Evaluation of the Performance of CFSR Reanalysis Data Set for Estimating Potential Evapotranspiration (PET) in Turkey

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Evaluation of the performance of CFSR reanalysis data set for estimating potential evapotranspiration (PET) in Turkey

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Abstract

Evapotranspiration is an important parameter for hydrological, meteorological and agricultural studies. However, the calculation of actual evapotranspiration is very challenging and costly. Therefore, Potential Evapotranspiration (PET) is typically calculated using meteorological data to calculate actual evapotranspiration. However, it is very difficult to get complete and accurate data from meteorology stations in, rural and mountainous regions. This study examined the availability of the Climate Forecast System Reanalysis (CFSR) reanalysis data set as an alternative to meteorological observation stations in the computation of potential annual and seasonal evapotranspiration. The PET calculations using the CFSR reanalysis dataset for the period 1987-2017 were compared to data observed at 259 weather stations observed in Turkey. As a result of the assessments, it was determined that the seasons in which the CFSR reanalysis data set had the best prediction performance were the winter (C'= 0.76 and PBias = -3.77) and the autumn (C' = 0.75 and PBias = -12.10). The worst performance was observed for the summer season. The performance of the annual prediction was determined as C'= 0.60 and PBias = -15.27. These findings indicate that the results of the PET calculation using the CFSR reanalysis data set are relatively successful for the study area. However, the data should be evaluated with observation data before being used especially in the summer models.

Keywords: CFSR re-analysis, Potential evapotranspiration, FAO56-PM, Turkey.

1. Introduction

The amount of water that evaporates from soil surfaces or open water and the transpiration of plant leaves in the atmosphere is known as evapotranspiration (Tabari et al. 2013; Anderson et al. 2019). Evapotranspiration for hydrological, meteorological, and agricultural studies is a parameter that

plays an important role in the planning of water resources, programming of irrigation time, and the creation of hydrological and agricultural models. Evapotranspiration; lysimeter (Gebler et al. 2015), Eddy-covariance method (Sun et al. 2008), Bowen ratio energy balance (Shi et al. 2008), scintillometer (Moorhead et al. 2017) and evaporation pans (Conceicao 2002) can be measured. However, these procedures are quite costly and difficult to apply in large basin conditions (Latrech et al. 2019).

Potential evapotranspiration is defined as the amount of water that can evaporate when the water in the soil is sufficient to meet the atmospheric moisture demand (Allen et al. 1998). The PET is extremely useful to measure the atmospheric water demand of the area. Therefore, it is used in a variety of applications, including irrigation planning, drought monitoring and understanding the impacts of climate change (Lang et al. 2017).

Numerous methodologies have been developed to determine potential evapotranspiration (PET) and actual evapotranspiration using meteorological data (Bandyopadhyay et al. 2012). These methods are mostly based on solar radiation (Priestley Taylor), temperature (Thornthwaite, Hargreaves, and Samani), and a combination of solar radiation and temperature (Penman-Monteith) (Seong et al. 2017; Purnadurga et al. 2019). The FAO56-PM method is considered a good way to estimate evapotranspiration globally, compared to other methods. (Sentelhas et al. 2010; Srivastava et al. 2013; Tabari et al. 2013; Tanguy et al. 2018).

Kite and Drooger (2000) assessed eight different PET calculation methods and explained that the FAO56-PM method is most compatible with field observations. The FAO56-PM is a combination of physiological and aerodynamic methods that require climate factors like maximum and minimum temperature, wind speed, relative humidity and solar radiation. However, the meteorological stations providing these data, particularly in developing countries, are not distributed uniformly (Alfaro et al. 2020). In addition, observations of these climatic variables are very difficult to obtain in rural and mountainous areas. In addition, setting up and maintaining the meteorological station at these locations is quite costly (Tabari et al. 2013; Lang et al. 2017). Therefore, alternative data sources are needed to better simulate hydrological processes. Therefore, additional data sources such as the reanalysis data set are necessary to better simulate hydrological processes. Reanalysis datasets with

high precision and high spatiotemporal resolution widely use in hydrological modelling (Alfaro et al. 2020).

Re-analysis data sets are generated using data from meteorology observation stations based on satellite data, weather forecast models, and data assimilation methods (Purnadurga et al. 2019). There are many commonly used re-analysis data sets. These are CFSR (Saha et al. 2010), NCEP/DOE (Kanamitsu et al. 2002), and NCEP/NCAR (Kalnay et al. 1996) datasets produced by NCEP, ERA-15 (Bromwich et al. 2005), ERA40 (Uppala et al. 2005) and ERA-Interim (Dee et al. 2011) datasets produced by ECMWF, JRA-55 (Ebita et al. 2011) datasets from Japanese meteorology agency and MERRA (Rienecker et al. 2011) datasets by NASA.

These datasets provide predictions of weather variables, including precipitation and temperature, for any terrestrial location around the world. The NCEP-CFSR re-analysis dataset uses numerical weather prediction techniques to predict atmospheric conditions with a resolution of 0.3125 (~ 38 km). In addition, forecasting models are restarted every 6 hours using information from the global network of weather stations (Fuka et al. 2013). The most important advantage of CFSR is that it provides complete and continuous recording of climate data such as precipitation, temperature, solar radiation, humidity, and wind speed since 1979 (Auerbach et al. 2016). In addition, the complete acquisition of these data allows the use of the FAO56-PM method.

Laurie et al. (2014) evaluated, reanalysis data for the Mekong basin as input to the hydrological model. They indicated that if there is a lack of data, CFSR temperature data can be used for hydrological modelling studies. Fuka et al. (2013) investigated the usability of the CFSR data set as historical weather data in modeling five basins with hydrological different climate regimes. As a result, they explained that the modeling made with CFSR temperature and precipitation data gives results as well as the modeling using observation and measurement stations, and they reported that the CFSR data set can be used in basins without observation and measurement stations. Dial and Srinivasan (2014) assessed whether or not the CFSR dataset is appropriate for hydrologic modeling. As a result of the evaluations, they explained that the CFSR data set is an important alternative for hydrological estimates in areas where observation data are not available. In other studies, Alemayehu et al. (2015) evaluated the ability to calculate potential evapotranspiration with sufficient accuracy,

using different reanalysis datasets. They compared the PET estimates calculated using the CFSR dataset with the results of the observation stations and reported that the CFSR dataset is a good alternative. Alfaro et al. (2020) calculated the potential evapotranspiration required for hydrological modeling with the CFSR reanalysis data set in their study. They explained that the predictive performance of the CFSR dataset was good by evaluating the results obtained.

