Modeling of Evapotranspiration (ETo) in a Medium Urban Park within a Megacity by Using Artificial Neural Network (ANN) Model

Hayder Algretawee[1*], Ghofran Alshama[1]

[1] Civil Engineering Department, Engineering College, University of Kerbala, P.O.B. 56001, Karbala, Iraq
[*] Corresponding author, e-mail: hayder.h@uokerbala.edu.iq

Abstract

Evapotranspiration (ETo) is considered a main component of the hydrological cycle. This study was carried out on a medium-size park within a highly urbanized area, close to the center of Melbourne city. The purpose of the study is to calculate the reference evapotranspiration (ETo), particularly at a specified spot in a corner of the park. The hand-held device used to collect data gave consistent results and reduced the need for assumptions. The Penman-Montieth equation was used to calculate the reserved ETo. To build an ETo model, Artificial Neural Network (ANN) was adopted to predict ETo. Three models were built to select the best model, based on the least Root Mean Square Error (RMSE) and the highest coefficient of determination (R^2). Results showed a contrast between the observed and predicted magnitudes of ETo. Both of the observed and predicted magnitudes for ETo are higher than most recent studies. Data from the specified location shows a difference in ETo magnitudes relative to the fixed meteorological stations. This study supports that climate change causes increasing magnitudes of reference evapotranspiration ETo.

Keywords

evapotranspiration, artificial neural networks, urban parks, Penman-Monteith equation

1 Introduction

The hydrological cycle consists of many consequences phases. One of the main phases which has effects on hydrological cycle is evapotranspiration (ET). ET moves water from wet surfaces and plants to the atmosphere [1]. Determining the magnitude of ET losses is very important for different sectors, such as in agricultural purposes [2], and managing water resources in each region, which effects operational and planned irrigation projects [3]. Many studies have focused on the estimation of evapotranspiration at different places around the world using different estimation methods, such as the Penman–Monteith equation, which is used to estimate reference evapotranspiration (ETo) [4, 5]. Consequently, calculation of the Penman-Monteith equation has been carried out by adopting the recommended steps of the Food and Agriculture Organization of the United Nations (FAO) [6]. Therefore, this method has been used widely in various places because the accuracy is relatively higher than other estimated methods, and many researchers have adopted it to compare with other investigation results [7, 8]. Consequently, many studies used and recommended Penman-Montieth equation for accurately estimate ET [9], however, this method uses various weather information records. In this study, and for the reasons above mentioned, Penman-Montieth equation was selected as a unique equation to calculate reference evapotranspiration (ETo).

Climate change topic arises as a big issue during these years and may be in the coming years. Thus, one of the important drivers to occur the change is temperature [10]. Therefore, temperature has effected directly on Reference ETo, which correlate to one of the important weather features. Consequently, reference ETo has been effected by climate weather, however, reference ET does not affected by crop characteristics, such as the type and development of a crop [6, 11]. There are many studies referred that climate change issue correlates with hydrological cycle parameters, particularly reference evapotranspiration ETo [5]. This study was selected to verify that is results will agree or disagree the concept that climate change effects on reference ETo.

Estimation ETo can be executed by using meteorological station data [6, 11]. Also, Various methods were used to model reference ETo have been adopted by recent studies [8]. Reference ETo can effect on many aspects, such as water storage, which caused issues on crop yield [12], transfer of mass by seeking the effect of ET on a large lake [13]. Another studies focused on the effect of both water and mass [14] but some researchers depended on radiation [15] and temperature method [16] to show the role of them on reference ETo. All mentioned studies adopted Penman-Monteith equation whether as a unique equation or within another equations to calculate evapotranspiration. Therefore, this study depended on Penman-Monteith equation to calculate reference evapotranspiration ETo by selecting a specified spot within urban park.

Studying the effect of urban parks on environment has been investigated for many aspects, such as cooling effect [17, 18] and land surface temperature [19]. However, urban park has another interaction with hydrological cycle, particularly evapotranspiration due to parks should be watering and parks have different types of vegetation, which caused evaporation and transpiration respectively. Therefore, this study selected a medium urban park to calculate reference evapotranspiration.

Estimation reference evapotranspiration ETo in different regions around the world were observed in many countries, such as the USA [20], Japan [21], British Columbia [22], China [23] and other countries, the calculation of ET was carried out on different categories, such as water body [24] and different types of vegetation [25]. The majority to obtain weather data is meteorological stations for the mentioned studies. However, there is a very few studies focused on the finding of magnitude ET within a hand-held device. Many studies selected large scale to calculate ET, such as three cities [26] but [27] chose one city, however, determining ET by choose small scale is rare. Also, collecting weather information by the researcher himself when using a hand-held device is still rare, and that the reason to choose small scale and using hand-held device to collect weather data for calculating reference evapotranspiration ETo.

