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Quantitative relationships among potential evapotranspiration, surface water, and vegetation in an urban area (Baghdad)

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Abstract. Potential evapotranspiration (PET) is the amount of water that evaporates from land, surface water and plant transpiration. Based on monthly surface water and vegetation cover areas derived from Sentinel-2 imagery and precipitation records from Baghdad station for the two years 2018 and 2019, the quantitative relationships such as PET versus water area, PET versus vegetation area and PET versus precipitation were investigated. Using Origin 9.2 program, a new multiple regression model was derived to estimate the monthly mean PET in dry and wet months. To improve the accuracy of the model, monthly errors, bias and mean absolute error were calculated to approximate reasonable estimates of PET. Based on this statistical analysis, the best value of about -1 mm/day should be added to the proposed model as a correction term.

Keywords: surface water, vegetation, potential evapotranspiration, statistical analysis, Baghdad.

1. INTRODUCTION

Surface water bodies and vegetation cover in urban areas have mostly suffered significant impacts in recent decades (Singh and Biswas, 2022) due to the effects of the continuous changes in urbanization expansion and climate conditions (Guo, Westra and Maier, 2017; Zhang et al., 2022). These natural resources are the main drivers in the study of potential evapotranspiration (PET) (Zhao and Ma, 2021), which is an important process in the hydrological cycle especially for non-limited water availability, and can be considered as one of the direct indicators of climate change in a given area (Li et al., 2022). PET represents the potential maximum amount of water that would be released from the Earth's surface into the atmosphere by the combined processes of evaporation and transpiration, if sufficient water were available. It is an input for various applications in hydrological models, so its estimation plays a key role in agricultural irrigation, dry-wet condition assessment, weather variability, water management and climate-related hazard assessment (Kirkham, 2014).

Baghdad, the capital of Iraq, has been notably suffered from the influence of global climate change and increased water demand (Jaber, Al-Saadi and Al-Jiboori, 2020) and has therefore received increased attention from many scientists and the country's central government. PET averages are generally influenced by meteorological conditions and the surrounding near-surface environment. Therefore, it can vary simultaneously with surface changes (Wang and Zheng, 2022).

To date, many studies have been conducted to investigate the spatial and temporal analysis of PET in watersheds (Zhang and Wang, 2021; Yan et al., 2017). In recent years, the trend directions of PET have also been investigated by some researchers in Iraq, such as Al-Hasani and Shahid (2022), who examined the spatial distribution of the trend of annual and seasonal scales using the modified classical Mann-Kendall test for the period 1981-2021. They found that PET has a significantly increasing trend over most of Iraq, especially in summer with an average of 0.5 mm/decade. In this paper, it is reasonable to hypothesize that PET could be affected by changes in the quantitative evolution of vegetation cover, surface water and precipitation, which still have less knowledge about the connection with the PET.

The relationship between PET and vegetation has also been established, for example in a large spatial banana plantation in Venezuela (Olivares et al., 2021). The relationship between precipitation and PET has been used to verify the possible climate type (dry or wet) and was found to vary greatly between seasons (Stefanidis and Alexandridis, 2021). Unfortunately, most empirical methods for estimating PET depend on several meteorological factors: air temperature, solar radiation, relative humidity, sunshine duration, and wind speed. These methods have shown that the weight of these variables on the estimation of PET varies between regions and spatial and temporal scales. However, it is known that vegetation, soil water content, and precipitation are directly correlated with PET as the primary causes of combined evaporation and transpiration. The main research gap is a lack of knowledge about linkage between ground-based PET estimates with cumulative precipitation, vegetation cover area and surface water area, which are jointly derived from remote sensing technologies in this paper. Therefore, the overall objective of this paper is to explore a multiple regression model formulated to estimate the mean PET in the Tigris River basin of Baghdad as a function of these variables at interannual scales in arid and semi-arid conditions. Prior to this relationship, the monthly relationships between PET estimates and influencing factors during the two years (2018 and 2021) characterized by different conditions were investigated. Finally, some statistical parameters such as bias and mean absolute error were tested to improve this model.