These studies show that reanalysis datasets such as CFSR are of sufficient quality and resolution to be used as inputs in basin modelling studies. In addition, this dataset can be an important alternative for overcoming problems encountered in obtaining meteorological observation data. The purpose of this study is to investigate the availability and use of the CFSR reanalysis dataset for the calculation of PET using the FAO56-Penman method in Turkey.

2. Material and Methods

2.1. Study area and meteorological data

Turkey is located between 36°-42° N and 26°-45° E. The total area is 779,452 square kilometers and the average altitude is 1141 meters. Turkey's climate is located between the temperate and sub-tropical zones. In coastal areas, milder climate features are observed with the effect of the seas. The mountains of North Anatolia and the mountains of Taurus prevent the effects of the sea from entering the interior parts and therefore the continental climatic characteristics are observed in the interior parts (Katipoglu et al. 2021).

In this study, meteorological observation data from 259 stations belonging to the Turkish State Meteorological Service were used for the calculation of PET. The locations of these stations are shown in Figure 1 on the elevation map of Turkey.

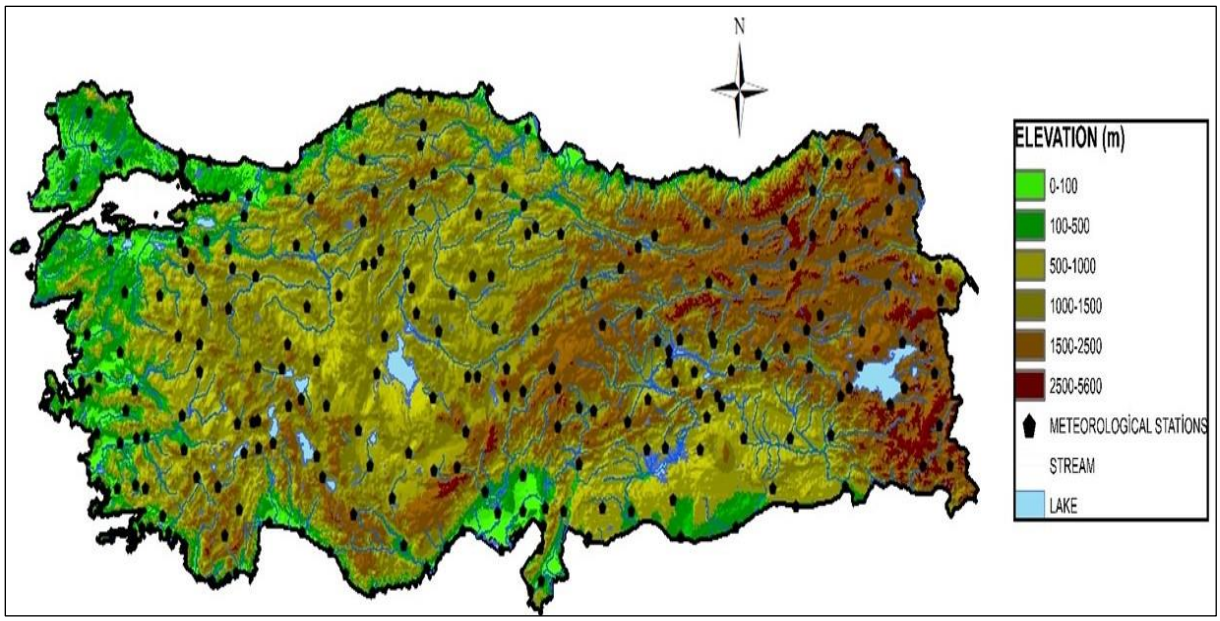


Figure 1. Study area and location of meteorological stations

The observed potential evapotranspiration values were obtained from the "Plant Water Consumption Guide" published by State Hydraulic Works and the Directorate-General for Agricultural Research and Policy (TAGEM 2017). CFSR data set containing daily data on temperature, humidity, precipitation, wind speed and solar radiation for the years 1987 to 2017.

2.2. CFSR reanalysis dataset

The CFSR dataset used in this study consists of six hours of weather prediction generated by the US National Weather Service. The CFSR reanalysis dataset contains the maximum and minimum temperatures (°C), precipitation (mm), wind velocity (m s^{-1}), humidity (%), and solar radiation (MJ m^{-2}) from of any location in the world (Dile and Srinivasan 2014; Irvem and Ozbuldu 2019). The spatial and temporal resolution of the CFSR is 0.35° (nearly 38 km) and 6 hours, respectively. CFSR datasets for Turkey (1987–2017) were obtained via the internet (https://rda.ucar.edu/).

2.3. FAO56-PM method

Penman (1948) developed an evaporation formula for open water surface based on climatic data. Monteith (1976) developed this formula by adding aerodynamics and surface strength factors. Daily potential evapotranspiration (PET, mm day^{-1}) estimated by Penman-Monteith equation (PM) is calculated by given Eq.1.;

$$PET = \frac{0.408\,\Delta\,(R_n - G) + \frac{900\,\gamma}{T+278}\,u_2\,(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34\,u_2)} \quad \textbf{(1)}$$

where; Δ is the slope of the relationship between saturation vapor pressure and mean daily air temperature (kPa °C^{-1}), R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), γ is the psychrometric constant which depends on the altitude of each location (kPa °C^{-1}), T is the mean daily air temperature (°C), u_2 is the wind speed at 2 m height (m s^{-1}); e_s is the saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa).