The majority of obtaining data to calculate reference ETo is meteorological stations whether using Penman-Monteith equation as a standard equation or empirical methods based on mass-transfer, radiation, and temperature [8]. Similarly, [28] adopted weather data from eight meteorological stations to predict reference ETo. Consequently, a study used weather records from eight climatological stations to assess the accuracy of Penman-Monteith equation [29]. In the same approach, [5] referred to use Penman–Monteith equation to calculate the reserved ET and compare with a climate model, this study concluded that forecasting daily ET can be achieved by Penman–Monteith model. Therefore, this study is adopted Penman-Monteith equation to obtain correct and precise results.

The aim of this study is covering the gap search, which mentioned above. This study chose a medium urban park as a case study for calculation reference evapotranspiration ETo during a whole year by using hand-held device to record all the necessary weather data.

2 Study area

A medium urban park (Dunstan Reserve), area (4.5 ha) was used in this study as a case study to calculate reference evapotranspiration ETo. Dunstan reserve is one of many urban parks in Melbourne, this park locates north Melbourne city within Brunswick west (37°75′60″S 144°94′06″E). Brunswick city soccer club building including within park area, and the main activity is soccer training on this reserve (Figs. 1 and 2).

Fig. 1 A medium urban park (Dunstan reserve)

Fig. 2 Edge of the Dunstan reserve (park)

3 Methodology

To calculate reference evapotranspiration ET, a Kestrel 4000 series hand-held and environmental meter device (Fig. 3) was used to collect all weather data including: maximum and minimum air temperature (with a temperature accuracy of +/- 0.5 °C), wind speed at 1.5 m (changed to 2 m) [6], density, radiation, pressure, and dew point. In this study, edge of the park was selected to stand close it then recording all weather information from the device after waiting for 2 to 5 minutes till the reading become constant. This point was sampled twelve times per day (every 2 hours) once per season (four months per year) and four times per day (every 6 hours) once per month for the remaining eight months. These measurements equated eighty records. From field data, reference evapotranspiration (ETo) was calculated by two methods, both of them were depended on Penman-Monteith equation.

3.1 Calculating reference evapotranspiration ETo by Penman-Monteith equation

Study period extended one year to collect weather data along 12 months, strategy of methodology was visiting the park at any time during the day. The process was repeating the visiting 22 times for both winter and summer, and 18 times for both autumn and spring. Hence, the total data are 80 records. The reason of selecting data during winter and summer more than other seasons was the period of these seasons are higher than the others in Melbourne.

After collecting these data, The FAO Penman-Monteith method was used for calculating reference evapotranspiration ETo, this equation can be written as [6]:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} U_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 U_2)}, \quad (1)$$

where:

ET_o = reference evapotranspiration (mm/day).
Δ = the slope of vapor pressure curve (kPa/°C).
R_n = the net radiation at the crop surface (MJ/m² d).
G = the soil heat flux density (MJ/m² d)
T = average air temperature at 2 m height (°C) computed from maximum and minimum air temperature (T_{max} and T_{min}, °C).
$e_s - e_a$ = the saturation vapor pressure deficit (kPa).
U_2 = is wind speed at 2 m height.
γ = psychrometric constant [kPa/°C].

Fig. 3 A Kestrel 4000 series hand-held and environmental meter device

$$e_s = \frac{e_{(T_{max})} + e_{(T_{min})}}{2}, \quad (2)$$

where:

$$e_{(T_{min})} = 0.610 \exp\left(\frac{17.27 T_{min}}{T_{min} + 237.3}\right), \quad (3)$$

$$e_{(T_{max})} = 0.610 \exp\left(\frac{17.27 T_{max}}{T_{max} + 237.3}\right), \quad (4)$$

$$e_\alpha = \frac{RH_{mean}}{100}\left[\frac{e_{(Tmax)} + e_{(T_{min})}}{2}\right], \quad (5)$$

$$\Delta = 4098\left[\frac{0.6108 \exp\left(\frac{17.27 T}{T + 273.3}\right)}{(T + 273.3)^2}\right], \quad (6)$$

$$\gamma = 0,665 \times 10^{-3} P \quad (7)$$

where:

$$P = 101.3\left(\frac{293 - 0.0056 Z}{293}\right)^{5.26}, \quad (8)$$

$$R_n = R_{ns} - R_{nl}. \quad (9)$$

To apply Penman-Monteith equation, edge of the park was selected to a place of calculating ETo. This place was turf has average height can be estimated as 12 cm. To calculate soil heat flux at day times, Eq. (2) is adopted [6].

$$G_{hr} = 0.1 Rn. \quad (10)$$

3.2 Artificial Neural Network (ANN) model

Artificial Neural Network (ANN) were adopted in many engineering aspects, particularly in modeling and analyzing data whether linear or non-linear type [30], and forecasting water level in reservoir dams [31], predicting failure issues related to water pipes networks [32]. Therefore, in this study, ANN model is adopted because this software program has used widely by researchers with high accuracies of results.

