Modelling of daily reference evapotranspiration using deep neural network in different climates

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Abstract

Precise and reliable estimation of reference evapotranspiration ($ET_0$) is an essential for the irrigation and water resources management. $ET_0$ is difficult to predict due to its complex processes. This complexity can be solved using machine learning methods. This study investigates the performance of artificial neural network (ANN) and deep neural network (DNN) models for estimating daily $ET_0$. Previously proposed ANN and DNN methods have been realized, and their performances have been compared. Six input data including maximum air temperature ($T_{\text{max}}$), minimum air temperature ($T_{\text{min}}$), solar radiation ($R_n$), maximum relative humidity ($RH_{\text{max}}$), minimum relative humidity ($RH_{\text{min}}$) and wind speed ($U_2$) are used from 4 meteorological stations (Adana, Aksaray, Isparta and Nide) during 1999-2018 in Turkey. The results have shown that our proposed DNN models achieves satisfactory accuracy for daily $ET_0$ estimation compared to previous ANN and DNN models. The best performance has been observed with the proposed model of DNN with SeLU activation function (P-DNN-SeLU) in Aksaray with coefficient of determination ($R^2$) of 0.9934, root mean square error (RMSE) of 0.2073 and mean absolute error (MAE) of 0.1590, respectively. Therefore, the P-DNN-SeLU model could be recommended for estimation of $ET_0$ in other climate zones of the world.

Keywords: Penman Monteith equation, Artificial Neural Networks, Deep Learning, Machine Learning, Meteorological data, Deep Neural Networks

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1. Introduction

Reference evapotranspiration ($ET_o$) is an essential hydrological component for the sustainable and efficient management of agricultural water resources and the optimum irrigation scheduling (Huang et al., 2019; Wu et al., 2019; Yama and Todorovic, 2020). Many direct and indirect methods have been recommended to estimate $ET_o$. The direct method of $ET_o$ estimation could be accomplished by water budget measurement (e.g. weighting lysimeters) or water vapor transfer methods (e.g. eddy covariance and Bowen ratio) (Huang et al., 2019). Unfortunately, these methods are time consuming and costly. Additionally, they have some spatial and temporal limitations (Irmak et al., 2003; Dinpashoh, 2006; Peng et al., 2017). As an alternative to the direct methods, mathematical models based on meteorological data provided by weather stations can be used to estimate $ET_o$ (Tao et al., 2018).

The FAO-56 Penman-Monteith (FAO-56 PM) equation is recommended by the Food and Agriculture Organization (FAO) of the United Nations as a reference model for $ET_o$ estimate (Allen et al., 1998). The FAO-56 PM incorporates both the aerodynamics and thermodynamics aspects and has more accurate results compared to the other empirical methods (Fan et al., 2018; Wu et al., 2019). The FAO-56 PM model has been evaluated against various other methods under diverse areas, climates and time steps (daily, weekly and monthly). The results show that FAO-56 PM method has better performance than other empirical equations (Pereira et al., 2015; López-Urrea et al., 2006). However, the FAO-56 PM requires numerous features for $ET_o$ estimation, including the geological variables such as elevation and latitude, and meteorological variables such as maximum and minimum temperature, maximum and minimum relative humidity, wind speed and net solar radiation (Shiri et al., 2014; Feng et al., 2017; Peng et al., 2017). These requirements bring a major drawback to the application of the FAO-56 PM model. Due to the limited availability of meteorological data, mainly in developing countries, simplified empirical models with fewer requirements have been proposed (Valiantzas, 2013; Ahooigahlandari et al., 2016), such as temperature based (Hargreaves and Samani, 1985), mass transfer based (Trabert, 2019) and radiation based models (Priestley and Taylor, 1972). These simplified methods are more accurate for monthly and weekly $ET_o$ estimation while they are less accurate on a daily $ET_o$ estimation (Torres et al., 2011).

The estimation of $ET_o$ is considered as a complex and highly nonlinear dynamic process depending on quality of meteorological variables (Wu et al.,
However, it is usually difficult to develop accurate empirical models considering all these nonlinear and complicated processes, especially when some important input parameters are lacking. Recently, machine learning methods have been widely used to estimate complex process of $ET_o$ estimation because these methods do not require knowledge of internal variables to solve non-linear and multi-variable functions (Kisi, 2015; Yama et al., 2020). Thus, various machine learning methods have been suggested for estimation of $ET_o$. Among these, (1) artificial neural networks (ANN) (Antonopoulos and Antonopoulos, 2017; Ferreira et al., 2019), (2) support vector machines (SVM) (Fan et al., 2018; Ferreira et al., 2019), (3) tree based assemble methods (Kisi and Kilic, 2016; Fan et al., 2018), (4) boosting (Fan et al., 2019) can be mentioned.