2.4. Inverse Distance Weighting (IDW) method

In this study, the IDW interpolation method was used to produce a spatial distribution of the PET values. IDW is the most widely used non-geostatistical interpolation method, requiring minimal operator parameters. It can particularly be used where the data set is deficient and other techniques are affected by errors. The IDW method is a local intermediate value estimation method because it generates estimates from neighbouring points. The assigned weights at each nearby point are the opposite of its distance from the cell is estimated. The IDW method estimates unknown points using point-to-point distances in the weight calculation. The calculation formula of IDW was given in Eq.2. (Salekin et al. 2018).

$$Z_J = \frac{\sum_{i=1}^{n} \frac{Z_i}{\left(h_{ijk} + \delta\right)^{\beta}}}{\sum_{i=1}^{n} \frac{1}{\left(h_{ijk} + \delta\right)^{\beta}}} \quad \textbf{(2)}$$

where Z_j is the unsampled location value, Z_i is the known cell's value, β is the weight, and δ is the parameter. The separation distance h_{ijk} is measured by a three-dimensional Euclidian distance. h_{ijk} is calculated by the Eq.3. (Salekin et al. 2018).

$$h_{ijk} = \sqrt{(\Delta x)^2 + (\Delta y)^2 + (\Delta z)^2} \quad \textbf{(3)}$$

where Δx and Δy are the distances between the unknown and known point according to the reference axes, respectively, and Δz refer to the height as the third point of measure.

2.5. Evaluation criteria

The four statistical methods were used to assess the PET estimates from the CFSA dataset against the PET calculated using meteorological station data. These are coefficient of determination (R^2), root-mean-square error (RMSE), PBias (percent bias), and the performance index (C').

R^2 shows to what extent the PET estimates calculated with the CFSR dataset are similar to the PET values calculated with the observation data. R^2 varies between 0 and 1, higher values indicate less error variation. Generally, values above 0.50 are considered acceptable (Moriasi et al. 2007) and calculated based on Eq 4.;

$$R^2 = \left(\frac{n\sum(O_i M_i) - (\sum O_i)(\sum M_i)}{\sqrt{(n(\sum O_i^2) - (\sum O_i)^2)(n(M_i^2) - (\sum M_i)^2)}} \right)^2 \quad \textbf{(4)}$$

The value of RMSE should always be positive and it is desired to be close to zero. This indicates that the lower the value, the better the model will perform. RMSE provides performance information for correlations by comparing the difference between model results and observed values (Piñeiro et al. 2008). RMSE is calculated by Eq.5.

$$RMSE = \sqrt{\frac{1}{n}\sum(Predict_i - Obs_i)^2} \quad \textbf{(5)}$$

PBias is used to determine how far the model predicted values are in the negative or positive direction from the observed values. Whereas positive values indicate that the observed values are higher than the simulated values, negative values indicate the opposite situation (Gupta et al. 1999). PBias is determined by Eq.6.

$$PBias = 100\ (\sum Obs_i - Predict_i\ /\ \sum Obs_i\ ) \quad \textbf{(6)}$$

The Willmott index of agreement (d) shows the degree of fit between observed and predicted measurements between 0 and 1. The closer the result is to 1, the better the model performance is determined (Willmott 1981; Tran et al. 2020). It is calculated by Eq. 7.

$$d = \frac{\sum(Obs_i - Predict_i)^2}{\sum([Predict_i - Obs_{mean}] + [Obs_i - Obs_{mean}])^2} \quad \textbf{(7)}$$

The performance index (C') was calculated by combining accuracy and precision criteria into the relationship between the model and the predictive data. The Pearson linear correlation coefficient, which measures the degree and direction of distribution among variables, was used as a precision criterion. The Willmott's index of agreement was chosen as an accuracy criterion because it measures the degree of fit between the predicted and observed data. The performance index of the model was computed by Eq. 8 and evaluated using Table 1 (Santos et al. 2020).

$$C' = Correlation\ Coefficient\ (CC) * \text{Willmott's index of agreement}(d) \quad \textbf{(8)}$$

Table 1. Model performance evaluation table (Moriasi et al. 2007; Santos et al. 2020).

Classification	**C'**	**PBias**
Very Good	0.75 - 1.00	< ± 10
Good	0.65 - 0.75	± 10 - ± 15
Satisfactory	0.60 - 0.65	± 15 - ± 25
Unsatisfactory	< 0.50	> ± 25

3. Results and Discussion

Using meteorological data from the CFSR data set, the average seasonal and annual potential evapotranspiration amounts for each observation station for 1987-2017 were estimated. The PET estimates were compared with the PET computed using ground observation data. The accuracy and usability of the CFSR reanalysis dataset were evaluated through statistical analysis. The results of that analysis are presented in Table 2. In addition, maps were generated using IDW interpolation techniques to show area distributions of PET results for the different seasons and the long-term annual mean.

3.1. Results of PET estimation for the winter

The PET prediction results using the CFSR dataset for the winter season (December, January, February) were compared with the PET results obtained from the observed data. The obtained values for the stations were used to generate PET maps of Turkey.