Artificial Neural Network (ANN) system consists of as minimum three main parts, the first part is defined as input layer, the second part is defined as hidden layer at least one layer and this layer processing of input layer and the third layer is defined as the output layer. The reason why Sigmoid function was used rather than other functions such as Tannh and Gaussian because Sigmoid function is comfortable, differentiable, monotonic, and limited. The weights were determined during this study, the number of hidden layer depending on training. The difference in ANN architecture was developed by changing the number of nodes in the hidden layer. Fig. 4 shows the structure of neural network. The methodology was chosen depended on the processing countinuted to training until the error becomes less than the selected. Therefore, the error between output results of the network and target outputs are computed at the end of each process.

The development of the Artificial Neural Network model (ANN) is dependent on input and output layers, input layers include climate change parameters (radiation, minimum and maximum temperature, pressure, wind speed at 2 m level (U2)), the output layer includes ETo.

The prediction of ETo was done by ANN including the following steps:

1. An ANN model was built for a data set that was collected for a year and over a period of months, including 80 readings, and this data was collected at the edge of a medium greening park in Melbourne.
2. By using specialized statistical program SPSS program, which we used it to execute a simulation for finding the input layer (climate change).
3. Input data found from step 2 into the best model to find ETo.
4. The models were calibrated with the data obtained to verify the accuracy of the model.

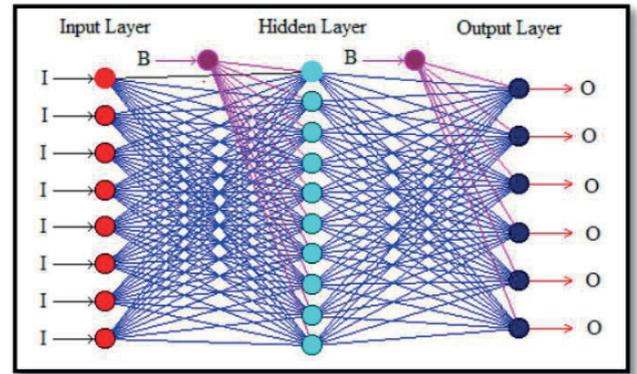Three models were built, which depended on the number of hidden layers.1 The number of nodes in each layer

Fig. 4 Structure of neural network system

following this is chosen as the best depending on several statistical indexes including root mean square error RMSE and correlation coefficient Square R². Therefore, the best model chosen has the least RMSE (nearest to zero) and the greatest R² (nearest to 1). The set of Eqs. (3) and (4) relative to RMSE and R², respectively.

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Oi-Mi\right)^2}\,,\tag{11}$$

where:
N is the number of verification data.
O is the observed data.
M is the modeled data.

$$R^2 = \frac{(\sum_1^N (O-S')(S-S'))^2}{\sum_1^N (O-S')^2 \sum_1^N (S-S')^2}\,,\tag{12}$$

where:
n is a numbers of verification data.
S is a predicted value by ANN.
O is an observation data.
S' is a mean value of S value.

3.2.1 Model 1

The first model was built consists of many parts. The first part is input layer includes climate change parameters (radiation, minimum and maximum temperature, pressure, wind speed at 2 m height), the second layer is hidden layer includes one layer (the number of nodes in this layer are 6) that prossing climate change parameter, and third layer is output layer includes ETo.