Because of promising results and enormous potential for image processing and data analysis, the Deep Neural Network (DNN) methods have become increasingly popular in recent years (Kamilaris and Prenafeta-Bold, 2018). The DNN methods are actually improved versions of the ANN methods (LeCun et al., 2015). The ANN with single hidden layer is commonly called as multi-layer perceptrons (MLP) or feed forward neural networks, while the ANN with more than two hidden layers are called Deep Neural Networks. DNNs are interchangeably called as deep neural networks, deep learning methods, or deep neural nets. The DNN methods have been applied to different domains, such as speech recognition (Amodei et al., 2016), natural language processing (Young et al., 2018), and game playing (Guo et al., 2014). Likewise, the use of DNN methods recently increased in the area of hydrological (Wang et al., 2020; Lee et al., 2020; Bui et al., 2020) and agricultural (Golhani et al., 2018; Grinblat et al., 2016; Dyrmann et al., 2016) studies.

The current study makes following contributions: (1) Previously proposed methods are categorized in Table 1 and Table 2. (2) Previously proposed methods have been realized and their performances have been compared in current meteorological dataset (Table 5). (3) Different from previously proposed DNN method (Saggi and Jain, 2019), dropout layer has been used and its performance is measured. (4) Moreover, two activation function which are called rectifier linear units (ReLU) and scaled exponential linear units (SeLU) has been used in DNN method and compared with the other methods. (5) All methods (previous and new) are compared using 5-fold cross validation instead of using single train-test dataset split. In 5-fold cross validation, models were trained on dataset with 5 different splits.
2. Related works

In this section, previous studies were reviewed for estimation of daily $ET_o$ value. Table 1 summarizes the previous ANN methods in the literature. Table 2 demonstrates the dataset information of the previous ANN methods.

Various ANN methods were proposed for estimation of $ET_o$ value (Table 1). However, only two DNN methods were proposed in the literature (Saggi and Jain, 2019; Ferreira and da Cunha, 2020). The first DNN method used only 3 hidden layers with Rectifier Linear Units (ReLU) (Saggi and Jain, 2019). The second DNN method employed convolutional neural networks on hourly data (Ferreira and da Cunha, 2020). Since the currently proposed DNN methods use daily data, they are not comparable to the second DNN method.

Table 1: Previously proposed neural network models for $ET_o$ estimation

| Study               | Neural Network Architecture | Activation Functions | Software     |
|---------------------|----------------------------|----------------------|--------------|
| Landeras et al. (2008) | (4-6)(1-14)-1              | NI                   | Statistica   |
| Traore et al. (2010)  | (3-5)-(1-20)-1             | Sigmoid              | NeuroSolution|
| Huo et al. (2012)    | 5-8-1, 3-4-5-1, 4-5-6-1, 3-4-5-1 | Sigmoidal logistic   | Matlab       |
| Rahimikhoob (2014)   | 4-(1-10)-1                 | Logsigmoid           | Weka         |
| Shiri et al. (2014)  | (4-5)-(1-14)-1             | Sigmoid, linear      | Matlab       |
| Goci et al. (2015)   | 5-3-6-10-1                 | Continuous logsigmoid| Matlab       |
| Kisi and Kilic (2016) | 4-(3-9)-1.2-(3-10)-1      | Sigmoid, linear      | NI           |
| Yassin et al. (2016) | (4-9)-(2-20)-1             | Sigmoid, linear      | Multiple Back-Propagation |
| Feng et al. (2016)   | (2,3,5)-6-1                | NI                   | Matlab       |
| Antonopoulos and Antomopoulos (2017) | (2-4)-6-1, 2-4-1 | Sigmoid            | NI           |
| Dou and Yang (2018)  | 4-11-1, 4-15-1             | Sigmoid, linear      | Matlab       |
| Saggi and Jain (2019) | 7-40-60-40-1               | ReLU, softmax $H_2O$ |             |

As can be seen in Table 1 all of the architectures had standard input layer, hidden layer(s) and output layer. For example, architecture of Landeras et al. (2008) was "(4-6)(1-14)-1". This means that they used 4 to 6 neurons in the input layer, 1 to 14 neurons in the single hidden layer and 1 neuron in the output layer. They performed empirical experiments and reported their best results among the tried number of neurons. Also, other studies performed similar empirical experiments (Landeras et al. 2008; Traore et al. 2010; Rahimikhoob, 2014; Shiri et al. 2014; Kisi and Kilic, 2016; Yassin...
et al., 2016). As another example, Goci et al. (2015) used architecture of "5-3-6-10-1". This means that they used 5 neurons in the input layer, 3-6-10 neurons in the 3-hidden layers and 1 neuron in the output layer. Since model of Goci et al. (2015) used more than 2 layers in the architecture, they could have chosen to call their method DNN but they did not. This could be the fact that they did not use any other DNN improvements in their experiments.

Activation functions that are used in literature are given in the third column (Table 1). All the previous studies used standard sigmoid and linear functions except for the previously applied DNN method (Saggi and Jain, 2019). In addition, last column shows the software that was used in studies. Most of the studies (5/12) used Matlab neural network toolbox. Unfortunately, some studies did not report the activation functions and software, making reproducibility of their studies harder if not impossible.

