Development of mass-transfer evaporation model for Lake Nasser, Egypt
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ABSTRACT

Evaporation from free water surface is considered a very important constituent in both the energy and hydrologic cycles. Precise measurement of evaporation from the free water surface is almost impossible. This is why we need a calculation model for free water evaporation. In this study, a simple mass-transfer evaporation model was developed to be applicable over Lake Nasser in the hyper-arid region located in the south of Egypt. Measured meteorological data (2011–2014) at two stations, Aswan and Abu-Simbel, were used to calculate free water surface evaporation using Priestly–Taylor equation. Priestly–Taylor equation was used because it is the most appropriate equation for Lake Nasser evaporation according to the literature. Results from this model were used to develop a simple mass-transfer evaporation model. The statistical analysis for both calibration and validation periods were very good. The slope of the regression line is about 0.9, with a coefficient of determination of 0.98. The t value is 0.6, at p value of 0.544, which is much greater than 0.05. The developed model could be used with confidence at Aswan meteorological station or on the average of the two meteorological stations, while it should be used carefully on Abu-Simbel meteorological station.

Key words | equation, evaporation, Lake Nasser, mass-transfer, model

INTRODUCTION

The global warming phenomenon has attracted broad interest among the scientific community regarding evaporation and transpiration for their immense impact on the global hydrologic cycle. Traditionally, free water surface evaporation calculation measurements have been used for water resources planning and management (Elsawwaf et al. 2010; Li et al. 2016). For most of the man-made lakes, evaporation is the main cause of water losses (Balbag et al. 2007). Direct measurement of evaporation is too difficult (Wartena 1974). In order to know how and where to record data and to be able to explicate the data of measurements, theoretical and practical developments are required (Tytler et al. 2006). This provides another and very important reason for both development of theory and measurements of evaporation (Howard & Lloyd 1979). Many attempts have been made to find a precise evaporation model applicable for Lake Nasser, Egypt, which is a hyper-arid region. Given the nonlinear and complex behavior of the evaporation phenomenon, and because this parameter is not measured at some meteorological stations, and that the meteorological stations measuring this component are not properly distributed in many developing countries, modeling techniques should be used to predict evaporation. Moazenzadeh et al. (2018) used selected parameters, under separate scenarios, as inputs to support vector regression (SVR) and the SVR model coupled with firefly algorithm (SVR-FA) to predict daily values of evaporation in Iran. Seven different scenarios were tested and showed that the errors in evaporation prediction decreases as the number of inputs increases. Using a threshold value equal to the average measured evaporation at each station, both the SVR and SVR-FA models provided more precise results when predicting evaporation...
values lower than the threshold. Ghorbani et al. (2018) developed a hybrid artificial intelligence (AI) procedure based on a multi-layer perceptron framework and quantum-performed particle swarm optimization (MLP-QPSO) procedure. The developed procedure was evaluated for its precision in the daily pan evaporation estimation in northern Iran. The study showed that the accuracy of the hybrid MLP-QPSO model was greater than hybrid MLP-PSO and a standalone MLP model applied in the context of daily pan evaporation. It was highlighted that an operational application of the integrated hybrid MLP-QPSO model could be expanded by merging the model into a Bayesian model averaging (BMA) algorithm, which has the ability to assess the model selection uncertainty. Qasem et al. (2019) investigated the efficiency of some data-driven techniques including artificial neural networks (ANN) and SVR, and a combination of them with wavelet transforms (WSVR and WANN) in evaporation prediction at Tabriz (Iran) and Antalya (Turkey) stations. For evaluating the techniques’ performances, four different statistical indicators were utilized, namely, the mean absolute error (MAE), the root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), and the correlation coefficient (R). Also, Taylor diagrams were used to test the similarity among the observed and predicted data. The results showed that, at Tabriz station, the third input combination, that is, air temperatures and solar radiation used by ANN (ANN3) with RMSE of 0.701, MAE of 0.525, R of 0.990, and NSE of 0.977 had better performances in comparison with WANN, SVR, and WSVR. Thus, the wavelet transforms did not increase the precision of ANN and SVR predictions at Tabriz station. Also, at Antalya station, the fifth input combination, that is, air temperature, relative humidity, and solar radiation used by ANN (ANN5) with RMSE of 0.923, MAE of 0.697, R of 0.962, and NSE of 0.898 demonstrated the most precise predictions.