Fig. 5 shows structural of neural network for Model 1, and Fig. 6 shows weight distribuation for Model 1.
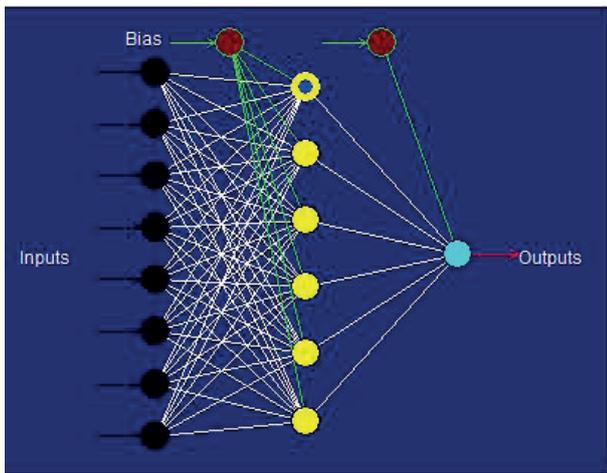
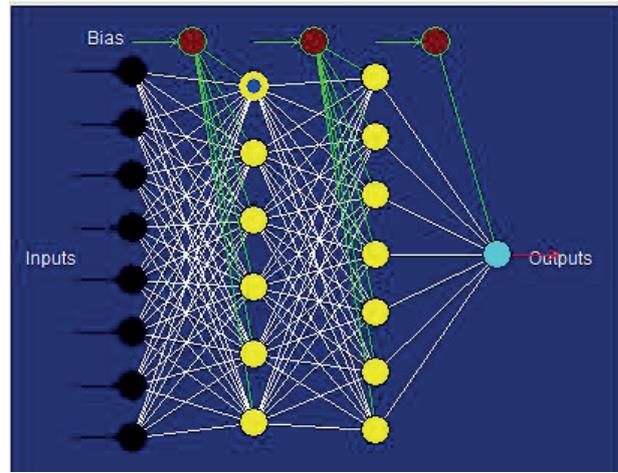**Fig. 5** Structural of neural network for Model 1

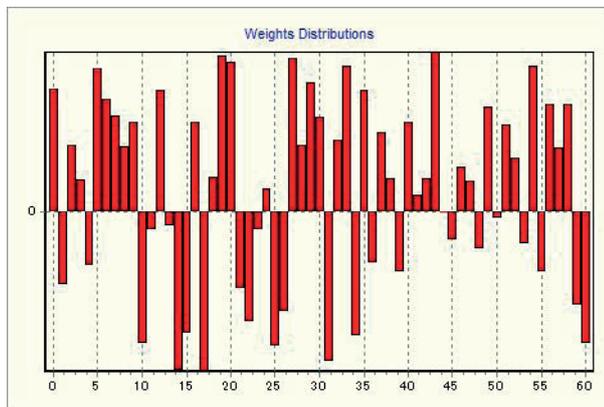**Fig. 7** Structural of neural network for Model 2
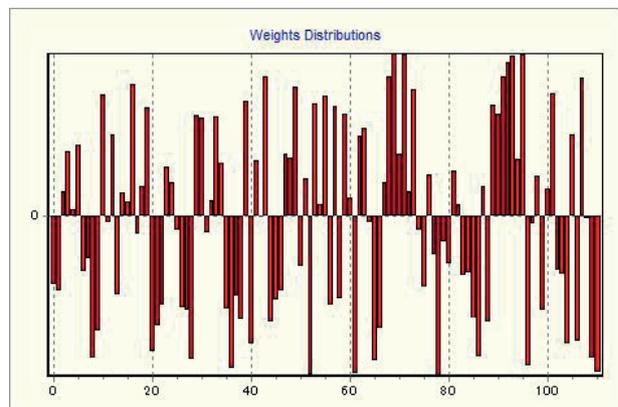

Fig. 6 Weight distribution for Model 1

Fig. 8 Weight distribution for Model 2

3.2.2 Model 2

The second model was built consists of three layers, first layer represents input layer includes climate change parameter (radiation, minimum and maximum temperature, pressure, wind speed at 2 m level (U2)), second layer is hidden layer includes two layers (the number of nodes in this layer are 6, 7) that prossing climate change parameter, and third layer is output layer includes ETo.

Fig. 7 shows structural of neural network for Model 2 and Fig. 8 shows weight distribuation for Model 2.

3.2.3 Model 3

Third model was built which consists of three layers, first layer is input layer includes climate change parameters (radiation, minimum and maximum temperature, pressure, wind speed at 2 m level (U2)), second layer is hidden layer includes three layers (the number of nodes in this layer are 6, 7, 8) that prossing climate change parameters, and third layer is output layer includes ETo.

Fig. 9 show structural of neural network for Model 3 and Fig. 10 shows weight distribuation for Model 3.

4 Results

Evapotranspiration is a complex and non-linear phenomenon because it depends on several interacting climatological factors such as (radiation, minimum and maximum temperatures, pressure, wind speed at 2 m level (U2)). The data used in ANN model was selected by the SPSS program randomly 95% for training and 5% for verification.
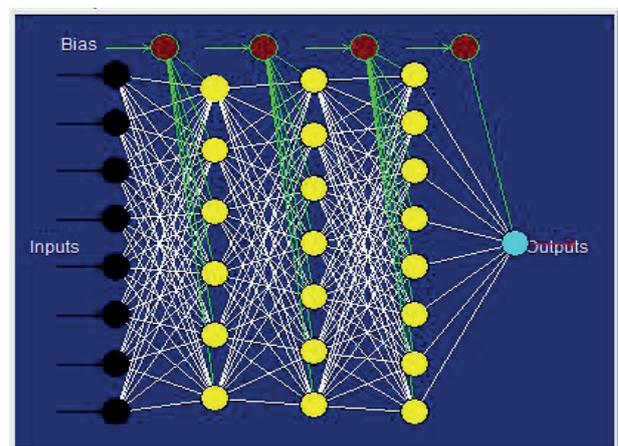