2. STUDY AREA AND DATA SOURCES

2.1. Briefly description of study area

This study was carried out in an urban area such as Baghdad (see Fig. 1), the capital of Iraq, which is a medium-density city and part of the Tigris River basin with several meanders, i.e. it is a low-lying and alluvial plain. It covers an area of 894.3 km^2, has an average elevation of 34 m above sea level and is located at 33° 21' N latitude and 44° 20' E longitude. Baghdad's climate is hot and dry in summer and cold in winter. The rainy season lasts from October to May, with an average annual rainfall of 140 mm. The vegetation cover often consists of palm orchards in the north, farms, parks, and domestic gardens. In addition to the Tigris, there are small permanent ponds on both sides of the river.

2.2.Briefly description of data

Monthly weather data for air temperature (Ta), solar radiation (SR), relative humidity (RH) and evaporation rates were obtained from the Baghdad meteorological station belonging to the Iraqi Meteorological Organization for two years 2018 and 2021. The reason for selecting these years was that they were characterized by completely different conditions, with 2018 being semi-arid and 2021 being severely arid (Abd Al Rukabie, Naif and Al-Jiboori, 2024). In addition, Sentinel-2 satellite images (downloaded from https://scihubcopernicus.eu) were used to identify urban surface water and vegetation by

Figure 1. Study area of the paper: left (Iraq) and right (Baghdad) in which green (vegetation), blue (water bodies) and other colours (housing districts and barren land).

calculating spectral indices for Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Vegetation Index (NDVI). For more details, pre- and post-processing of the satellite images, such as clipping, compositing, merging bands and extraction of the study area, are explained through the two references Ahmed et al. (2024) and Mahdi, Tawfeek and Al-Jiboori (2024), respectively.

3. METHODOLOGY

3.1. PET estimation

To execute the objectives of this paper, the Turc method for two different ranges of relative humidity, wet: 50-100% and dry: 0-49%, was widely used to estimate PET because it is a simple and more accurate empirical equation to (Turc, 1961; Jensen, Burman and Allen, 1990). Furthermore, several studies have shown that the Turc equation is the most appropriate and has been consistently well implemented in many places around the world due to its justification for local climatic conditions (Trajkovic and Stojnic, 2007; Fisher and Pringle III, 2013; Santos et al., 2019). It is also the second best method after the Penman-Monteith method when compared to the other available methods. However, the Turc method depends on the mean Ta (in °C), SR (in $MJ.m^{-2}.day^{-1}$) and RH (in %) given by the following equation:

$$PET = 0.01333((239000 * RS) + 50)\left(\frac{Ta}{Ta+15}\right) \quad \text{for } RH>50\% \tag{1}$$

$$PET = 0.01333((239000 * RS) + 50)\left(\frac{Ta}{Ta+15}\right)\left(1+\left(\frac{50-RH}{70}\right)\right) \quad \text{for } RH<50\% \tag{2}$$

3.2. Spectral indices of surface water and vegetation

Modified Normalized Difference Water Index (MNDWI) is a power method used to classify the urban scenes into two categories consisted of water and non-water objects given as (Chen et al., 2020)

$$MNDWI = \frac{\text{Green (Band 3)}-\text{SWIR (Band11)}}{\text{Green (Band 3)}+\text{SWIR (Band 11)}} \tag{3}$$

While the NDVI is defined as the ratio of the spectral difference between the red and near infrared (NIR) bands divided by their sum, as given by (Bannari et al., 1995):

$$NDVI = \frac{\text{NIR(band 8)}-\text{Red (band 4)}}{\text{NIR(band 8)}+\text{Red (band 4)}} \tag{4}$$

Both MNDWI and NDVI have values ranging from -1 to +1, with higher values corresponding to increased water bodies and vegetation (Abdullah et al., 2019), respectively. In this study after extracting digital images of MNDWI and NDVI, all pixels were classified into only two groups for each index separately. Pixesl with MDWI greater than 0.5 where considered surface water areas and, similarly, pixels with NDVI greater than 0.2 were considered as vegetated areas. Therefore, surface water and vegetation areas in km^2 were extracted using the r.report function in the toolbox of the QGIS program.

