum	Minimum	Average	Standard deviation
1	30	Penman-Monteith (PM)	1,383.95	941.93	1,146.43	106.58
2	30	Priestly-Taylor (PT)	1,321.41	1,017.63	1,124.69	53.27
3	30	Hargreaves (HA)	1,583.15	1,049.21	1,200.20	105.90

Figure 6. Predicted annual average of evapotranspiration (ET)

Table 6. Quantitative statistics for actual evapotranspiration (AET)

Order	Observations	Variable	Maximum	Minimum	Average	Standard deviation
1	30	Penman-Monteith	757.08	448.60	652.97	76.95
2	30	Priestly-Taylor	765.44	449.39	655.13	81.28
3	30	Hargreaves	751.99	455.99	669.85	73.24

4. Conclusion

The study performance evaluation and comparison of the SWAT model for predicted PET and AET trends of SPW in northern Thailand during 1991-2020. In this study, the authors used the SWAT model to estimate PET and AET. The SWAT provides three methods for computing PET: PM, HA, and PT. The MapWindow SWAT model was created using spatial, meteorology, soil, topography, and LULC data as input factors to generate missing weather data and to fill in gaps in measured records. Our case showed interesting results. The three validated models were able to simulate PET and AET in similar results, but with different parameter responses. The PM and HA methods were found to have the least correlation in the input parameters and produce results that were comparable to PET and AET. However, the PT underestimated the average PET. In conclusion, the SWAT model can be used to meet the challenge where a lack of reliable meteorological data exists by using simulated meteorological data as a surrogate. The trend of the need for water may continue to rise in the future. Furthermore, the study may help watershed managers manage water resource problems sustainably in the watershed. Decision-makers should involve stakeholders to support improved water management for balanced and sustainable natural resources.

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