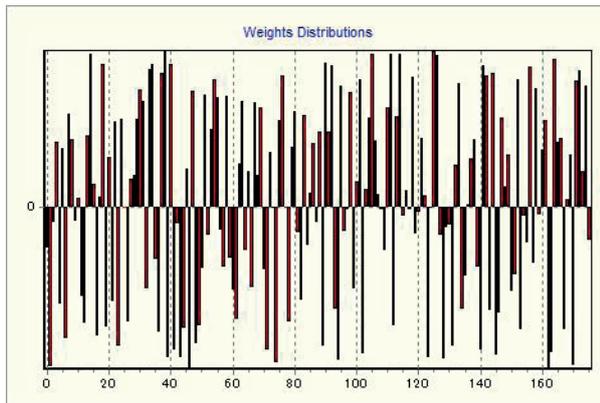**Fig. 9** Structural of neural network for Model 3

Fig. 10 Weight distribution for Model 3

This ratio was selected after checking and verification another two ratios: (1) randomly 75% for training and 25% for verification. (2) randomly 90% for training and 10% for verification, however, the results of 95% and 5% was the best relative to the values of R^2 (determination of coefficient) were closer to 1.0. This process was adopted by another study [33] that tried three different ratio groups and selected the best. Table 1 shows the results of three models comprises of number of models, number of hidden layers, determinant coefficient R^2, Root Mean Square Error (RMSE) for ANN models which were used to prediction ETo.

From Table 1, Model 2 has the best results. Therefore, this model is the best among the three models, which has two hidden layers, the highest (R^2) and the least (RMSE). Fig. 11 shows the relationship between ETo calculated, which were used Penman-Monteith equation, and ETo predicted that found from ANN model during the number of records through one year. This figure clarified that the relation between them is non-linear and it can be make a week relation with small magnitude of coefficient of determinant R^2 equal to 0.0172, which obtained from third degree equation, as shown in Eq. (13).

$$ETo\left(predicted\right) = -0.0151\left(ETo\ calculated\right)^3$$
$$+0.2217\left(ETo\ calculated\right)^2 \qquad (13)$$
$$-0.7481 ETo\ calculated + 3.4748$$

Table 1 Magnitudes of determinant coefficient (R^2) and Root Mean Square Error (RMSE) for the three models

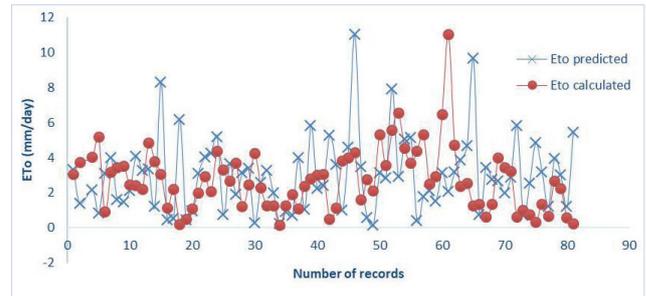| Number of model	Number of hidden layers	determinant coefficient (R^2)	RMSE
Model 1	1	0.651	1.01
Model 2	2	0.877	0.74
Model 3	3	0.808	1.2

Fig. 11 Relationship between ETo calculated and predicted during a whole year

5 Discussion
5.1 Calculating reference ETo by Penman-Monteith equation
Results of reference ETo by using Penman-Monteith varied between 2–11 mm/hr along the whole study period, which was close to other study results [20, 5] in some periods, however, the other points were realized between 6–11 mm/day is higher than [20] were observed measured reference ETo between 0–5 mm/day and between 0–8 mm/day [27]. Therefore, this study contradicts other studies because the different methodologies between them. However, study results are similar to [28], which both were mentioned to the same reference Evapotranspiration ETo were varied between 2–11 mm/day. The reason behind that is both studies were executed in arid and semiarid areas, which are the same weather conditions, however, they used different sources of data. On the other hand, study results showed a high difference from [34], which recorded reference Evapotranspiration ETo between 20–225 mm/day, however, they used meteorological data for 50 years ago, which could explain the high difference in the recordings.

