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Spatiotemporal prediction of reference evapotranspiration in Araban region, Turkey: A machine learning based approaches

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Abstract

Accurate prediction of Reference Evapotranspiration (ET_0) is crucial for climate change mitigation, water resources management and agricultural activities. Therefore, this study aimed at investigating the applicability of a recently developed Machine Learning (ML) model called Gaussian Process Regression (GPR), for the prediction of ET0 in Araban station, Gaziantep region Turkey. Artificial Neural Network (ANN) was also developed for comparison. Several meteorological variables including temperatures T_{min}, T_{max} and T_{mean} (minimum, maximum and mean), surface pressure (PS), wind speed (U_2) and relative humidity (RH) from 1990 – 2021 were used as the inputs. Determination coefficient (R^2), root mean square error (RMSE) and mean absolute deviation (MAD) were used as performance evaluation criteria. The obtained results revealed that GPR led to better performance with MAD = 0.0174, RMSE = 0.0236 and R2 = 0.9940 in the validation step. The general results demonstrated that GPR could be employed successfully to accurately predict ET0 in Araban station and thus, could be useful to decision makers and designers of water resources structures.

1. Introduction

Evapotranspiration (ET) plays a vital role in water resources management and planning and is amongst the most important components of hydrologic water cycle (Abdullahi et al. (2019). ET can be instrumentally measured or by reference evapotranspiration (ET_0) calculation (Gocic et al. 2015). The ET0 serve as the basis for computing crop evapotranspiration (ETc) as well as irrigation water requirement of crops (Dai et al. 2009). Penman Monteith model by Food and Agricultural Organization of United Nations (FAO) has been accepted as the main method for estimating ET0 in hourly, daily and monthly scales (Allen et al. 1998).

For the past decades, artificial neural network (ANN) has been given significant attention in numerous fields of study including ET0. Dimitriadou and Nikolakopoulos (2022) applied for ET_0 prediction at Peloponnese Peninsula, Greece. Farooque et al. (2022) employed ANN for daily ET_0 forecasting for sustainable irrigation scheduling. Under climate change scenarios, Maqsood et al. (2022) projected ET_0 using ANN. Despite the nonlinearity of ANN and its ability to deal with nonlinear aspect of ET_0, it has some limitations which include over-fitting, time delay in choosing the best befitting structure etc. To overcome these and other issues, a recently developed model called Gaussian Process Regression (GPR) was employed in this study to predict ET_0 at Araban station, Gaziantep region in Turkey.

2. Method

2.1. Study area

Araban is bordered from North by Adıyaman district with latitudes (37°22° and 37°31), from South by Gaziantep district and Urfa left on its east side and Kahramanmaraş district on the west side, the climate of Araban is designated as semi -arid region. Fig. 1 shows the study area.

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Figure 1. Study location in Turkey

2.2. Data Normalization and global statistical indicators

The data used in this study including temperatures Tmin, Tmax and Tmean (minimum, maximum and mean), surface pressure (PS), wind speed (U2) and relative humidity (RH) from 1990 – 2021 were obtained from Turkey meteorological organization and divided into 70% training (269) and 30% validation (115). Determination coefficient (R2), root mean square error (RMSE) and mean absolute deviation (MAD) were used as performance indicator and information regarding them can be found from Ibrahim et al. (2022) study.

2.3. Artificial neural network (ANN)

ANNs and the neural network analysis process share a number of features. Among feed-forward ANN models, multi-layered structures are the most widespread. The simple network design of the ANN is composed of input, hidden, and output layers. The number of inputs depends on how many nodes are present at the input layer, where the input group transferred to the network. Detail information on ANN can be found in Elbeltagi et al (2022a) study.

2.4. A Gaussian process regression (GPR)

A relatively new machine learning approach is the Gaussian process regression (GPR) model Elbeltagi et al. (2022b) state that the stochastic process explained by the multivariable Gaussian probability distribution (GPD) and the unbiased forecasting based on the linear combination of prior experimental observation are the two key characteristics of GPR. Detail information regarding GPR can be found in Elbeltagi et al (2022b).

2.5. Reference evapotranspiration (ET_0)

According to Allen et al. (1998), For estimating ETo the most common used energy balance physical-based equation is the Penman-Monteith equation (FAO56-PM) as it proposed by the the food and agriculture organization (FAO).

The (FAO56-PM) equation's performance is widely acknowledged as the most expert equation for estimating ETo (Sobh et al. 2022). Detail information can be found in Allen et al. (1998).

3. Results

In this study, the recently developed GPR model was applied to predict ET0 and compared with ANN model. Hence, the results are presented accordingly. For machine learning applications, the input size has a great role to play in determining highest performance. Therefore, 2 different input combination were developed given as:

$$M1=f(R_H, P, T_{mean}, T_{max}) \tag{1}$$

$$M2=f(T_{min}, Ps, U_2) \tag{2}$$

Where M1 and M2 are the developed models for ET0 prediction. The results of the ET0 prediction are shown in Tables 1 and 2.