Table 2 gives information about the years, frequency and dataset split (train, validation and test) in the literature. It was important to show the split of datasets (train, validation and test) because this split affects the machine learning performances. For example, Traore et al. (2010) reported that they used the meteorological dataset between 2004 and 2005 years as cross validation to optimize ANN performance. However, this usage was for validation dataset. Similar usage were done also by Landeras et al. (2008); Yassin et al. (2016).

Among the reviewed studies, 10 of 12 studies used the daily data for estimation of $ET_o$, while the other 2 studies used the monthly data. Interestingly, no study evaluated their approaches using true cross validation in their experiments. According to the best knowledge of the authors, the present study was the first study that uses true cross validation in the literature of $ET_o$ estimation.
Table 2: Dataset information of the previously proposed neural network methods for $ET_o$ estimation

| Study                | Years       | Frequency | Train Validation Test                                      |
|----------------------|-------------|-----------|-----------------------------------------------------------|
| 1 Landeras et al. (2008) | 1999-2003   | Daily     | 1999-2001 Train (75%) validation (25%), 2002-2003 Test   |
| 2 Traore et al. (2010) | 1996-2006   | Daily     | 1996-2003 Train, 2004-2005 Validation, 2006 Test         |
| 3 Huo et al. (2012)   | 1952-2001   | Daily     | 1952-1986 Train, 1987-2001 Test                           |
| 4 Rahimikhoob (2014)  | 1998-2007   | Monthly   | 1998-2004 Train, 2005-2007 Test                           |
| 5 Shiri et al. (2014) | 2000-2008   | Daily     | 2000-2005 Train, 2006-2008 Test                           |
| 6 Goci et al. (2015)  | 1980-2010   | Monthly   | 1980-1995 Train, 1996-2010 Test                           |
| 7 Kisi and Kilic (2016)| 1994-2009   | Daily     | 1998-2001 Train, 2002-2005 Validation, 2003-2009 Test    |
| 8 Yassin et al. (2016)| 1980-2010   | Daily     | Train (65%), Validation (35%) in 13 stations, Test using separate 6 stations |
| 9 Feng et al. (2016)  | 1994-2013   | Daily     | 65% Train, 35% Test                                      |
| 10 Antonopoulos and Antonopoulos (2017) | 20092013 | Daily | 1 year Train, other 4 years Test |
| 11 Dou and Yang (2018) | 2001-2009 but 6 years of data used | Daily | 4 years Train, 1 year Validation, 1 year Test |
| 12 Saggi and Jain (2019) | 19781999 and 20072016 H, 19701999 and 20072016 P | Daily | 55% Train, 30% Validation, 15% Test |

3. Materials and methods

In this study, two newly DNN models were proposed to estimate daily value of $ET_o$. These newly proposed models were called P-DNN-ReLU and P-DNN-SeLU that uses activation ReLU and SeLU functions. Previous DNN
and ANN models were reproduced and their results were also included in experiments. The dropout layer was also tried on all DNN models, though its effect on performance was not good.

In addition to current (P-DNN-ReLU and P-DNN-SeLU) and previous DNN model (Saggi and Jain, 2019), 11 previous ANN methods were also implemented (Landeras et al., 2008; Traore et al., 2010; Huo et al., 2012; Rahimikhoob, 2014; Shiri et al., 2014; Goci et al., 2015; Kisi and Kilic, 2016; Yassin et al., 2016; Feng et al., 2016; Antonopoulos and Antonopoulos, 2017; Dou and Yang, 2018). The ANN methods used neuron size between 1 to 30 in their hidden layers. Therefore, 30 different ANN models were trained for every station. For the DNN methods, the dropout layer was also used. Therefore, \((6 \times 6 \times 6) \times 3 = 648\) different DNN models were trained also for every station. In total, 678 models were trained in the present study. Finally, considering 4 stations and 5 cross validation, the experiments trained and tested \(678 \times 5 \times 4 = 13560\) different models. All of these experimental results are available as a supplementary data. The flowchart of the modeling procedure is presented in Figure 5.

3.1. Background knowledge

3.1.1. Study area and dataset description

The daily data from 4 meteorological stations in Turkey were obtained from Turkish State Meteorological Service for the period of 1999-2018. Data features are maximum air temperature \(T_{\text{max}}\), minimum air temperature \(T_{\text{min}}\), solar radiation \(R_n\), maximum relative humidity \(RH_{\text{max}}\), minimum relative humidity \(RH_{\text{min}}\) and wind speed \(U_2\). Table 3 shows the statistical parameters of meteorological variables at Adana, Aksaray, Isparta and Nide sites. The map of the study area and the location of the 4 meteorological stations are shown in Figure 1.