Omar & El-Bakry (1981) estimated monthly values of evaporation from Lake Nasser by the heat budget and bulk aerodynamic methods, using average monthly estimates of different meteorological elements over the lake. The annual lake evaporation was found to be about 7.4 mm/d with maximum evaporation in June (10.9 mm/d) and minimum evaporation in January (3.8 mm/d). It was found that the average of heat budget and bulk aerodynamic methods gave good results, since the heat budget method only underestimated the evaporation, while the aerodynamic method overestimated the evaporation.

El Bakry (1994) studied the net radiation over the water surface of Lake Nasser, Egypt. It was found that the outgoing radiation over the lake water surface during the cold season is higher than the warm season. An equation was developed to found net radiation by knowing the global solar radiation and the difference between water surface and air temperatures. It has been proven that the Swinbank formula is the best empirical formula to calculate the effective outgoing (long-wave) radiation over the lake.

Sadek et al. (1997) used five methods to calculate evaporation from Lake Nasser, namely, water budget method, energy budget method, bulk aerodynamic method (Dalton), combination method (Penman), and complementary relationship lake evaporation (CRLE) model (Morton). The annual averages (in mm) were 5.9 for the water balance, 5.9 for the energy balance, 7.1 for the bulk aerodynamic, 6.6 for the Penman, and 5.7 for the CRLE method, respectively. The paper found that the best method representing the evaporation from the lake is the CRLE method.

Shaltout & El Housry (1997) studied the evaporation from Lake Nasser. It was discovered that the lake evaporation ranged between 10 and 16 billion cubic meters (BCM) every year. The evaporation represented 20–30% of the Egyptian income from Nile water. Correlation analysis between ground station measurements for temperature, atmospheric infra-red, and water vapor content, on one side, and tile cloudiness observed by Meteosat in the infra-red band (10.25–12.5 μm), on the other side, was performed at the lake’s northern head near High Aswan Dam. Empirical relations for estimating the evaporation over the lake were developed and tested. The quantity of water evaporated every day was determined using Meteosat infra-red window observations and the developed empirical models.

Tolba (2004) studied evaporation from Lake Nasser using daily data of four hydro meteorological automatic floating stations at Aswan, Allaqi, Wadi El-Arab, and Abu Simble regions during the period 1999–2001 to estimate evaporation. In addition to water balance method, three different approaches were used: Harbeck (1962) and Vikulina (1973) models represented the aerodynamic
approach, Priestley–Taylor (1972) model represented the energy budget approach, and Penman (1948) model represented the combination approach. It is clear that the Penman method gave the lowest annual evaporation rate and Vikulina gave the highest annual rate while Priestley–Taylor and Harbeck methods gave close values of annual evaporation rates to actual (approximately 7.0 mm/d).

Dawod et al. (2006) studied the effect of climate change on evaporation of Lake Nasser. It was found that the annual average evaporation from class (A) pan has been decreased by about 0.69 mm and lake evaporation has been decreased by 0.3 mm. From this, the annual Lake Nasser evaporation in 2017 was expected to be decreased by about 0.5 billion cubic meter of water over the whole area of the lake.

Badawy (2009) studied climate change impacts on Lake Nasser; meteorological data for years (1986–2006) of three shore stations at the lake were used. In general, it was proved that the mean annual values of evaporation will not change much during the study period (2000–2050). The study proved that the evaporation change for the three stations Aswan, Allaquy, and Abu-Simble were −0.47, 1.9, and −0.57%, respectively, and the total change for the whole lake is 0.29%.

El-Sawwaf et al. (2010) published a paper providing a comprehensive ten-year analysis of seasonal variations in lake evaporation using the Bowen ratio energy budget method (BREB) and six traditional methods. Evaporation rates were obtained ranging from 2.5 to 11.2 mm day$^{-1}$ and averaged 5.90 mm day$^{-1}$. It was found that combination methods provide the best comparisons with the BREB evaporation.

El-Mahdy (2014) studied High Aswan Dam Lake evaporation rate using water budget method, energy budget method (Priestly–Taylor model, 1972), mass transfer method (Harbeck model, 1962; Vikulina model, 1962; and Hyvarinen model, 1973), radiation method (Turc model, 1970), temperature-based method (Ivanov model, 1970), combination method (Penman model, 1948; and Borrelli–Sharif model, 1989). Statistical analysis has been done to find the most appropriate technique of the lake evaporation calculation, where the water budget method was used to evaluate the other methods. The Priestley–Taylor model gave the best results and the closest to the water balance method.