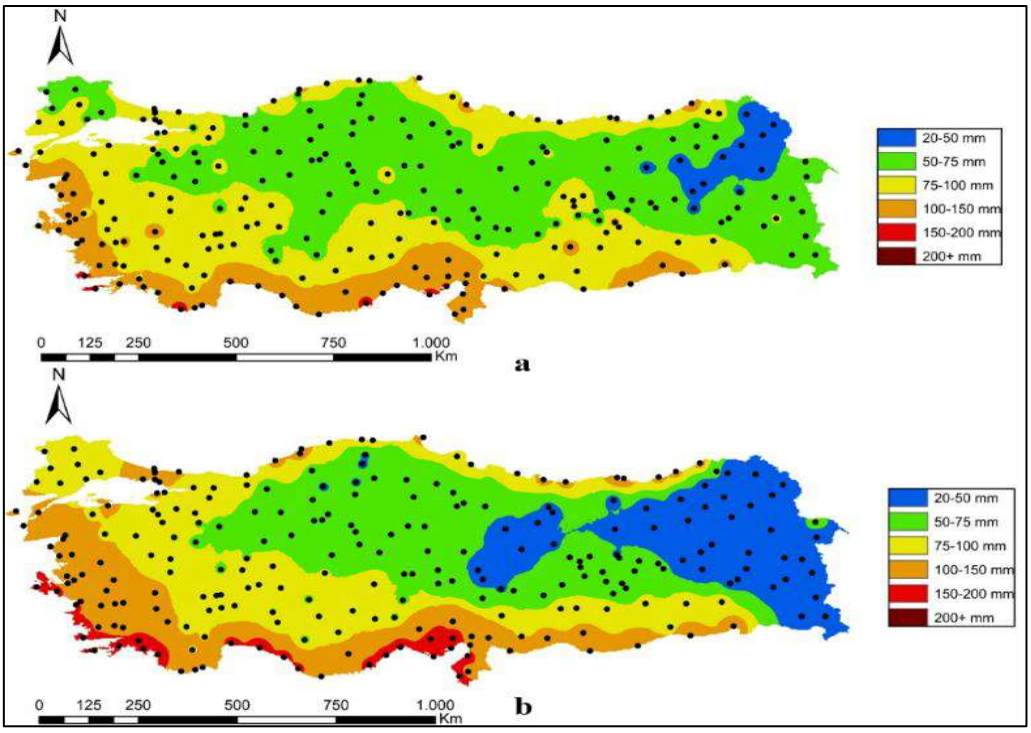
188 **Table 2.** Results of the statistical analysis

	Winter(DJF)	*Spring(MAM)*	*Summer(JJA)*	*Autumn(SON)*	*Annual*
R^2	0.73	0.67	0.67	0.79	0.68
RMSE	22.27	33.85	103.10	32.47	208.37
PBias	-3.77	-6.24	-16.94	-12.10	-15.27
d	0.89	0.85	0.70	0.85	0.74
C’	0.76	0.70	0.57	0.75	0.60

189

190 PET values were classified into 6 categories between 20 and 200 mm, as shown in Figure 2.
191 When the map is examined, it is seen that CFSR has higher estimates in the southern and western
192 regions, but lower forecasts at eastern stations. It can be explained that the CFSR reanalysis dataset
193 has relatively high data on temperature and solar radiation in those regions, unlike the eastern region.

194 Bhattacharya et al. (2020) reported similar results in their study in India. They explained that
195 the CFSR has a tendency to predict higher temperatures (>2°C) in the southwest in winter and colder
196 temperatures in the northeast. Station estimates were compared using the calculated PBias value (-
197 3.77) and PET calculated using CFSR data was determined to be relatively high. However, according
198 to Table 2, these estimates are in acceptable ranges (very well <±10).



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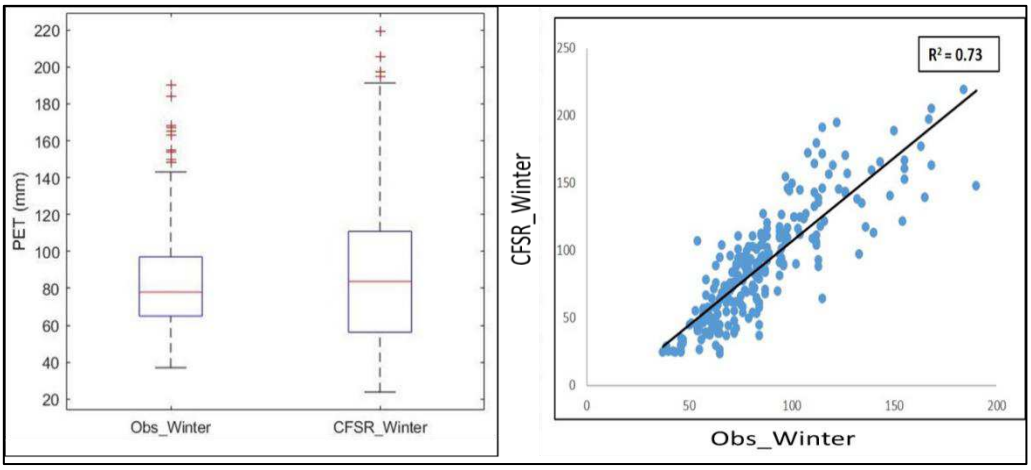
200 **Figure 2.** Average long-term PET map for the winter season a) observation b) CFSR



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202 **Figure 3.** Boxplot and scatter plot of the CFSR data set for the winter season.

203 The variation of the winter season between CFSR re-analysis and observation data sets is
204 shown in the boxplot graph in Figure 3. When we examine the two data sets, the difference between
205 the medians is very small and the interquartile range is similar. This shows that most of the predictions
206 made for the winter season of the CFSR data set are in line with the observation data. The R^2 value
207 calculated 0.73 as seen in the scatter plot in Figure 3. This shows that the CFSR re-analysis dataset has
208 a good correlation with the observation data. R^2 values between 0.50-0.99 are considered good
209 estimates for hydrological studies (Alfaro et al. 2020). The RMSE value, which shows the amount of

error in the data set, was 22.77 mm season^{-1}, and the C 'performance index, which shows the success of the predictions, was 0.76. According to the performance evaluation, it has been observed that the C' value of the CFSR estimates is quite good (>0.75). These results yielded similar results to the study conducted by Tian et al. (2014), and it was observed that the predictions made with the CFSR data set can be used safely for regions with missing PET estimates in the winter season.

3.2. Evaluating PET estimates for the spring

The spatial distributions of the estimated and observed PET results over Turkey for the spring season (March, April, May) are given in Figure 4. It was seen that there were relatively similar results for the stations, especially in the inner regions. However, as in the winter forecasts, the CFSR has shown overestimates in the southern and western regions, and underestimates at stations in the northeast region. It is seen that the CFSR reanalysis data set tends to predict PET higher than the observation data. This is likely due to the CFSR having overestimations for the stations having a relatively higher temperature, solar radiation, and wind speed than others (Paredes et al. 2017).