According to the Kppen Geiger climate classification (Kottek et al., 2006), the climate of Adana and Isparta sites have a warm temperature with a dry summer, while the climate of Aksaray and Nide sites have a semi-arid with cold and snowy winters. In this way, the meteorological data collected from 4 different sites in Turkey was applied to two different climate types in this study. Table 3 sums up the geographical and meteorological information of the 4 stations in Turkey.
3.1.2. FAO Penman-Monteith equation

The FAO Penman-Monteith (FAO-56 PM) equation was proposed by Allen et al. (1998). It is used to predict daily $ET_o$ (mm day$^{-1}$) and provided the reference data for the training and testing in the current study. The equation is given by:

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

where $ET_o$ is the reference evapotranspiration (mm day$^{-1}$), $R_n$ is the net solar radiation (MJ m$^{-2}$ day$^{-1}$), $G$ is the soil heat flux density (MJ m$^{-2}$ day$^{-1}$), $T$ is the mean daily air temperature at 2m height ($^\circ$C), $\Delta$ is the slope of the saturated vapour pressure curve (kPa $^\circ$C$^{-1}$), $\gamma$ is the psychometric constant (0.066 kPa $^\circ$C$^{-1}$), $e_s$ and $e_a$ are saturated and prevailing actual vapour pressure (kPa), respectively, and $U_2$ is the mean daily wind speed (m s$^{-1}$) measured at 2 m height.

The saturation vapor pressure $e_s$ was estimated as:

$$e_s = \frac{e^\circ(T_{max}) + e^\circ(T_{min})}{2}$$  \hspace{1cm} (2)
Table 3: Geographic information and statistical parameters of meteorological variables of the 4 stations (Adana, Aksaray, Isparta and Nide) in Turkey during 1999-2018

| Station | Station Code | Longitude | Latitude | Altitude | Variable | Min | Max | Mean | Std | Cv |
|---------|--------------|-----------|----------|----------|----------|-----|-----|------|-----|----|
| Adana   | 1            | 35.34     | 37.00    | 23       | $T_{\text{max}}$ | 5.30 | 44.40 | 25.74 | 7.68 | 0.30 |
|         |              |           |          |          | $T_{\text{min}}$ | -3.20 | 29.80 | 14.85 | 7.28 | 0.49 |
|         |              |           |          |          | $R_s$ | 0.00 | 33.68 | 15.90 | 6.98 | 0.44 |
|         |              |           |          |          | $R_{\text{E} \text{max}}$ | 27.00 | 100.00 | 86.22 | 11.38 | 0.13 |
|         |              |           |          |          | $R_{\text{E} \text{min}}$ | 0.00 | 96.00 | 42.57 | 17.09 | 0.40 |
|         |              |           |          |          | $U_2$ | 0.30 | 6.00 | 1.62 | 0.70 | 0.43 |
|         |              |           |          |          | $ET_0$ | 0.51 | 12.73 | 4.45 | 2.20 | 0.50 |
| Aksaray | 2            | 34.00     | 38.37    | 970      | $T_{\text{max}}$ | -10.00 | 40.00 | 19.30 | 10.06 | 0.52 |
|         |              |           |          |          | $T_{\text{min}}$ | -20.40 | 25.60 | 7.09 | 8.05 | 1.14 |
|         |              |           |          |          | $R_s$ | 0.69 | 32.43 | 16.98 | 7.82 | 0.46 |
|         |              |           |          |          | $R_{\text{E} \text{max}}$ | 20.00 | 100.00 | 71.40 | 16.46 | 0.23 |
|         |              |           |          |          | $R_{\text{E} \text{min}}$ | 0.00 | 98.00 | 37.69 | 17.01 | 0.45 |
|         |              |           |          |          | $U_2$ | 0.30 | 5.92 | 1.58 | 0.69 | 0.44 |
|         |              |           |          |          | $ET_0$ | 0.34 | 10.61 | 4.24 | 2.55 | 0.60 |
| Isparta | 3            | 30.57     | 37.78    | 997      | $T_{\text{max}}$ | -6.60 | 42.30 | 19.24 | 9.49 | 0.49 |
|         |              |           |          |          | $T_{\text{min}}$ | -16.00 | 23.30 | 6.53 | 7.19 | 1.10 |
|         |              |           |          |          | $R_s$ | 0.00 | 32.52 | 15.30 | 7.99 | 0.52 |
|         |              |           |          |          | $R_{\text{E} \text{max}}$ | 14.00 | 100.00 | 81.44 | 12.94 | 0.16 |
|         |              |           |          |          | $R_{\text{E} \text{min}}$ | 0.00 | 99.00 | 40.93 | 16.87 | 0.41 |
|         |              |           |          |          | $U_2$ | 0.00 | 5.78 | 1.32 | 0.70 | 0.53 |
|         |              |           |          |          | $ET_0$ | 0.42 | 9.60 | 3.73 | 2.30 | 0.62 |
| Nide    | 4            | 34.68     | 37.96    | 1211     | $T_{\text{max}}$ | -10.30 | 38.50 | 18.51 | 9.90 | 0.53 |
|         |              |           |          |          | $T_{\text{min}}$ | -19.80 | 23.00 | 6.02 | 7.89 | 1.31 |
|         |              |           |          |          | $R_s$ | 0.68 | 35.10 | 18.75 | 8.38 | 0.45 |
|         |              |           |          |          | $R_{\text{E} \text{max}}$ | 24.00 | 104.00 | 75.55 | 15.13 | 0.20 |
|         |              |           |          |          | $R_{\text{E} \text{min}}$ | 2.00 | 96.00 | 37.44 | 17.49 | 0.47 |
|         |              |           |          |          | $U_2$ | 0.38 | 7.95 | 1.83 | 0.70 | 0.38 |
|         |              |           |          |          | $ET_0$ | 0.39 | 10.99 | 4.49 | 2.67 | 0.59 |