Salih et al. (2019) proposed a novel approach called the co-active neuro-fuzzy inference system (CANFIS) for the modeling of evaporation from meteorological variables. Modifications were made in the back-propagation algorithm of CANFIS to enhance its prediction accuracy. The performance of the CANFIS model is compared with three well-established AI models for validation. The results showed that the accuracy of the CANFIS model in evaporation prediction was higher compared to the other AI models. It was also found that CANFIS was able to model evaporation from relative humidity and mean temperature only, with a NSE of 0.93, which was the highest among all other models.

From the literature, it is found that the most convenient evaporation model for Lake Nasser is the Priestly–Taylor 1972 model (Tolba 2004; El-Mahdy 2014). The main problem in application of the Priestly–Taylor, 1972 model is the shortage of data, since that the model requires a great deal of data such as solar radiation data, cloud cover data, albedo data, and others (Darwish 2012). There are many methods to calculate evaporation such as water budget method, energy budget method, mass-transfer method (aerodynamic method), radiation method, temperature-based method, combination method, and pan evaporation method.

Evaporation can be calculated from mass transfer across the air–water interface. The inference of the evaporation equations from the method of mass transfer is based on the concepts of the mass transfer of water vapor mass in the boundary layer between water and air (Hawkinson 1972). All mass-transfer equations depend on wind velocity and vapor pressure difference between actual and saturated vapor pressure. Evaporation is directly proportional to the product of vapor pressure differences and wind velocity. Jeffreys (1918) and Marciano & Harbeck (1954) were among the earliest researchers to study the mass-transfer evaporation concept. Following this, many scientists made improvements and progress in the area of evaporation assessment using mass-transfer theory (Prandtl 1935, 1952; Rossby 1936; Harbeck 1958, 1962; Hyvarinen et al. 1973; Vikulina 1973; Singh & Xu 1997).

The available literature investigated the evaporation from Lake Nasser using the existing models. None of them tried to develop a model specifically designed for the lake. The current study attempts to fill the gap by having a...
simple model with limited data, that could be applied to Lake Nasser and may be used for other lakes in arid regions.

**STUDY AREA**

Construction of the High Aswan Dam (HAD) across the River Nile during 1960–1971 was a landmark in recent Egyptian history. It is located 6 km south of Aswan city, Egypt. Its total length is about 3,600 m and its height above the river bed is about 111 m (Abu-Zeid & El-Shibini 1991).

High Aswan Dam Lake (Lake Nasser) (Figure 1) is an artificial lake created behind the dam, and it has attracted much interest by many researchers to study the whole topological, environmental, ecological, hydrological aspects of the lake. Lake Nasser is composed of two lakes: Lake Nasser in Egypt and Lake Nubia in Sudan. Lake Nasser is located in southern Egypt and northern Sudan between latitudes from 20° 27' N to 23° 58' N and longitudes from 30° 07' E to 33° 15' E (Sadek et al. 1997). Its surface area extends up to 6,500 km², with a volume of 162 BCM at an elevation of 182 m above mean sea level (amsl). The lake's total length is about 500 km (two-thirds of it in Egypt and the rest in Sudan).

**DATA**

The data used in this paper mainly consist of meteorological and radiation data. Temporal resolution of these data is daily during the years 2011–2014 for two stations: Aswan meteorological station (20° 27' N, 33° 15' E) and Abu-Simbel meteorological station (20° 27' N, 33° 15' E). The data were collected from the Egyptian Meteorological Organization. It is noticed that most of the researchers studied Lake Nasser evaporation based upon the data from Aswan meteorological station only, because of the limited data from other stations.

![Figure 1](http://iwaponline.com/jwcc/article-pdf/doi/10.2166/wcc.2019.116/640878/jwc2019116.pdf)
Here it is decided that the data should be based upon two meteorological stations, one on the downstream of the lake and the other at the upstream border of Lake Nasser in Egypt. Then, the data average for the two stations is used in the model development, calibration, and validation. The data average for the two stations is used to introduce values for the different parameters expressing the whole lake area (Tolba 2004). This approach is adopted to reach the most precise model, that is not only applicable over Aswan meteorological station impact area, but also applicable over the entire area of Lake Nasser.