5.2 Predicting ETo by using ANN
This study adopted Artificial Neural Network (ANN) program to predict reference Evapotranspiration (ETo) by using Penman–Monteith equation is varied between 0–11 mm/day. Consequently, an another study referred to use the same equation for prediction daily ETo by using weather information, which are the same to our study such as, maximum and minimum temperature, wind speed. They used prediction analytical method (AM) by collecting data from eight meteorological station to build a prediction model [27]. Although both studies used the same equation and similar method, there is a difference in magnitudes of estimated ETo where estimated ETo varied from 0–6 mm/day [28] is lower than 0–10 mm/day at this study but [35] estimated ETo is equal to 2–16 mm/day by using

different model, which higher than our study, however, they used the same equation (Penman–Monteith equation) to calculate evapotranspiration. The explanation of this variance is could due to the different in collecting data way (meteorological stations), study period and different model inputs. Similarly, another study estimated ETo was varied between 2-8 mm/day by using ANN program [36]. Although this study used the same program, there is a small difference between them because both studies used different study periods and data sources. A study predicted reference evapotranspiration ETo using ANN model without using multi linear regression and Penman-Monteith equation [37], they mentioned to low magnitudes of ETo between 0–1 mm/day, which lower than most study results above mentioned. Their results revealed that Penman-Monteith equation results has higher accuracy than other methods. Study results referred to the relationship between calculated ETo and predicted ETo is non-linear but [38] mentioned to this relationship is linear with high magnitude of coefficient of determinant, however, this study was focused on the prediction of ETo by estimating the missing parameters values, particularly temperature and dew point. Therefore, this could be the reason of contrasting between them, in addition to the high difference between case studies and methodologies.

6 Conclusions

This study was carried out on a medium park within high urbanized area, which close to the center of Melbourne city to calculate the reference evapotranspiration (ETo), particularly at a specified spot in the corners of the park. Penman-Montieth equation was used to calculate the reserved ETo. Thus, to build reference evapotranspiration ETo model, the Artificial Neural Network (ANN) was used to predict ETo, which both observed and estimated ETo magnitudes were contrasted during the whole year. After compare and contrast of the results with the contemporary studies, it can be conclude that both magnitudes of ETo (observed and predicted) are higher than most studies, which means this study supported the concept that climate change effects on reference ETo. Consequently, Artificial Neural Network (ANN) can be adopted to estimate and predict ETo for similar studies. Also, this study referred that Penman-Montieth equation has high accurate. In addition, using hand-held device to collect data gave perfect results and reduce the unnecessary assumptions. Also, selection specified spot shows the difference in ETo magnitude relative to using meteorological stations. Last point relative to climate change phenomenon, which still has a large effect on many aspects, particularly reference evapotranspiration, which increasing the magnitudes of ETo during the whole study period.

References

[1] Khoob, A. R. "Comparative study of Hargreaves's and artificial neural network's methodologies in estimating reference evapotranspiration in a semiarid environment", Irrigation Science, 26, pp. 253–259, 2008.
https://doi.org/10.1007/s00271-007-0090-z

[2] Tran, T. H. N., Honti, M. "Application of Different Evapotranspiration Models to Calculate Total Agricultural Water Demand in a Tropical Region", Periodica Polytechnica Civil Engineering, 61(4), pp. 904–910, 2017.
https://doi.org/10.3311/PPci.10283

[3] Xu, C.-Y., Singh, V. P. "Evaluation and generalization of temperature-based methods for calculating evaporation", Hydrological Processes, 15(2), pp. 305–319, 2001.
https://doi.org/10.1002/hyp.119

[4] Lakatos, M., Weidinger, T., Hoffmann, L., Bihari, Z., Horváth, Á. "Computation of Daily Penman–Monteith Reference Evapotranspiration in the Carpathian Region and Comparison with Thornthwaite Estimates", Advances in Science and Research, 16, pp. 251–259, 2020.
https://doi.org/10.5194/asr-16-251-2020

[5] Yan, X., Mohammadian, A. "Forecasting daily reference evapotranspiration for Canada using the Penman–Monteith model and statistically downscaled global climate model projections", Alexandria Engineering Journal, 59(2), pp. 883–891, 2020.
https://doi.org/10.1016/j.aej.2020.03.020

[6] Allen, R. G., Pereira, L. S., Raes, D., Smith, M. "Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage paper 56", FAO - Food and Agriculture Organization of the United Nations, Rome, Italy, 1998. [online] Available at: http://www.fao.org/3/x0490e/x0490e00.htm

[7] Chiew, F. H. S., Kamaladasa, N. N., Malano, H. M. McMahon, T. A. "Penman-Monteith, FAO-24 reference crop evapotranspiration and class-A pan data in Australia", Agricultural Water Management, 28(1), pp. 9–21, 1995.
https://doi.org/10.1016/0378-3774(95)01172-F