1 Std: Standard deviation  
2 Cv: Covariance of variance

where $e^o(T)$ is the saturation vapour pressure (kPa) at the air temperature ($T$), and $T_{\text{max}}$ and $T_{\text{min}}$ are maximum and minimum daily air temperature ($^\circ\text{C}$), respectively. The saturation vapor pressure at the air temperature T was calculated as:
\[ e^o(T) = 0.6108 \ e^{\frac{17.27 \ T}{T+237.3}} \] (3)

The actual vapor pressure \( (e_a) \) was calculated as:

\[ e_a = \frac{e^o(T_{\text{min}}) \ RH_{\text{max}}}{100} + e^o(T_{\text{max}}) \ RH_{\text{min}}}{2} \] (4)

where \( RH_{\text{max}} \) is the maximum daily relative humidity, \( RH_{\text{min}} \) is the minimum daily relative humidity, \( e^o(T_{\text{min}}) \) is the saturation vapor pressure (kPa) at the minimum daily air temperature and \( e^o(T_{\text{max}}) \) is the saturation vapor pressure (kPa) at the maximum daily air temperature, respectively.

3.1.3. Artificial neural networks and deep neural networks

Artificial neural networks (ANN) are powerful machine learning methods that take their roots from biological neurons. The ANN uses artificial neurons modeled from biological neurons as fundamental building block. An artificial neuron has 3 characteristics. (1) inputs, (2) summation unit and (3) transfer (activation) function (Figure 2).

![A Single Neuron](image)

Figure 2: Visualization of the artificial neuron.

In the estimation of \( ET_o \), inputs are features used in the FAO-56 PM equation. Inputs are multiplied with weights and added together in summation
The summation value is sent to activation function and the output of this activation function is the output of the neuron. Diverse transfer functions are proposed in the neural network literature (Nwankpa et al., 2018). The most common activation functions are sigmoid, Gaussian and linear. Different transfer function are used for different purposes. For example, sigmoid function is used for binary classification whereas linear function is used for regression.

The ANN method is the umbrella term for machine learning methods that use neurons as building blocks. Nonetheless, most studies use terms of Neural Networks, Artificial Neural Networks (ANN), Multi Layer Perceptrons (MLP) and Feed Forward Neural Networks interchangeably. In the current study, artificial neural network term is preferred since this term is commonly used in related literature.

In the ANN architecture, multiple neurons are used in multiple layers. Most of the time, ANN architecture is identified with layer neuron counts such as $3 - 5 - 1$. Here, it has 3 layers (one input, one hidden and one output layer) and there are 3 neurons in input layer, 5 neurons in one hidden layer and 1 neuron in output layer. According to number of features used, input layer have corresponding number of neurons. An example for an ANN architecture is depicted in Figure 3.
3.1.4. **Deep neural networks**

Deep neural networks (DNN) are advanced versions of ANN methods (Nielsen, 2015; LeCun et al., 2015). However, the differences between the classical ANN and DNN methods are not clearly defined in the literature, but following improvements are mostly related to DNN studies.

1. Using more than 2 hidden layers, so called deep layers.
2. Different neuron types, such as convolutional, pooling and dropout.
3. Introduction of new activation functions, such as rectified linear units (ReLU), softmax and scaled exponential linear units (SeLU) functions and many others.
4. Different training methods for back propagation that are more suited to using parallelization using multiple GPUs and CPUs.
5. Different initialization methods for neuron weights.

3.1.5. **Cross validation**

The k-fold cross validation ($k = 5$) method was used in this study. The data were divided into $k$ parts and algorithms were trained using $k-1$ parts. After that the trained model was tested on remaining 1 part. This procedure was repeated $k$ times. As an example, in the 5 fold cross validation, dataset was divided into 5 parts. Using 4 parts, ANN and DNN models were trained, then tested on remaining 1 part. This procedure was repeated 5 times (Figure 4). Since experiments were repeated 5 times and performance metrics averaged, obtained performance metrics are more reliable than using only one train-test split.

![Figure 4: The visualization of 5-fold cross validation.](image-url)
3.1.6. Performance evaluation of model parameters

The performance of the models were evaluated using the root mean square error (RMSE), mean absolute error (MAE), coefficient of determination ($R^2$) in the training and testing subsets.