METHODS

Despite the enormous diversity in the requirements of modeling practical hydrological applications, reliable and intelligent systems utilized prediction purposes are still needed for development. The main challenge in achieving the standards of an expert system is mainly due to the behavior and influence of the natural fluctuations of hydrological processes (Yaseen et al. 2018). In hydrology, the most widely employed computational intelligence (CI) approaches are based on fuzzy logics, artificial neural networks (ANNs), support vector machines (SVMs), wavelet models (W-CI), and evolutionary computing (EC), along with hybrid approaches which are a combination of the previously mentioned approaches (Fotovatikhah et al. 2018).

The main challenge to estimate free water surface evaporation is the lack of data. The standard meteorological records (e.g., air temperature, wind speed, relative humidity, radiation, air vapor pressure, and atmospheric pressure) might be available for some sites in a specific period of time. However, the data of water profile temperatures, which are essential to calculate the energy budget equation, are usually unavailable. Early researchers suggested the 1972 Priestly–Taylor model to calculate the evaporation from Lake Nasser but the model is very demanding in terms of data. Thus, here it is suggested to develop a model, that requires lesser data, with acceptable precision. The model will be based upon mass-transfer equation. The constants of the model will be optimized to get the most precise values. Statistical measures aimed to judge the quality of the model have been used. The statistical measures commonly used to compare two data sets are multiplicative form of the square error (mult), summation form of the square error (sum), two sample t-test, coefficient of determination (R²), chi square (χ²), NSE, coefficient of determination multiplied by the coefficient of the regression line between measured and simulated data (hR²), sum of squares of the difference of the measured and simulated values (SSQR), mean relative bias (PBIAS), Kling–Gupta efficiency (KGE), ratio of the RMSE to the standard deviation of measured data (RSR), and modified Nash–Sutcliffe efficiency (MNS) (Tasker 1982). The coefficient of determination R² is used to test the similarity between the developed model and the actual one. The coefficient of determination R² is the most widely used method to compare the data similarity of two data sets (Ross 2014). The two sample t-test is the most widely used test to check if the difference between the means of the two models is significant (Akritas 2016).

MODEL FORMULATION

The mass-transfer method is one of the simplest and oldest methods and is, till now, a widely used method for estimating free water surface evaporation because of its simplicity and reasonable accuracy (Valipour 2017). The mass-transfer methods are based on the Dalton equation, which for free water surface can be written as (Singh & Xu 1997):

$$E_0 = C(e_s - e_a)$$

(1)

where $E_0$ is free water surface evaporation (mm/day), $e_s$ is the saturated vapor pressure (mb), $e_a$ is the actual vapor pressure in the air (mb), and $C$ is aerodynamic conductance. Although $C$ depends on the horizontal wind speed, surface roughness, and thermally induced turbulence, it is normally assumed to be dependent on wind speed, $u$ (Sarma et al. 2017). Therefore, Equation (1) can be expressed as:

$$E_0 = f(u)(e_s - e_a)$$

(2)

The general form of $f(u)$ can be expressed as suggested by Singh & Xu (1997) as:

$$f(u) = A(1 + Bu)$$

(3)
Figure 2 | Comparison of Priestly–Taylor model versus El-Mahdy model on daily basis.
where $A$ and $B$ are constants and $u$ is the wind speed at 2 m height above ground (m/s).

Substituting from Equation (3) into Equation (2) would result in:

$$E_0 = A(1 + Bu)(e_s - e_a)$$

with considering that $(e_s - e_a)$ can be written as:

$$(e_s - e_a) = (1 - RH)e_s$$

where $RH$ is the relative humidity ($\%$).

Then, Equation (4) can be rewritten as:

$$E_0 = A(1 + Bu)(1 - RH)e_s$$

Thus, by knowing $u$, $RH$, and $e_s$, the only unknowns will be the constants $A$ and $B$.

**MODEL APPLICATION**

The current paper used spreadsheet software, Microsoft Excel 2010, for the purpose of calculating the two constants of the linear suggested model. The spreadsheet solver can calibrate the constants using two different ways without knowing the exact details of optimization techniques (Barati 2013). These procedures consist of (1) evolutionary solver and (2) generalized reduced gradient (GRG) solver (Fylstra et al. 1998). The results of the simulation of parameter estimation of the linear model indicated that Excel solver is a promising tool to reduce problems of the parameter estimation of the linear model.