3.3. Statistical analysis

It is conventional to test our empirical relationship with statistical analysis. First, scatter plots were used to show the variation between PET, surface water, vegetation, precipitation and evaporation. Once the nature of the relationship was established, R^2 (or goodness of fit) was calculated, which is a statistical measure of how well the regression line approximates the real data if it follows the regression equation. Meanwhile, the Pearson correlation coefficient (r) with a range of -1 to 1 and the p-value were calculated by Student t-test to assess the level of significance at 0.95. The standard deviation (SD), represented by vertical lines and defined as a measure of the dispersion of a dataset relative to its mean, was also calculated. Overall accuracy measures the quality of the prediction by comparing the actual values with the predicted values. Other measures of accuracy were chosen, such as bias and mean absolute error (MAE). Bias refers to deviations that are not due to chance alone and MAE is a measure of how close a fitted line to the data points, which is a common measure of prediction error in time series analysis. However, they were calculated as (Al-Jiboori et al., 2020):

$$Bias = \frac{1}{n} * \sum_{i=1}^{n}(\varepsilon_i) \tag{5}$$

$$MAE = \frac{1}{n} * \sum_{i=1}^{n}|\varepsilon_i|^2 \tag{6}$$

where ε is the error due to the difference between observed and estimated values and n the total number.

4. RESULTS

4.1. Inter-annual variations of PET estimations, MNDWI and NDVI areas

Table 1 shows monthly variation of PET in the two years: 2018 and 2021 characterized with semiarid and dry conditions, respectively. Also, quantitative areas for both surface water and vegetation represented by the calculation of spectral indices for both MNDWI and NDVI respectively were displayed in this table. In addition, in order to see the annual differences in these variables between the two years, the annual means with their SD were calculated, as shown in the last row of Table 1. During the two years, the highest values of PET are found in the summer months and the lowest values in the winter months. Under arid conditions, PET has high values in the months of 2021 compared to the semi-arid year of 2018.

In general, the surface water areas in 2018 are relatively larger than those in 2021, especially in the six months (i.e., February, March, April, May, June and November). While in summer (i.e., July, August and September) the areas are about the same with an average value of 18 km^2. The only exception is January and December, where more water areas were recorded, especially in January. This distribution of water areas was mostly reflected in the growth of vegetation in Baghdad, where the total area of pixels for vegetation (NDVI) in months: January, March, April, June, October and December of 2018 were larger than those of 2021. The remaining months have almost the same NDVI areas, especially in May.

Table 1. Monthly values for PET, surface water area, and vegetation area in two years 2018 and 2021.

Months	PET (mm/day)		MNDWI area (km^2)		NDVI area (km^2)	
	2018	2021	2018	2021	2018	2021
Jan.	1.9	1.7	37	77.2	120.1	115.7
Feb.	3.2	2.2	36.9	35.4	107	118
Mar.	4.2	3.5	29	24	187.7	84.9
Apr.	4.3	5.6	28.5	22.8	201.7	150.4
May	6.3	8	29.6	19.5	197.8	197.8
June	8.8	8.9	28.5	18.7	163.5	119.3
July	8.3	8.7	18.7	20	120.1	124.8
Aug.	7.5	8.3	20	21	162.8	124.3
Sep.	6.2	6.6	18.7	21.8	122.9	139.4
Oct.	3.3	4.5	21.3	23.1	172.8	129.2
Nov.	2	2	40.7	32.1	147.4	154.8
Dec.	1.6	1.5	39.9	47.1	291.8	138.8
Aver.±SD	4.8±2.6	5.1±2.9	29.1±8.2	30.2±17	166.3± 50.9	133.1± 27.4

4.2. Relationship among PET, MNDWI, and NDVI, precipitation

To explore the nature of the relationship, the PET estimates were plotted separately against MNDWI and NDVI, and the best line fit was derived using Origin 9.2. Before that, we explored the relationship between two related parameters, monthly PET estimates with evaporation rates (Fig. 2a) and with surface water area measurements (Fig. 2b). They are represented by different symbols, with green and red dots representing semi-arid (2018) and arid (2021) conditions, respectively, as shown in the panel of the figures below. Monthly means of PET cannot exceed free water evaporation under the same weather conditions.