The daily $ET_o$ values, generated by the models ($S_i$), were transformed into daily errors, comparing them with observed values ($O_i$). $\bar{O}$ is the mean value of the observed values and $\bar{S}$ is the mean value of the observed values.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{5}
\]

\[
MAE = \left|\frac{\sum_{i=1}^{n}(S_i - O_i)}{n}\right| \tag{6}
\]

\[
R^2 = \frac{\left[\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})\right]^2}{\sum_{i=1}^{n}(O_i - \bar{O})\sum_{i=1}^{n}(S_i - \bar{S})} \tag{7}
\]

Smaller values of RMSE and MAE and higher values of $R^2$ indicates higher model performance.

Figure 5: The flowchart of the experimental procedures
3.2. Activation functions

As mentioned in section 3.1.4, differences between the DNN and ANN methods are the number of layers, activation functions, and neuron types. Figure 6 shows used activation functions in present study. Classical ANN methods mostly uses sigmoid function (Equation 8).

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (8)$$

ReLU function (Equation 9) was made popular by DNN methods (Glorot et al., 2011). Only the previously applied DNN method (Saggi and Jain, 2019) was used ReLU function in the hidden layers.

$$\text{ReLU}(x) = \max(0, x) \quad (9)$$

In addition to ReLU function, SeLU function (Equation 10) was also tried in the experiments. The SeLU function was introduced by Klambauer et al. (2017). Klambauer et al proposed the best constant values for $(\alpha, \lambda)$ as $(1.67326324, 1.05070098)$, respectively.

$$\text{SeLU}(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha e^x - \alpha & \text{if } x \leq 0 \end{cases} \quad (10)$$
3.3. Dropout layer

The dropout layer was first proposed by Srivastava et al. (2014). Dropout layer is one of the most popular solutions to over fitting problem in DNN methods. Dropout layer is used with single parameter, dropout rate, which changes between 0 and 1. Dropout rate controls chance of dropping out connections when neural network is training. For example, if dropout rate is 0.5, coming neural connections to dropout layer is dropped with 50% chance. An example can be seen in Figure 7 in which connections of crossed neurons are dropped out.

![Figure 7: The architecture of dropout in neural networks.](Srivastava et al. 2014)

To be able to see if dropout layer is helpful for over fitting in the estimation of $ET_o$ value, different dropout rates were tried between the hidden layers. Therefore, 3 different dropout layers were introduced in DNN models (Figure 8b and Figure 8d). In the experiment, dropout rate changed from 0 to 0.5 with a rate of 0.1 increase. In total, 6 dropout rates were tried [0, 0.1, 0.2, 0.3, 0.4, 0.5]. In the end, using 3 DNN models with 3 different layers and 6 dropout layers (3 DNN * 6 (Dropout Layer 2) * 6 (Dropout Layer 2) * 6 (Dropout Layer 3), 648 models were applied in the experiments. According to our results, dropout layer is not useful for the estimation of $ET_o$ values.

3.4. Proposed deep neural network models

In this study, 3 layer architecture (1-60-90-60-1) were proposed for DNN model. For this 3 layer architecture, both ReLU and SeLU activation functions
were used. Additionally, different dropout rates were also tried in the DNN model. Figure 8 shows the proposed DNN models.

4. Results and discussion

4.1. Comparison of all the applied models

The best twenty performances metric of current and previous models for estimating daily \( E_{T_o} \) at the 4 meteorological stations are presented in Table 4. As can be seen in the Table 4, \( R^2 \), RMSE and MAE performance metrics ranged between 0.9913-0.9933, 0.1811-0.2471 mm day\(^{-1}\), 0.1333-0.1874 mm day\(^{-1}\), respectively. It was found that \( R^2 \) values of all the applied models were higher than 0.991, indicating a strong relationship between the \( E_{T_o} \) values from the FAO-56 PM equation and those predicted by the applied models. The RMSE and MAE values were lower than 0.25 and 0.19 mm day\(^{-1}\), which shows excellent performance for the estimation of daily \( E_{T_o} \). The proposed models (P-DNN-SeLU and P-DNN-ReLU) performed better than the previous models, with \( R^2 \), RMSE and MAE ranging 0.9933-0.9932, 0.1811-0.2182 mm day\(^{-1}\), 0.1333-0.1678 mm day\(^{-1}\), respectively. These results confirmed that proposed DNN models are superior to previously applied ANN and DNN models for estimation of daily \( E_{T_o} \).
Table 4: The best twenty performance metric of all the currently and previously proposed models for estimation of $ET_o$ at the 4 meteorological stations according to $R^2$