Table 1. Results of the predicted ET_0 based on ANN and GPR in the training phase

Model type	Model N0.	MAD	RMSE	R^2
ANN	M1	0.0286	0.0401	0.9813
	M2	0.0283	0.0397	0.9817
GPR	M1	0.0173	0.0224	0.9941
	M2	0.0241	0.0311	0.9888

Table 2. Results of the predicted ET_0 based on ANN and GPR in the validation phase

Model type	Model N0.	MAD	RMSE	R^2
ANN	M1	0.0299	0.0412	0.9816
	M2	0.0299	0.0412	0.9816
GPR	M1	0.0174	0.0236	0.994
	M2	0.0244	0.0323	0.9887

The performances of ANN and GPR models as presented in Tables 1 and 2 show good performance of the applied models in predicted ET_0 at Araban region Turkey. It can be seen that a goodness of fit performance with R^2 up to 0.9887 in the validation phase. It can be observed from Tables 3 and 4 that using any of the proposed modeling combination, accurate predictions were achieved.

Figures 2 and 3 shows the scatter plots and histogram of the actual versus predicted ET_0 values for both ANN and GPR.

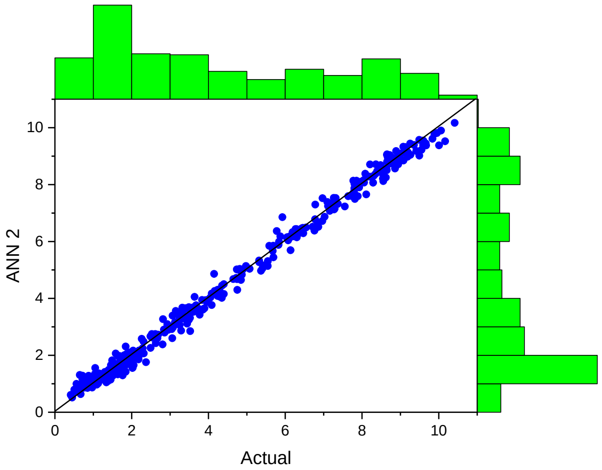

Figure 2. Graphical comparison of the observed and predicted ET_0 values for the best ANN model

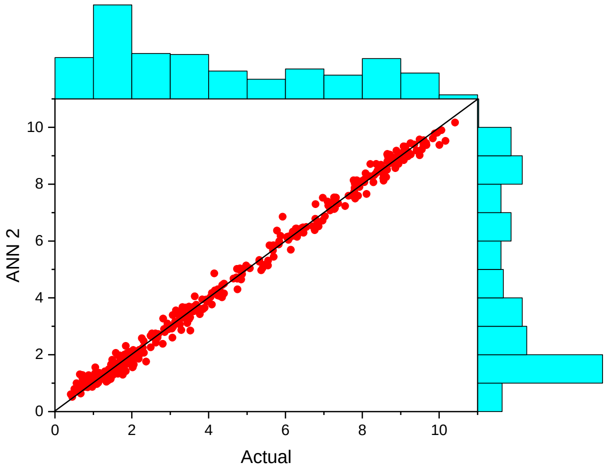

Figure 3. Graphical comparison of the observed and predicted ET_0 values for the best GPR model

4. Discussion

As seen in Tables 1 and 2, using different input combinations, different performances are achieved for both ANN and GPR models. For ANN models, similar performances are obtained. Although, there is slight difference between the M1 and M2 in the training step, the results are same in the validation step with RMSE and R2 values of 0.0412 and 0.9816, respectively. This shows that the accurate prediction of ET0 by machine learning (ML) does not defend on the quantity of inputs used, rather on the quality of inputs. As such, M2 with 3 inputs can appropriately predict the behavior of the ET0 with less computational difficulties and less time consuming. The improved performance of M2 could be attributed to inclusion of U2 as input. According to Nourani et al. (2020), despite having less influence on ET0 prediction when single input single output prediction is considered, U2 significantly improve performance when combined with other variables as ET_0 inputs.

5. Conclusion

This study was performed to assess the possibility of employing a recently developed model called gaussian process regression (GPR) to improve performance of machine learning (ML) based artificial neural network (ANN) for the spatiotemporal prediction of reference evapotranspiration (ET_0) in Araban, Gaziantep region, Turkey. To achieve this, 2 different input combination models were developed using R_H, P, T_{mean} and T_{max} as M1 and Tmin, P_S and U_2 as M2 for both ANN and GPR models for data that spanned from 1990 - 2021.

The obtained results showed that the ML models are sophisticated tools for ascertaining the stochastic phenomena surrounding ET_0. Both M1 and M2 can lead to high performance but M2 slightly outperform M1. However, when less simulation difficulties as well as less time consuming are more important, M1 is preferable. The general results indicated and improved GPR performance over ANN.

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