There is no significant difference between the two years and they have almost the same behaviour, except for a slightly higher value occurred in 2018 due to the high rainfall received in 2018 (284.2 mm). This was also explained through the annual means of PET and SD reported in Table 1, which are almost similar to values of 4.8±2.6 and 5.1±2.9 mm/day in 2018 and 2021, respectively. However, the monthly PET values and evaporation rates were very well correlated and found to have a positive relation with $r=0.95$ and $p<0.00001$. The fitted curve has been passed through the data points, which obey the exponential polynomial function with an excellent correlation ($R^2=0.95$).

$$PET = EXP(0.23 + 0.0071 * \text{evaporation rate} - 6.6 * 10^{-6}) \quad (7)$$

Fig. 2b shows the relationship between PET and surface water area (Aw) derived from MNDWI, where the highest PET values were concentrated around small water areas found during the non-wet months (May to October), while the lowest PET values were found in large surface water areas. Despite this decreasing behaviour, these two variables were negatively well correlated ($r=-0.68$) and $p<0.00001$. The decreasing exponential function could fit these data points with an $R^2=0.7$, given as

$$PET = 1.02 + 28.1 * EXP(-Aw/13.2) \quad (8)$$

where Aw is the surface water area. Ahemd et al. (2024) have recently investigated the relationship between PET and vegetation area (Av) represented by NDVI for the same Sentinel-2 images, time period, and study area. They were linearly correlated and expressed by the regression model with a $R^2=0.72$.

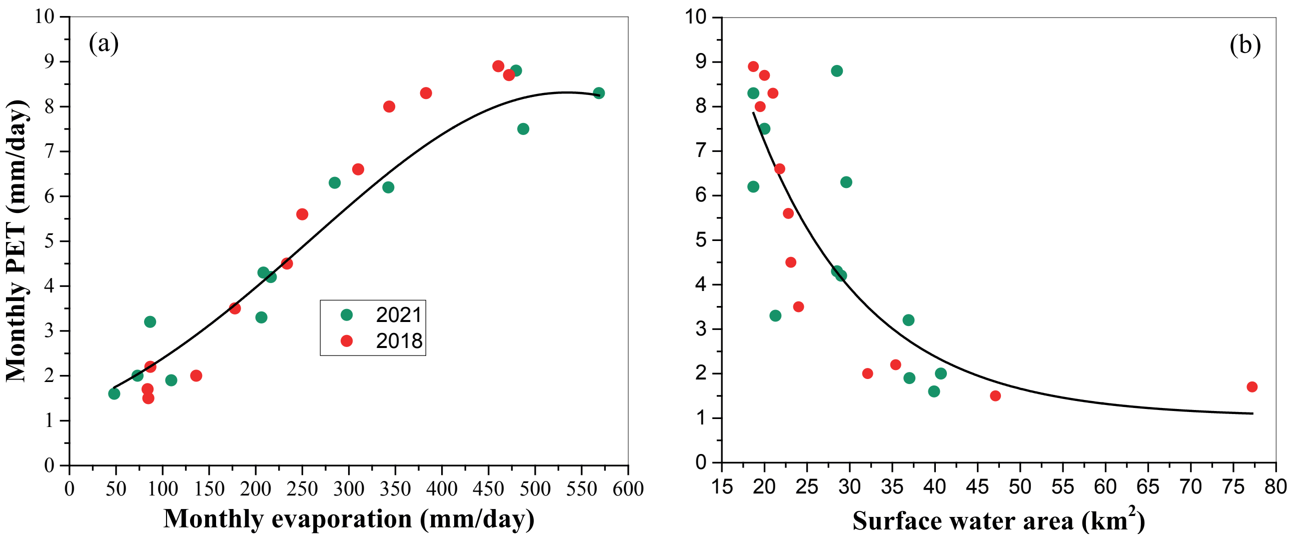

Figure 2. Monthly variations between (a) PET and evaporation, and (b) PET and surface water area.