| Order | model name          | station name | $R^2$  | RMSE  | MAE  |
|-------|---------------------|--------------|--------|-------|------|
| 01    | P-DNN-SeLU $^1$     | Aksaray      | 0.9934 | 0.2073| 0.1591|
| 02    | P-DNN-ReLU          | Nigde        | 0.9933 | 0.2182| 0.1678|
| 03    | P-DNN-SeLU          | Adana        | 0.9932 | 0.1812| 0.1333|
| 04    | L-DNN-Saggi         | Nigde        | 0.9930 | 0.2240| 0.1740|
| 05    | L-DNN-Saggi         | Aksaray      | 0.9928 | 0.2160| 0.1654|
| 06    | P-DNN-ReLU          | Aksaray      | 0.9928 | 0.2165| 0.1651|
| 07    | L-DNN-Saggi         | Aksaray      | 0.9926 | 0.2197| 0.1683|
| 08    | L-ANN (60, 90, 60) $^2$ | Nigde    | 0.9919 | 0.2400| 0.1826|
| 09    | P-DNN-SeLU dropout 0 0.1 0 | Aksaray | 0.9919 | 0.2298| 0.1788|
| 10    | L-ANN (9)           | Aksaray      | 0.9918 | 0.2311| 0.1786|
| 11    | L-ANN (19)          | Nigde        | 0.9918 | 0.2421| 0.1854|
| 12    | L-ANN (19)          | Aksaray      | 0.9916 | 0.2334| 0.1788|
| 13    | P-DNN-SeLU dropout 0 0.1 0 | Adana  | 0.9916 | 0.2023| 0.1483|
| 14    | L-ANN (12)          | Nigde        | 0.9916 | 0.2453| 0.1871|
| 15    | L-ANN (21)          | Aksaray      | 0.9915 | 0.2348| 0.1796|
| 16    | L-ANN (22)          | Aksaray      | 0.9915 | 0.2353| 0.1799|
| 17    | L-ANN (16)          | Aksaray      | 0.9915 | 0.2354| 0.1793|
| 18    | L-ANN (28)          | Aksaray      | 0.9915 | 0.2355| 0.1797|
| 19    | L-ANN (26)          | Nigde        | 0.9914 | 0.2472| 0.1875|
| 20    | L-ANN (60, 90, 60)  | Aksaray      | 0.9913 | 0.2372| 0.1804|

$^1$ P- means currently proposed, L mean Literature.

$^2$ ANN(..) refers to Artificial Neural Network hidden layer neuron counts, for example (21) means 1 hidden layer with 21 neurons while (60,90,60) means 3 hidden layers with 60, 90 and 60 neurons.

However, the performance of the proposed activation SeLU decreased when dropout layer used (proposed activation SeLU dropout 0 0.1 0). This means that using dropout layers did not improve the modeling performances for the estimation of daily $ET_o$.

In general, it is observed that among the previously applied models, the Saggi and Jain model had the highest performance based on the performance metrics. Among the stations in the top twenty best performing models, Aksaray and Nide stations located in the semi-arid region were the most appearing, while Adana and Isparta stations located in Mediterranean region...
were the least appearing. This can be explained by the fact that the models performed better in semi arid region than the Mediterranean region.

4.2. Comparison of proposed and previously applied ANN and DNN models

Table 5: The highest performances of previously proposed methods for ET\textsubscript{o} estimation according to R\textsuperscript{2} score

| Study | Hidden Layers | Best (R\textsuperscript{2}) | Best (R\textsuperscript{2}) | Best (R\textsuperscript{2}) | Best (R\textsuperscript{2}) |
|-------|--------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| 1 | Landeras et al. (2008), Traore et al. (2010), Rahimikhoob (2014), Shiri et al. (2014), Yassin et al. (2016), Kisi and Kilic (2016), Antonopoulos and Antonopoulous (2017) | (1-30) | 0.9864 | 0.9918 | 0.9880 | 0.9918 |
| 2 | Huo et al. (2012) | 4-5, 5-6 | 0.9814 | 0.9883 | 0.9837 | 0.9885 |
| 3 | Saggi and Jain (2019) | 40-60-40 | 0.9905 | 0.9928 | 0.9896 | 0.9931 |
| 4 | Proposed ReLU | 60-90-60 | 0.9888 | 0.9928 | 0.9890 | 0.9934 |
| 4 | Proposed SeLU | 60-90-60 | 0.9925 | 0.9940 | 0.9887 | 0.9936 |

The comparison results of the previous models (ANN and DNN) and two current DNN models can be seen in Table 5. The table showed only the best performances among the experiments. According to Table 5, it was seen that R\textsuperscript{2} values of all the previously applied and proposed models were higher than 0.98. DNN models compared to ANN models improved R\textsuperscript{2} values in the 3-4 decimal points. If the complexity of the models and time to train are taken into account, these results may be considered as diminishing improvements according to requirements for ET\textsubscript{o}.