[8] Xu, C.-Y., Singh, V. P. "Cross Comparison of Empirical Equations for Calculating Potential Evapotranspiration with Data from Switzerland", Water Resources Management, 16, pp. 197–219, 2002.
https://doi.org/10.1023/A:1020282515975

[9] Droogers, P., Allen, R. G. "Estimating Reference Evapotranspiration Under Inaccurate Data Conditions", Irrigation and Drainage Systems, 16, pp. 33–45, 2002.
https://doi.org/10.1023/A:1015508322413

[10] Jump, A. S., Hunt, J. M. "Martinez-Izquierdo, J. A., Peñuelas J. "Natural selection and climate change: temperature-linked spatial and temporal trends in gene frequency in Fagus sylvatica", Molecular Ecology, 15(11), pp. 3469–3480, 2006.
https://doi.org/10.1111/j.1365-294X.2006.03027.x

[11] Gong, L., Xu, C.-Y., Chen, D., Halldin, S., Chen, Y. D. "Sensitivity of the Penman–Monteith reference evapotranspiration to key climatic variables in the Changjiang (Yangtze River) basin", Journal of Hydrology, 329, pp. 620–629, 2006.
https://doi.org/10.1016/j.jhydrol.2006.03.027

[12] Guitjoes, J. "The Effect of Reference ET on Water Balance, Which Caused Issues on Crop yield", Journal of the Irrigation and Drainage Division, 108, pp. 212–222, 1982.

[13] Harbeck, G. E. "A Practical Field Technique for Measuring Reservoir Evaporation Utilizing Mass-Transfer Theory", US Government Printing Office, Washington, DC, USA, Paper 272, 1962.

[14] Penman, H. L "Natural evaporation from open water, bare soil and grass", Proceedings of the Royal Society A, Mathematical and Physical Sciences, 193, pp. 120–145, 1948.
https://doi.org/10.1098/rspa.1948.0037

[15] Priestley, C. H. B., Taylor, R. J. "On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters", Monthly Weather Review, 100, pp. 81–92, 1972.
https://doi.org/10.1175/1520-0493(1972)100%3C0081:OTAOSH%3E2.3.CO;2

[16] Thornthwaite, C. W. "An Approach Toward a Rational Classification of Climate", Geographical Review, 38(1), pp. 55–94, 1948.
https://doi.org/10.2307/210739

[17] Algretawee, H., Rayburg, S., Neave, M. "The Cooling Effect of a Medium Sized Park on an Urban Environment", International Journal of Geomate, 11, pp. 2541–2546, 2016.

[18] Algretawee, H., Rayburg, S., Neave, M. "Studying the Mitigation of the Urban Heat Island (UHI) by a Small park in Melbourne City", In: The First MoHESR and HCED Iraqi Scholars Conference in Australia, Melbourne, Australia, 2017, pp. 152–158.

[19] Algretawee, H., Rayburg, S., Neave, M. "Estimating the Effect of Park Proximity to the Central of Melbourne City on Urban Heat Island (UHI) Relative to Land Surface Temperature (LST)", Ecological Engineering, 138, pp. 374–390, 2019.
https://doi.org/10.1016/j.ecoleng.2019.07.034

[20] Irmak, S., Kabenge, I., Skaggs, K. E., Mutiibwa, D. "Trend and magnitude of changes in climate variables and reference evapotranspiration over 116-yr period in the Platte River Basin, central Nebraska–USA", Journal of Hydrology, 420, pp. 228–244, 2012.
https://doi.org/10.1016/j.jhydrol.2011.12.006

[21] Ingle, P. M., Purohit, R. C. "Assessment of reference evapotranspiration using ANN at Mulde, Maharashtra", Journal of Agrometeorology, 22(2), pp. 220–225, 2020.

[22] Nicholls, E. M., Drewitt, G. B., Fraser, S., Carey, S. K. "The influence of vegetation cover on evapotranspiration atop waste rock piles, Elk Valley, British Columbia", Hydrological Processes, 33(20), pp. 2594–2606, 2019.
https://doi.org/10.1002/hyp.13542

[23] Jiang, S., Wei, L., Ren, L., Xu, C.-Y., Zhong, F., Wang, M., Zhang, L., Yuan, F., Liu, Y. "Utility of Integrated IMERG Precipitation and GLEAM Potential Evapotranspiration Products for Drought Monitoring Over Mainland China", Atmospheric Research, 247, Article number: 105141, 2020.
https://doi.org/10.1016/j.atmosres.2020.105141