![Figure 3](http://iwaponline.com/jwcc/article-pdf/doi/10.2166/wcc.2019.116/640878/jwc2019116.pdf)  
**Figure 3** | Comparison of Priestly-Taylor model versus El-Mahdy model on monthly basis.
The two constants, $A$ and $B$, were calculated using spreadsheet solver over the years 2011–2013. The results found the values of $A$ and $B$ constants to be 0.06164 and 0.62633, respectively. Equation (6) can be rewritten as follows:

$$E_0 = 0.06164 \cdot (1 + 0.62633 \cdot u)(1 - RH)e_s \tag{7}$$

The new model, the El-Mahdy model, outputs when compared with the outputs of the Priestley–Taylor model (1972) gave moderately accurate results, as shown in Figure 2. The authors then retried the comparison of the results on a monthly basis, as shown in Figures 3 and 4, to find if the constants vary from one month to another. In Figure 3, it is noted that the new model underestimates the evaporation values in the months from January to May, and overestimates the evaporation values in the rest of the months. The underestimation in cold months, January to May, could be attributed to lower wind speed, while the overestimation in hot months because of higher values of wind speed. Also, in Figure 4, the values of the coefficient of determination could be higher. It is clear now that using different values for the two constants for each month will be more realistic, the same as Albedo values that vary from one month to another (Sud & Fennessy 1982).

| Month     | A value | B value |
|-----------|---------|---------|
| January   | 0.09824 | 0.38428 |
| February  | 0.09475 | 0.35425 |
| March     | 0.11093 | 0.36043 |
| April     | 0.09804 | 0.38643 |
| May       | 0.08544 | 0.35864 |
| June      | 0.08233 | 0.35074 |
| July      | 0.08184 | 0.35018 |
| August    | 0.08249 | 0.35202 |
| September | 0.07787 | 0.3416  |
| October   | 0.07721 | 0.34058 |
| November  | 0.08519 | 0.34124 |
| December  | 0.09676 | 0.29949 |
MONTHLY MODEL CORRELATION

To correlate a model, it is recommended to use as much large time-series as available, so that the values of the constants become trusted. Since the available time-series of data are from 2011 to 2014, it was decided to use the 2011–2013 time-series for the correlation period, while dedicating the 2014 time-series for validation. The results of the correlation period gave a value for the constants, $(A)$ and $(B)$, for each month as shown in Table 1. The values of $(A)$ constant ranges from 0.07721 in October to 0.11093 in March. The $(A)$ factor value is very important in the equation, because it is multiplied by the value of wind speed, relative humidity, and saturated vapor pressure. Any small change in the value of $(A)$ factor will be reflected linearly on the value of evaporation. In other words, if the value of $(A)$ factor increased by 10%, with all other parameters constant, the value of evaporation will increase by 10% also. The maximum value of the $(A)$ factor equals about one and half times the minimum value, which reflects the variability of the weather and its impact on evaporation. On the other hand, the $(B)$ factor values range from 0.29949 in December to 0.38643 in April. The range of $(B)$ factor is narrower than that of $(A)$ factor, reflecting the relative importance of each one of them.

![Figure 5](https://i.imgur.com/5.png)  
**Figure 5** | Daily correlation of El-Mahdy model to Priestly-Taylor model.
Both Figure 5, for daily correlation, and Figure 6, for monthly correlation, showed a good match between the developed model and the base model. This means that the values of the developed factors (A) and (B) are representative of the Lake Nasser case.

To ensure that the developed values are accurate, a regression analysis between the models had been done, as shown in Figure 7. The slope of the regression line for the three years of calibration 2011–2013 is 0.968, 1.073, and 1.043, which could be considered satisfactorily. The coefficient of determination ($R^2$) for the three years is 0.979, 0.989, and 0.991, respectively, reflecting the good accuracy of the developed model.

One of the most widely used correlation tests to measure the match between two data sets is the t-test (Heeren & D’Agostino 1987). This test was applied to the results of the model and successfully produced a good result, as shown in Table 2. The t value is almost zero at $p$ value about 0.999, which leads to rejection of the null hypothesis and accepting the alternative hypothesis. It is clear there is no significant difference between the mean of the developed model and the base model.

From the regression analysis and t-test, one can notice that the values of the factors (A) and (B) could be trusted in the calculation of Lake Nasser evaporation, but only after validation of the developed model.