$$PET = 1.8 + 0.03 * Av \qquad (9)$$

where Av is the vegetation cover area. Al Rukabie, Salwa and Al-Jiboori (2024) have studied the impact of monthly precipitation (P) on PET for the same site, data and period and found an empirical relation describing its behavior (R^2=0.69) given below

$$PET = 2.9 + 1.5 * (EXP(-76.2 * P)) \qquad (10)$$

From the above discussions, an integrated multiple regression model for PET in arid and semi-arid regions can be derived as follows:

$$PET \propto F(Aw,Av,P)$$
$$PET = \beta + F\,(Aw,Av,P) \mp \varepsilon \qquad (11)$$

where b is a general empirical constant based on the above independent variables. As there are no directly measured observations for PET, the PET values in this paper were considered more reliable when testing this model, as shown in the next section. To obtain the mean PET predictions resulting from the ecological parameters studied in this paper, we substitute Eqs. (8), (9) and (10) in Eq. (5) with summation constants in the first terms.

$$\overline{PET} = \frac{1}{3} * [5.72 + 28.1 * EXP(-Aw/13.2) + 0.03 * Av + 1.5 * EXP(-76.2*P)] \qquad (12)$$

When P approaches zero as in dry months as shown in Fig. 2, Eq. 6 becomes

$$\overline{PET} = \frac{1}{2} * (7.22 + 28.1 * EXP(-Aw / 13.2) + 0.03 * Av) \qquad (13)$$

The three-dimensional graph in Fig. 3 shows the combined effect of monthly water and vegetation on PET due to free precipitation. In general, PET values were higher in 2018 due to water availability than in the dry year 2021. The highest PET values were associated with small water areas (~18 km^2) and large vegetation areas. Meanwhile, the lowest PET values were found in large water areas and low vegetation areas.

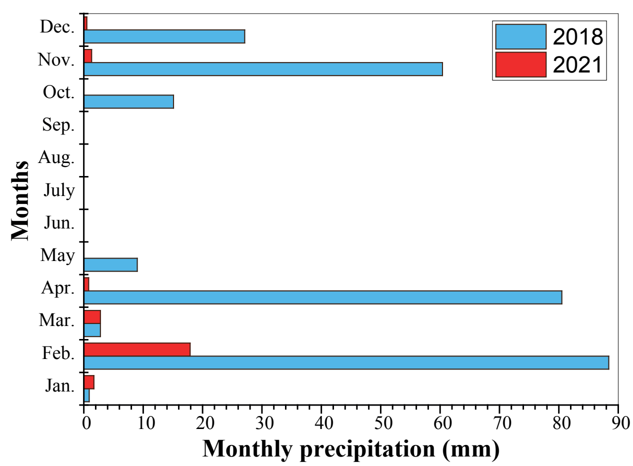

Figure 3. Monthly variation of cumulative precipitation during two years (2018 and 2021) observed at meteorological Baghdad station.

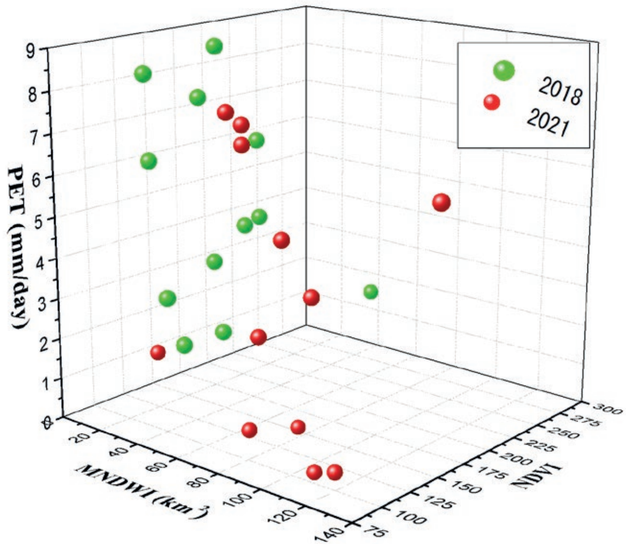

Figure 4. Monthly variations of PET with surface water and vegetation areas during 2018 and 2021.