The R^2 value was found 0.67 as seen in the scatter plot in Figure 5. This shows that the CFSR re-analysis dataset has a good correlation with the observed data. The RMSE value was 33.85 mm season^{-1}, and the C 'performance index, was 0.70. When the station estimates are compared, the calculated PBias (-6.24) value indicates that the CFSR re-analysis made relatively overestimates, but according to Table 2, it is in acceptable ranges (very good <±10). According to these performance evaluations, it was concluded that estimations of PET using the CFSR data set are also good for spring seasons.

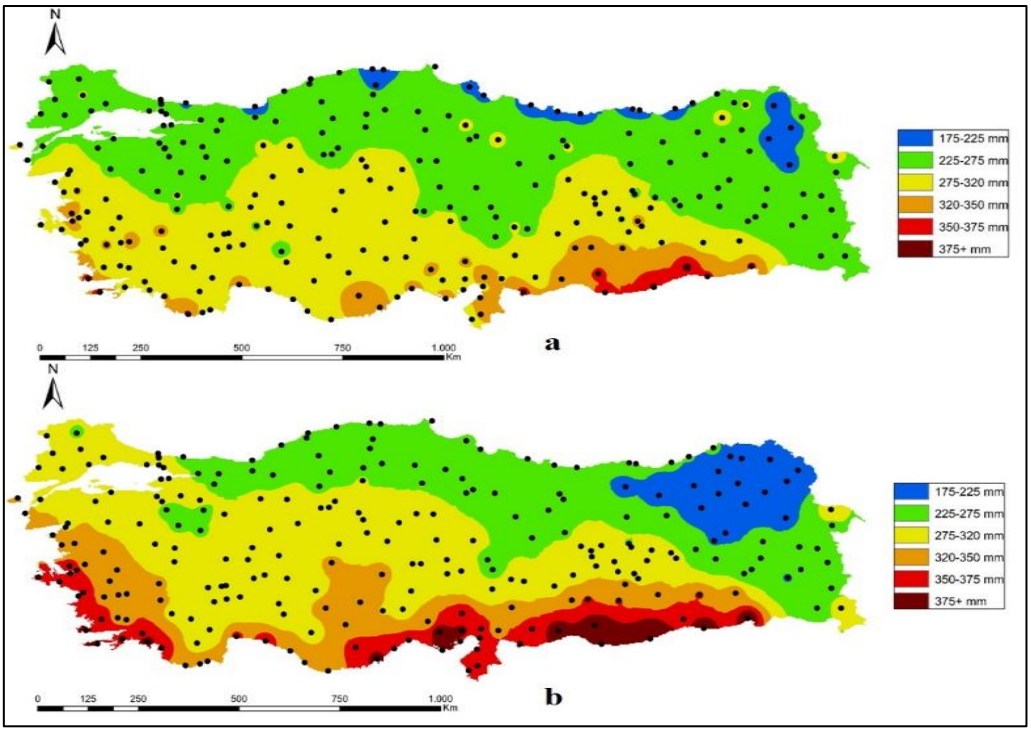

Figure 4. Average long-term PET map for the spring season a) observation b) CFSR

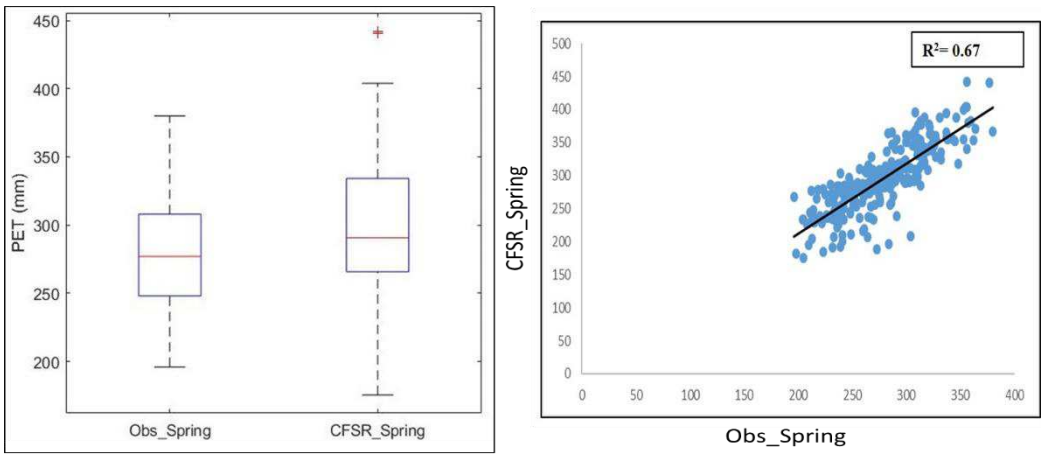

Figure 5. Boxplot and scatter plot of the CFSR data set for the spring season.

3.3. Evaluating PET estimates for the summer season

When the predictions made by the CFSR for the summer season (June, July, August) are compared with the observation data, the differences between the results are higher than in other seasons as seen in Figure 6. The reason for this thought is that temperature and solar radiation increase considerably in the summer months and the CFSR reanalysis data set cannot accurately predict these changes. CFSR was generally overestimated from the observation data where differences were higher between winter and summer seasons, especially in the southeastern and western regions.

PBias value was calculated -16.94 for the summer season. It shows that the CFSR re-analysis made higher estimates in summer than winter and spring, but estimated PET for the summer is still in acceptable (<± 25) ranges.