**MONTHLY MODEL VALIDATION**

Model validation is an important step to judge the model performance (Legates & McCabe 1999; Pontius & Schneider 2001; van Emmerik et al. 2017). The validation process was done on the data of year 2014. The results of
validation as shown in Figure 8 for daily validation and simplified to monthly results as represented in Figure 9, ensured that the values of $A$ and $B$ are good enough to be applied with confidence. The regression analysis of the validation period, as shown in Figure 10, clarified that the slope of the regression line is about 0.9, which is very close to 1, with a coefficient of determination of 0.98, reflecting the strength of the model. Also, the t-test was done on the validation period, and the results are found in Table 3. The t value is 0.6, which is close to zero, at $p$ value of 0.544. Since the $p$ value is much greater than 0.05, the null hypothesis is rejected and the alternate hypothesis is accepted, so it could be said that no significant difference exists between the means of the two models.

Knowing that both the coefficient of determination test values and the t-test values in model varied values each month are more trustworthy that that of constant values, the excellence of the monthly varied model emerged.

MODEL EFFICIENCY ON EACH STATION

It was interesting to test the model for each one of the two stations separately. Thus, we tested the performance of the developed model in both Aswan and Abu-Simbel meteorological stations.

Aswan meteorological station

The validation process was reimplemented on the data of year 2014 for Aswan meteorological station. The results of validation as shown in Figure 11 for daily validation and simplified to monthly results as represented in Figure 12, ensured that the values of $A$ and $B$ are good enough to be
applied with confidence on Aswan meteorological station. The regression analysis of the validation period, as shown in Figure 13, clarified that the slope of the regression line is about 1.01, which is very close to 1, with a coefficient of determination of 0.98, reflecting the strength of the model.

Also, the t-test was done on the validation period. The t value is 0.9, which is close to zero, at p value of 0.425. Since the p value is much greater than 0.05, the null hypothesis is rejected and the alternate hypothesis is accepted, so it could be said that there is no significant difference between the means of the two models.

Abu-Simbel meteorological station

The validation process was reimplemented on the data of year 2014 for Abu-Simbel meteorological station. The results of validation as shown in Figure 14 for daily validation and simplified to monthly results as represented in Figure 15, showed that the values of A and B underestimated the evaporation on Abu-Simbel meteorological station by around 20%. The regression analysis of the validation period, as shown in Figure 16, clarified that the slope of the regression line is about 0.73, which is far from 1, with a coefficient of determination of 0.94, reflecting the relative weakness of the model. Also, the t-test was done on the validation period. The t value is 2.03, which is close to zero, at p value of 0.04. Since the p value is
lower than 0.05, the null hypothesis is accepted and the alternate hypothesis is rejected, so it could be said that there is a significant difference between the means of the two models.

The validation process for the two meteorological stations showed that the developed model could be used with confidence on Aswan meteorological station, while it should be used carefully on Abu-Simbel meteorological station.

**CONCLUSIONS**

In Lake Nasser, Egypt, measured meteorological data at Aswan and Abu-Simbel were used to calculate free water surface evaporation using the Priestly-Taylor (1972) equation. Results from this model were used to develop a simple mass-transfer evaporation model. The new model was developed in two stages: stage 1 for unique values for the two factors of the equation; stage 2, which is better than stage 1 according to the statistical analysis, for different values of the factors each single month.

The free water surface evaporation was calculated for the years 2011–2013 for calibration and for year 2014 for validation. The slope of the regression line for the three years of calibration 2011–2013 is 0.968, 1.073, and 1.043. The coefficient of determination ($R^2$) for the three years is 0.979, 0.989, and 0.991, respectively, and the t value is almost zero at $p$ value about 0.999. For the validation period, the slope of the regression line is about 0.9, with a coefficient of determination of 0.98, reflecting the strength of the model. Also, the t value is 0.6, at $p$ value of 0.544. Since the $p$ value is much greater than 0.05, the statistical analyses for both calibration and validation periods were very good. Finally, we obtained a simple, less data requiring, and easy to apply evaporation model applicable over Lake...
Nasser, Egypt. The developed model could be used with confidence on Aswan meteorological station or on the average of the two meteorological stations, while it should be used carefully on Abu-Simbel meteorological station. The model could be tested for application in arid regions simply. Future research could conduct comparisons between the results from the current study, and SVR and the firefly algorithms, in order to particularize their performance in the area of water resources management.

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**Figure 14** | Daily validation of El-Mahdy model to Priestly-Taylor model for Abu-Simbel station.

**Figure 15** | Monthly validation of El-Mahdy model to Priestly-Taylor model for Abu-Simbel station.

**Figure 16** | Monthly validation statistics of El-Mahdy model to Priestly-Taylor model for Abu-Simbel station.
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