4. DISCUSSION

This study is not the only attempt to estimate PET using remote sensing measurements, which is an alternative approach to estimating PET, but there have been several studies describing the spatial distribution of PET over a given region at different time scales (Rossato et al., 2005; Olivares et al., 2021; Gebremedhin et al., 2022). Rossato et al. (2005) in Brazil found a linear correlation between monthly PET and NDVI over the period 1981-2000. Olivares et al. (2021) also studied the Spearman coupling of NDVI with PET in a banana plantation in Venezuela under drought conditions and found that the influence of PET on NDVI was more evident with a lag of 1 month.

This paper could present a comprehensive analysis to estimate the monthly PET by using a multi-regression model of Eq. (12) or (13) including more possible factors related to the PET. The proposed model will of course improve the results of PET estimation as it depends on several factors rather than one variable, e.g., vegetation, surface water or precipitation. Also, this model can enhance the policy makers to set the relevant plans to monitor monthly or seasonal changes, especially in semi-arid environments that are characterized by low precipitation, high evaporation rates that exceed precipitation, and wide temperature ranges both daily and seasonally.

The monthly correlation analysis between PET and its factors (surface water, vegetation cover and precipitation) has a different shape depending on the prevailing climate type in a given year. For the dry year (2021), PET showed the high values especially in the summer months due to the permanent water available in the Tigris River and other water ponds, as reported by Mahdi et al. (2024), and the high amounts of solar radiation received by the surface, which primarily provides heat (or energy) for evaporation. The proposed multiple regression models (Eq. 8 and Eq. 9) reflect the combined effect of the above variables on PET estimates. It should be noted that wind speed can play a relative role in exceeding PET values (Zhang and Wang, 2021), but it is not included in this paper because the urban environments are characterized by low wind due to the high surface roughness, while it was found to be 1.2 m as reported in Haraj and Al-Jiboori (2021).

Eqs. (8) and (9) were multiplied by factors of 1/3 and ½, respectively, depending on the number of terms contributing to PET in the atmosphere. For further discussion, we divided the months of both years into two groups: wet months (14 in total) with precipitation activity (from October to May), and dry months that never have precipitation (June-September), with no rain even in two months (May and October) of 2021, as shown in Fig. 2.

Now we turn to discuss the statistical parameters such as bias or error with standard deviation, mean square deviation and root mean square deviation. Using the results of MNDWI, NDVI and precipitation presented in the previous section, the predictions of mean PET were obtained from Eqs. (8) and (9) for wet and dry months respectively. In order to improve the performance of these equations, the monthly errors between the PET values obtained from Eqs. (8) and (9) and their predictions were averaged to find the bias (using Eq. (1)) with standard deviation for both wet and dry periods. The negative bias values were 1.04 mm/day with SD=±1.3 mm/day in dry period and 1.16 mm/day with SD=±1.2 mm/day in wet period. With these results, the bias in dry months was slightly less than that in wet months. These negative values should be subtracted from the mean monthly predictions obtained by Eqs. (8) and (9) to obtain better results. To check the accuracy of these predictions, the results of the monthly MAE were also obtained from Eq. (2) for the same period, which were found to be 1.3 mm/day with SD=1.2 mm/day and 1.4 mm/day with SD=0.9 mm/day, respectively. This means that the accuracy of equation (9) has less predictable error compared to that of equation (8). This small difference between the outputs of these equations reflects the weak role of precipitation in enhancing evaporation and transpiration in arid urban environments, where high rainfall variability is a significant feature.

5. CONCLUSION

This study used monthly digital areas for both MNDWI and NDVI derived from the Sentinel-2 products reported in Mahdi et al. (2024) and Ahmed et al. (2024), respectively, for the same study area (Baghdad) and time period (2018 and 2021) associated with completely different wet and dry conditions. In addition to the monthly cumulative evaporation and precipitation rates, the monthly PET estimates calculated by the Truc method using the ground-based data for solar radiation, temperature and relative humidity were combined with the above areas to establish empirical relationships. PET estimates were closely related to evaporation with an exponential polynomial function and to MNDWI areas with a decreasing exponential function. The results showed that PET values were linearly correlated with vegetation and non-linearly correlated with evaporation, precipitation and surface water. This study could also derive a general relationship for estimating mean PET including all the above variables together. Understanding this relationship would allow for better planning of natural resources, suggesting relevant and applicable adaptation strategies to avoid adverse environmental impacts in the future.

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