4.3. Comparison of meteorological station performances

The best five performance metric of currently proposed and previous models for estimation of ET\textsubscript{o} at the Adana, Aksaray, Isparta and Nigde
Table 6: The best five performance metric of proposed and previously applied models for estimation of $ET_o$ at the Adana, Aksaray, Isparta and Nide stations respectively according to $R^2$ score

| Rank | Model Name | Station Name | $R^2$ | RMSE | MAE |
|------|------------|--------------|-------|------|-----|
| 01   | P-DNN-SeLU | Adana        | 0.9925| 0.1912| 0.1409 |
| 02   | P-DNN-SeLU dropout 0.0 0.1 0.0 | Adana | 0.9916| 0.2023| 0.1483 |
| 03   | L-DNN-Saggi | Adana        | 0.9905| 0.2151| 0.1520 |
| 04   | P-DNN-ReLU | Adana        | 0.9888| 0.2336| 0.1664 |
| 05   | ANN (60, 90, 60) | Adana | 0.9865| 0.2557| 0.1860 |
| 01   | P-DNN-SeLU | Aksaray      | 0.9940| 0.1977| 0.1503 |
| 02   | L-DNN-Saggi | Aksaray      | 0.9928| 0.2160| 0.1654 |
| 03   | P-DNN-ReLU | Aksaray      | 0.9928| 0.2165| 0.1652 |
| 04   | P-DNN-SeLU dropout 0.0 0.1 0.0 | Aksaray | 0.9919| 0.2298| 0.1788 |
| 05   | ANN (9) | Aksaray      | 0.9918| 0.2311| 0.1786 |
| 01   | L-DNN-Saggi | Isparta      | 0.9896| 0.2346| 0.1779 |
| 02   | P-DNN-ReLU | Isparta      | 0.9890| 0.2405| 0.1848 |
| 03   | P-DNN-SeLU | Isparta      | 0.9887| 0.2438| 0.1864 |
| 04   | ANN (16) | Isparta      | 0.9880| 0.2513| 0.1942 |
| 05   | P-DNN-SeLU dropout 0.0 0.0 0.1 | Isparta | 0.9878| 0.2538| 0.1938 |
| 01   | P-DNN-SeLU | Nigde        | 0.9936| 0.2132| 0.1644 |
| 02   | P-DNN-ReLU | Nigde        | 0.9934| 0.2168| 0.1681 |
| 03   | L-DNN-Saggi | Nigde        | 0.9931| 0.2219| 0.1708 |
| 04   | ANN (60, 90, 60) | Nigde | 0.9919| 0.2400| 0.1826 |
| 05   | ANN (19) | Nigde        | 0.9918| 0.2421| 0.1854 |

stations are presented in Table 6. In general, Table 6 showed that the P-DNN-SeLU model had the highest performance in Aksaray, Nide and Adana stations. In that case, $R^2$ values of P-DNN-SeLU model are 0.9939, 0.9936 and 0.9924, RMSE values are 0.1977, 0.2131 and 0.1911, MAE values are 0.1502, 0.1643 and 0.1409. However, Saggi and Jain model had the highest performance in Isparta station with the value of $R^2$ to 0.9896, RMSE to 0.2346 and MAE to 0.1779, respectively. Obviously, the proposed activation SeLU model in Aksaray and Nide stations had slightly better prediction accuracy than the P-DNN-SeLU model in Adana and Isparta stations. It can be seen that the P-DNN-SeLU model showed more improvements in daily $ET_o$ estimation in the semi arid region, compared with those in the Mediterranean regions.
The scatter plot of estimated $ET_o$ values by P-DNN-SeLU, P-DNN-ReLU and Saggi and Jain models compared with the FAO-56 PM values at the Adana, Aksaray, Isparta and Nide stations are presented in Figure 9. The figure showed that the plotted data points mostly correlated close towards the 1:1 line. However, the models in Isparta station yielded more scattered daily $ET_o$ values compared to other three stations. The models were more close to those obtained with FAO-56 PM equation in Aksaray station. These results indicated that the models showed a much higher prediction accuracy of daily $ET_o$ value in Aksaray station.

Figure 9: Scatter plots for 3 Deep Neural Networks.
5. Conclusions

This study assessed the application of 14 ANN methods (2 new DNN, 1 previous DNN and 11 previous ANN) for estimation of daily $ET_o$ in the two different climate zones of Turkey. The models used 6 input meteorological data including $T_{\text{max}}$, $T_{\text{min}}$, $R_n$, $RH_{\text{max}}$, $RH_{\text{min}}$ and $U_2$ from 4 weather stations (Adana, Aksaray, Isparta and Nide) during 1999-2018 in Turkey. The results demonstrated that all models of DNN and ANN achieved satisfactory accuracy for estimation of daily $ET_o$ using available meteorological data. Especially, the DNN methods were highly effective in estimating $ET_o$ value. It can be seen from the results that the performance of the models became more reliable when cross validation was used in the study. However, the result showed that dropout layer was not useful for $ET_o$ estimation. In addition, using more powerful architecture did not improve the estimation of $ET_o$.

In general, among the meteorological stations, Aksaray station offered the best prediction accuracy, while Isparta station performed the least prediction accuracy in all the DNN and ANN models. The overall results indicated that the proposed model of P-DNN-SeLU made a significant improvement in accuracy among the other models. Therefore, P-DNN-SeLU model has a very high potential for estimation of daily $ET_o$ in different climatic zones of Turkey, even possibly in other zones of the world. In short, P-DNN-SeLU model could be applied in the future studies to estimate $ET_o$ under different climate conditions. Finally, further studies should be carried out to evaluate the applicability of P-DNN-SeLU model under limited input data, in places where meteorological variables are limited.

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