Although PET estimates are acceptable in terms of R^2 (0.67), the RMSE had the highest error (RMSE=103.10 mm season^{-1}), and the C' performance index is 0.57. According to these performance evaluations, the C' value of the CFSR estimates is not acceptable (<0.60). The reason why the PET prediction of the CFSR re-analysis dataset underperforms in the summer is due to the decrease in solar radiation and temperature prediction capabilities. The reason can be explained that more convective warming occurs in summer compared to other seasons. This type of convection may cause the formation of different weather conditions on a small scale that CFSR cannot predict due to its coarse resolution (Tian et al., 2014). Using the CFSR data set directly on models for the summer months will result in unsuccessful simulation results. For this reason, preliminary procedures that will reduce this dataset to a regional scale should be applied and re-evaluated before using it.

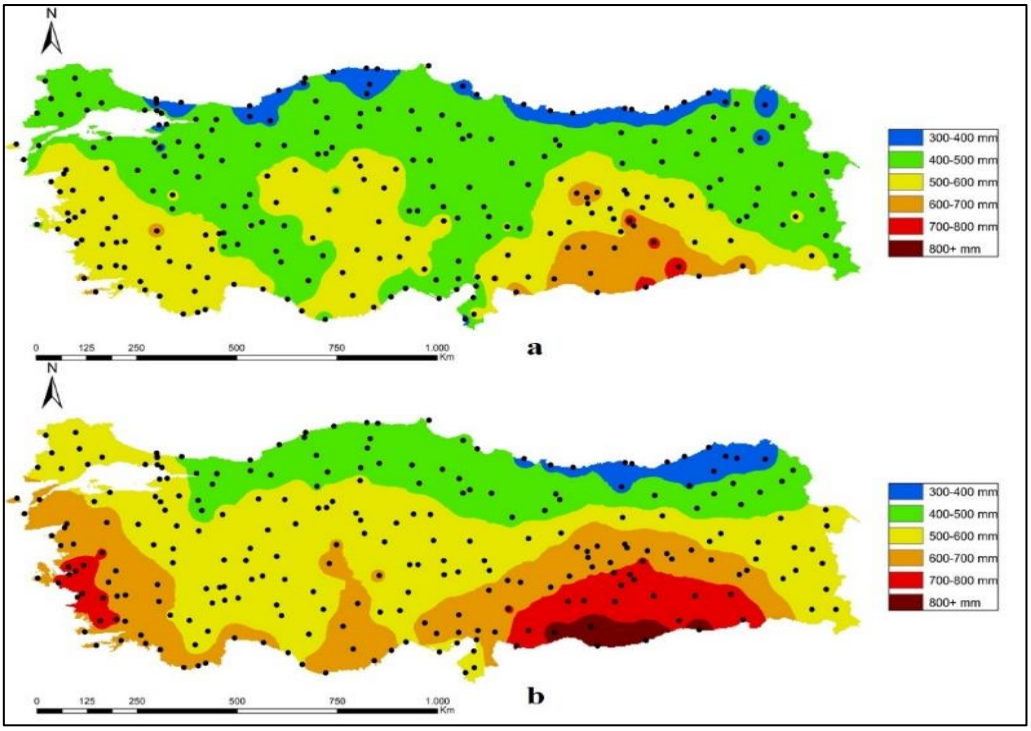

Figure 6. Average long-term PET map for the summer season a) observation b) CFSR

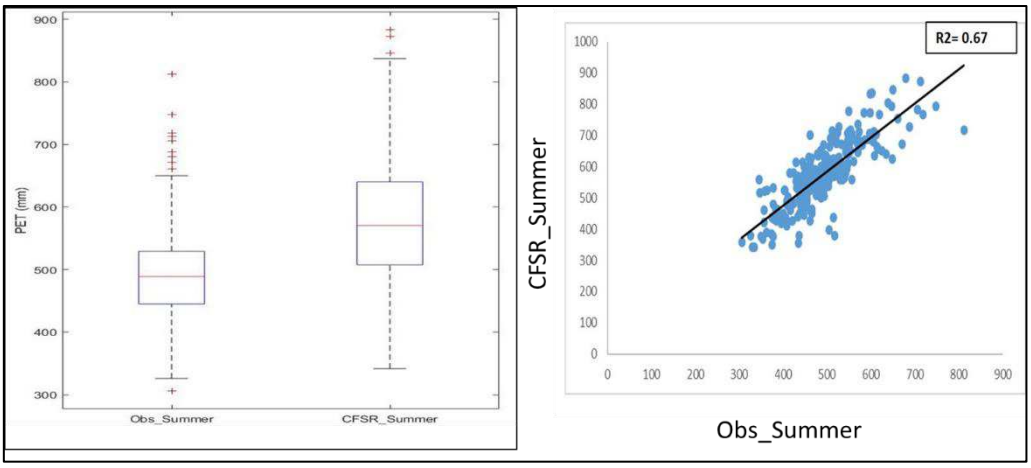

Figure 7. Boxplot and scatter plot of the CFSR data set for the summer season.

3.4. Evaluating PET estimates for the autumn

The predictions made by the CFSR for the autumn season (September, October, November) PET estimated higher than observation data as seen in Figure 8. The PBias was found -12.10. This shows that the CFSR re-analysis estimates PET is good (<± 15).