[24] Hill, A. J., Neary, V. S. "Estimating Evapotranspiration and Seepage for a Sinkhole Wetland From Diurnal Surface‐Water Cycles", JAWRA Journal of the American Water Resources Association, 43(6), pp.1373–1382, 2007.
https://doi.org/10.1111/j.1752-1688.2007.00117.x

[25] Zhang, L., Dawes, W. R., Walker, G. R. "Response of mean annual evapotranspiration to vegetation changes at catchment scale", Water Resources Research, 37(3), pp. 701–708, 2001.
https://doi.org/10.1029/2000WR900325

[26] Isikwue, B. C., Audu, M. O., Eweh, E. J. "Correlation of Evapotranspiration with Climatic Parameters in Some Selected Cities in Nigeria", Journal of Earth Sciences and Geotechnical Engineering, 5(4), pp. 103–115, 2015.

[27] Allen, R. G., Clemmens, A. J., Burt, C. M., Solomon, K., O'Halloran, T. "Prediction Accuracy for Project Wide Evapotranspiration Using Crop Coefficients and Reference Evapotranspiration", Journal of Irrigation and Drainage Engineering, 131(1), pp. 24–36, 2005.
https://doi.org/10.1061/(ASCE)0733-9437(2005)131:1(24)

[28] Cai, J., Liu, Y., Lei, T., Pereira, L. S. "Estimating reference evapotranspiration with the FAO Penman–Monteith equation using daily weather forecast messages", Agricultural and Forest Meteorology, 145, pp. 22–35, 2007.
https://doi.org/10.1016/j.agrformet.2007.04.012

[29] Koudahe, K., Djaman, K., Adewumi, J. K. "Evaluation of the Penman–Monteith reference evapotranspiration under limited data and its sensitivity to key climatic variables under humid and semi-arid conditions", Modeling Earth Systems and Environment, 4, pp. 1239–1257, 2018.
https://doi.org/10.1007/s40808-018-0497-y

[30] Kutyłowska, M. "Prediction of Failure Frequency of Water-Pipe Network in the Selected City", Periodica Polytechnica Civil Engineering, 61(3), pp. 548–553, 2017.
https://doi.org/10.3311/PPci.9997

[31] Üneş, F., Demirci, M., Kişi, Ö. "Prediction of Millers Ferry Dam Reservoir Level in USA Using Artificial Neural Network", Periodica Polytechnica Civil Engineering, 59(3), pp. 309–318 2015.
http://doi.org/10.3311/PPci.7379

[32] Kutyłowska, M. "Comparison of Two Types of Artificial Neural Networks for Predicting Failure Frequency of Water Conduits", Periodica Polytechnica Civil Engineering, 61(1), pp. 1–6, 2017.
https://doi.org/10.3311/PPci.8737

[33] Li, Q., Chan, M. F. "Predictive time-series modeling using artificial neural networks for Linac beam symmetry: an empirical study", ANNALS of the New York Academy of Sciences, 1387(1), pp. 84–94, 2017.
https://doi.org/10.1111/nyas.13215

[34] Vicente-Serrano, S. M., Azorin-Molina, C., Sanchez-Lorenzo, A., Revuelto, J., Morán-Tejeda, E., López-Moreno, J. I., Espejo, F. "Sensitivity of Reference Evapotranspiration to Changes in Meteorological Parameters in Spain (1961–2011)", Water Resources Research, 50(11), pp. 8458–8480, 2014.
https://doi.org/10.1002/2014WR015427

[35] Abbas, S. A., Hassan, A. A., Al-Rekabi, W. S. "Estimation of Mean Reference Evapotranspiration in Basrah City, South of Iraq Using Fuzzy Logic", Journal of Babylon University/Engineering Sciences, 25(1), pp. 98–108, 2017.

[36] Chandra Sekhar Reddy, K., Mallikarjuna, P. "Monthly Reference Evapotranspiration Estimation Using Artificial Neural Networks", presented at National Conference on 21st Century Emerging Trends in Civil Engineering Globe, Kadapa, India, Sept. 3–4, 2010.

[37] Abdullahi, J., Elkiran, G., Nourani, V. "Application of Artificial Neural Network to Predict Reference Evapotranspiration in Famagusta, North Cyprus", In: 11th International Scientific Conference on Production Engineering Development and Modernization of Production, Bihac, Bosnia, 2017, pp. 549–554.

[38] Paredes, P., Pereira, L. S., Almorox, J., Darouich, H. "Reference grass evapotranspiration with reduced data sets: Parameterization of the FAO Penman-Monteith temperature approach and the Hargeaves-Samani equation using local climatic variables", Agricultural Water Management, 240, Article number: 106210, 2020.
https://doi.org/10.1016/j.agwat.2020.106210