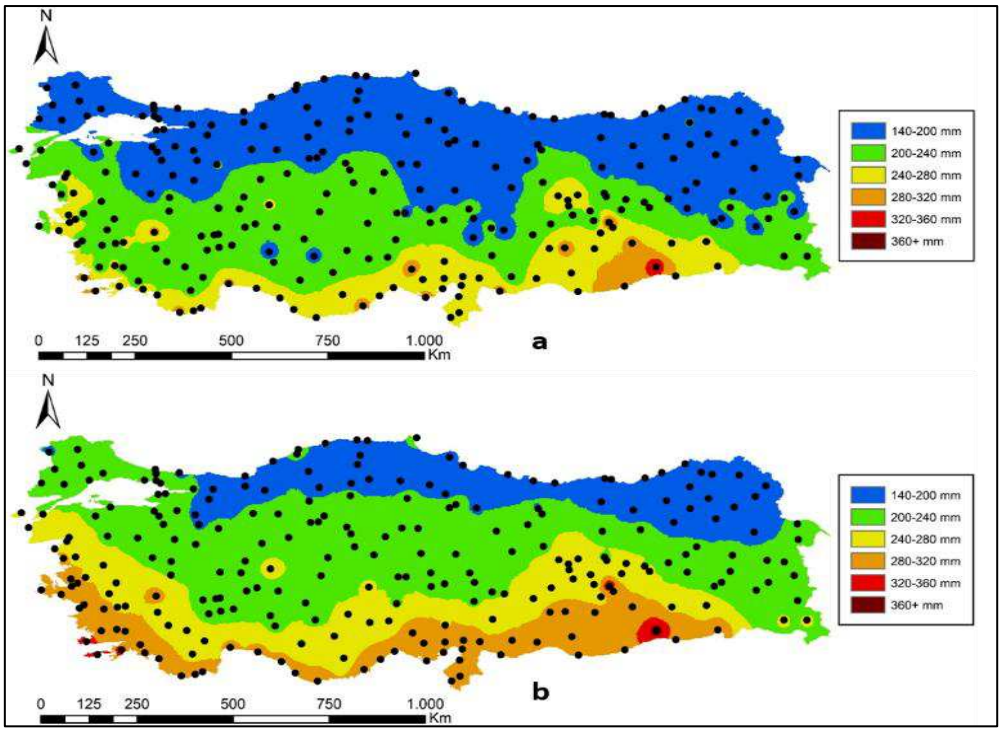

Figure 8. Average long-term PET map for the autumn season a) observation b) CFSR

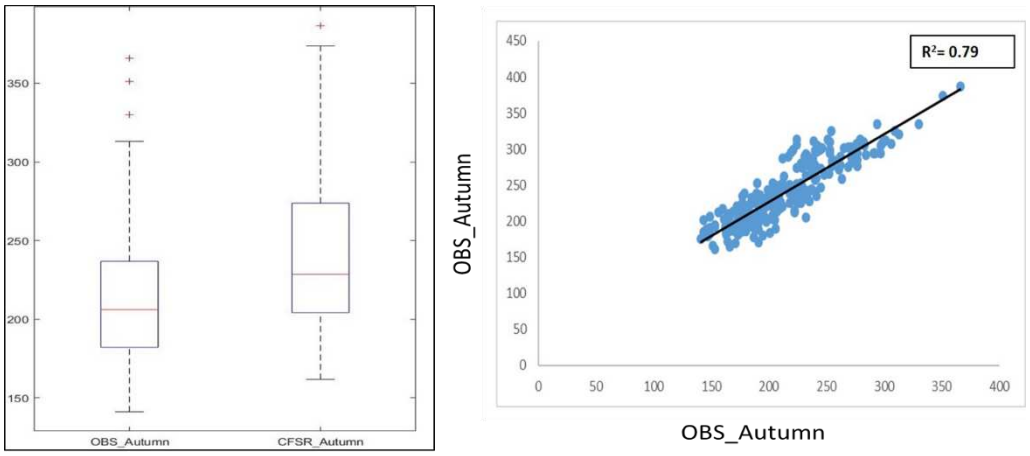

Figure 9. Boxplot and scatter plot of the CFSR data set for the spring season.

The boxplot graph for the autumn season between the CFSR reanalysis and observation data sets is given in Figure 9. When comparing the situation between quarters, it is seen that the higher estimates of CFSR for the autumn season are more intense. Because of the R^2 value found 0.79, PET estimates of CFSR data are good for the autumn season. This shows that the CFSR re-analysis dataset has a good correlation with the observed data. The RMSE value and C' performance index were calculated 32.47 mm season^{-1}, and 0.75 respectively. According to the performance evaluation, the C 'value of the CFSR estimates is quite good (>0.75). These results show that the CFSR estimates of PET for the autumn season can be used safely.

3.5. Evaluating long-term average annual pet estimates

The long-term annual average PET estimations using the CFSR data set and observed data for the years 1987-2017 are shown in Figure 10. PET was estimated between 1300-1900 mm/year for Southern and Western regions in Turkey. In this region, PET was calculated between 1100-1700 mm using data from meteorological observation stations. In contrast, estimated and observed PET were found lower in the northern and eastern regions of Turkey. Estimated PET using CFSR was between 700-1100 mm year^{-1} in the northern and eastern regions and 900-1300 mm in inland regions. These estimates are very close to the observation data as can be seen in Figure 10. In the study conducted in China, while PET estimates for the south and west regions were high, it was observed that the PET estimates for other regions were similar to the station results (Tian et al. 2018).

When the station estimates are compared, the calculated Pbias (-15.27) value shows that the CFSR reanalysis estimates are acceptable (<± 25). The negative result of the PBias indicates that the long-year average CFSR PET estimates are higher than the observation calculations.

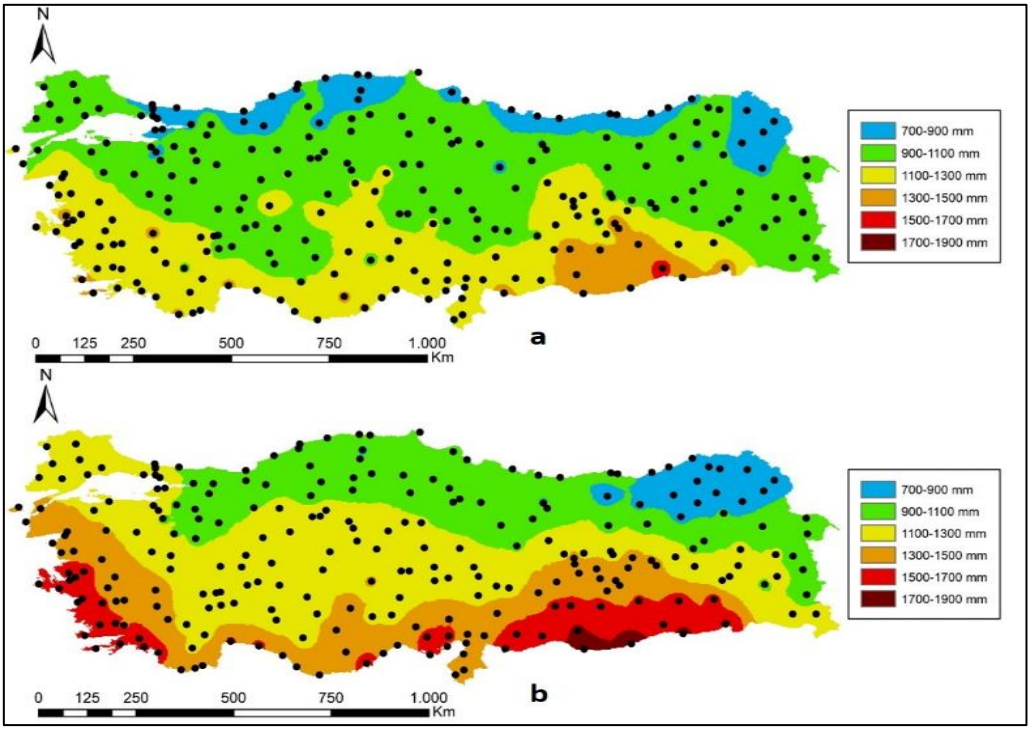

Figure 10. Average long-term annual PET map a) observation b) CFSR and

Calculated and estimated PET distributions using the average long annual data are shown in Figure 11 with the boxplot. When comparing the situation between quarters, it is seen that the higher estimates are more intense. It has been observed that the minimum values are close to each other, but in the difference between the maximum values, it is seen that the CFSR tends to overestimate PET annually from the observation data. The R^2 value (0.68) shows that the annual PET estimates are acceptable and have a good correlation with observation data. The RMSE value showing the amount of error in the data set was calculated as 208.37 mm $year^{-1}$. The C 'performance index, which shows the success of the predictions, was obtained as 0.60. According to the performance evaluation, it has been observed that the C' value of the CFSR estimates is acceptable (> 0.60). Alfaro et al. (2020) calculated the C 'performance index of the CFSR reanalysis data set as 0.72 in their study conducted in Brazil and explained that the prediction performance was acceptable similar to our study results.

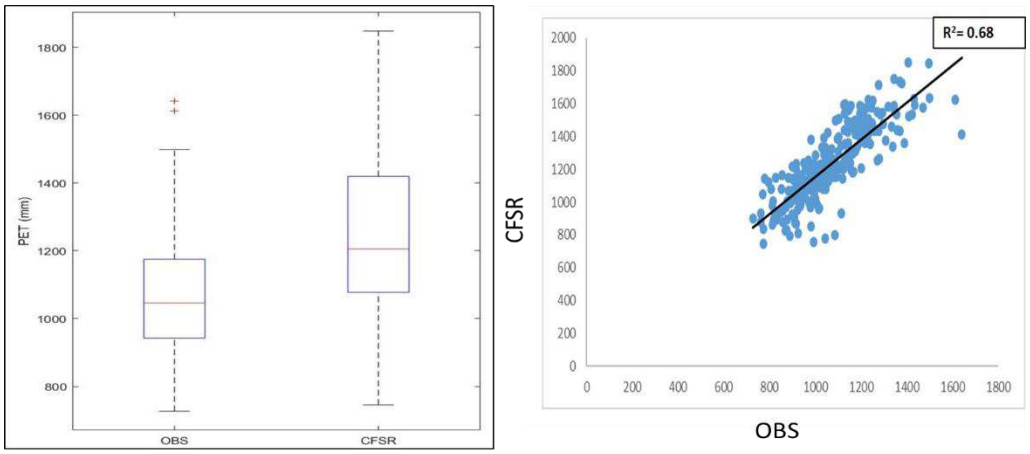

Figure 11. Boxplot and scatter plot of long-term average annual CFSR re-analysis data set

4. Conclusion

PET is a very important parameter for hydrological, meteorological, and agricultural studies. However, it is very difficult to obtain the meteorological data for calculation or estimation of this parameter in developing countries for the required regions. In this study, PET was estimated by the FAO56-PM method using observed and CFSR data set for Turkey. Accuracy of seasonal and annual estimations was statistically evaluated by comparing calculated PET. Data from 259 stations covers the period from 1987 to 2017 used to calculate PET.

As a result of the evaluations, the periods in which the prediction performance of the CFSR reanalysis data set was the highest were determined as Winter (C'= 0.76 and PBias = -3.77) and Autumn (C' = 0.75 and PBias = -12.10) seasons. Also, the lowest RMSE values were calculated (22.27 and 32.47) in these two seasons. The worst performance was seen for the Summer season (C'= 0.57 and PBias = -16.94). The reason for this, the increase in solar radiation and temperature values during the summer months cannot be estimated by the CFSR accurately as mentioned by Tian et al. (2014). In terms of annual performance, it has been calculated as C'= 0.60 and PBias = -15.27. These results show that the PET prediction ability of the CFSR re-analysis dataset is relatively good for the study area.

PBias value was calculated as negative in annual and seasonal evaluations. Especially in the southern and western regions, it has been observed that CFSR tends to overestimate the observation

data. Similar results have been observed in studies conducted by Bhattacharya et al. (2020) and Tian et al. (2017).

Therefore, when the CFSR reanalysis data set is evaluated in general, it can be seen as a good potential data source. However, it is recommended to evaluate the data with observation data before being used especially in summer seasons and to be used after regionalization with downscaling methods before being used in models.

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All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Ahmet Irvem and Mustafa Ozbuldu.

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Data availability

The data that support the findings of this study will be made available from the corresponding author on reasonable request.

Code availability

Not applicable.

Ethics declarations

Ethics approval:

The authors have agreed for authorship, read and approved the manuscript, and given consent for submission and subsequent publication of the manuscript.

348 **Consent to participate**

349 All authors consent to participate of the present study.

350 **Consent for publication**

351 All authors consent to participate of the present study.

352 **Conflict of interest**

353 The authors declare no competing interests.

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