A New Copula-Bayesian Post-Processing Method for NMME Precipitation Forecasts: Extreme and Non-Extreme Values

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Abstract

In this study, an effective post-processing approach has been examined to improve skill of NMME precipitation forecasts. This method is based on the existence of a correlation between the historical raw forecast and observational data. In this respect, the Copula-Bayesian approach was used along with the Normal Kernel Density marginal distribution, kernel Copula function, and a novel approach to select final improved forecast data amongst the existing candidates on the calculated Conditional Probability Distribution Functions (CPDF). In this approach, called the Double Copula method, four input variables are effective for determining the improved NMME data. These are 1) the likelihood of an improved forecast (as a probable observation) for a given raw forecast (CPDFf) 2) the likelihood of raw forecast for the corresponding improved forecast (CPDFo) 3) the probability of occurrence of raw and 4) the probability of occurrence of improved forecast data (as PDF). The evaluation of the proposed method for improving the precipitation forecast by the NMME model has been performed in Karoon basin, Iran. Here, the data of 1982-2010 for the calibration period (hindcast) and 2011-2018 (forecast) to validate the results have been used. The results show that the improved forecast data is more reliable due to several achievements namely; 1) higher spatial and temporal accuracy and consistency are observed, 2) extreme values of precipitation are better detected, and finally, 3) during different length of time, the involved uncertainties have been reduced significantly in comparison with raw data.

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Key Points:

- A new post-processing approach is presented for NMME precipitation estimations.
- The proposed method is based on the Copula-Bayesian approach.
- The forecast skill of NAME data is improved significantly, especially in the extreme precipitation values.

Abstract

In this study, an effective post-processing approach has been examined to improve skill of NMME precipitation forecasts. This method is based on the existence of a correlation between the historical raw forecast and observational data. In this respect, the Copula-Bayesian approach was used along with the Normal Kernel Density marginal distribution, kernel Copula function, and a novel approach to select final improved forecast data amongst the existing candidates on the calculated Conditional Probability Distribution Functions (CPDF). In this approach, called the Double Copula method, four input variables are effective for determining the improved NMME data. These are 1) the likelihood of an improved forecast (as a probable observation) for a given raw forecast (CPDFf) 2) the likelihood of raw forecast for the corresponding improved forecast (CPDFo) 3) the probability of occurrence of raw and 4) the probability of occurrence of improved forecast data (as PDF). The evaluation of the proposed method for improving the precipitation forecast by the NMME model has been performed in Karoon basin, Iran. Here, the data of 1982-2010 for the calibration period (hindcast) and 2011-2018 (forecast) to validate the results have been used. The results show that the improved forecast data is more reliable due to several achievements namely; 1) higher spatial and temporal accuracy and consistency are observed, 2) extreme values of precipitation are better detected, and finally, 3) during different length of time, the involved uncertainties have been reduced significantly in comparison with raw data.

1. Introduction

Accurate precipitation forecasting is one of the most important and challenging issues, especially in flood prone areas. These areas are extremely vulnerable to flash flooding during heavy storms. Between 1987 and 1997, 15 percent of natural disasters were due to floods which not equally distributed around the world. According the World Meteorological Organization (2011) report in this same period, 44% of them occurred in Asia, claimed more than 228,000 lives (equivalent to 93% of flood deaths in the world). Based on the third NU World Conference in Sendai (Japan), the flood risk reduction was outlined as one of the desired targets of 2015-2030. (Ibrahim et al., 2017; Salvati et al., 2018). In this regard, accurate precipitation forecasting is one of the advances in the right direction of flood early warning systems. The longer the forecast horizon for precipitation data, the greater the preparedness for possible warnings. Recently different dynamic models have been developed to predict various climate variables such as monthly and seasonal precipitation (Dehban et al., 2020). Amongst many, the North American Multi-Model Ensemble (NMME) is one of the most well-known GCMs (General Circulation Models) which provide an effective seasonal precipitation forecast (Becker et al., 2020; Roy et al., 2020; Slater et al., 2019). The NMME models predictions are accompanied by some uncertainties due to initial assumptions, model limitations, and inaccurate forecast ensembles (Rayner et al., 2005; Tao et al., 2014; Wu et al., 2011). Not surprisingly, many works have been tried to improve the accuracy of predictions by statistical post-processing methods. In all these methods establishing a good relationship between the observational and the predicted NMME model's data is the most common important task. In this regard, the bivariate joint distributions, Meta-Gaussian distribution function (Kelly & Krzysztofowicz, 1997), Bayesian Joint Probability (BJP)(Robertson et al., 2013), Neural Networks (Pakdaman et al., 2020), Hybrid Models (Xu et al., 2018; Yazdandoost et al., 2020) and Copula base models (Amir AghaKouchak et al., 2010; Khajehei et al., 2018; Sadegh et al., 2017), have been widely used. Most of these post-processing methods used parametric distributions to simulate each variable's behavior (observation or predicted data) or parametric bivariate functions. However, within the context of Copula-based models, there is a unique ability to use parametric, non-parametric, and semi-parametric distributions for fitting the bivariate distribution that best fit observed and predicted variables (Chen & Huang, 2007). Fully parametrically estimation of copulas is performed by determining parametric models for marginal distributions and copulas (firstly suggested by Oakes (1982) in the context of Clayton copula). Later, semiparametric estimation was suggested to use non-parametric marginal distributions to achieve a parametric copula (Genest et al., 1995; Oakes, 1986). One of these methods' deficiencies is the elimination of the relation between extreme observed data with the forecasts or vice versa. Consequently, they could not predict the extreme values of precipitation. However, accurate estimation of extreme values is the most important issue in flood prone areas (Exum et al., 2018). Using the non-parametric estimations for both of the marginal distributions and copula function (such that they are parameter-free) can overcome the mentioned weakness (Bouri et al., 2019; Chen & Huang, 2007). Therefore, proposing a non-parametric estimator can play an effective role compared to the parametric copula model.

Based on the literature, while preparing for possible future floods has always been emphasized, very little attention has been paid (from academics) to the assessment and improvement of NMME models' skill for extreme forecast precipitation, which may lead to flooding (Slater et al., 2019). Following these efforts, this study aims to improve NMME precipitation forecasts in a region that has experienced several extreme rainfall events over the past few years. Hence, in this study, the proposed post-processing is employed by non-parametric Copula -Bayesian approach with focuses on extreme and non-extreme values.

The Copula-Bayesian method causes the conditional probability density function (CPDF), which describes the likelihood of observational data event, given each raw forecast data. There are diverse methods for choosing the improved forecast found on CPDF (Khajehei & Moradkhani, 2017; Madadgar & Moradkhani, 2012). One of the most common methods is picking out the

Maximum Likelihood (ML) of CPDF as the desired improved forecast. In the parametric method, it is an individual point, but in semi-parametric and non-parametric methods, there are multiple relative maximum points in the CPDF.

However, in using this method, there is no assurance that the selected data is the most accurate data. Therefore, another objective of this paper is to introduce a novel method based on the non-parametric copula estimator to recognize the extreme values as better as possible by distinguishing between the maximum relative values and choose the best one.

The rest of the paper is organized as the following. First, the study area and the used data are presented in section 2. Then, in section 3, the proposed methodology of research is introduced through four subsections, pursing; 1) preparation of input data for the following steps, 2) estimation of CPDF based on Copula-Bayesian method for each raw forecast data, 3) description of the proposed new approach for selecting the best improved data and 4) introduction of some statistical criteria for evaluating the skill of forecast data. Section 4 presents the obtained results, and finally, the concluding remarks are condensed in section 5.

2. Case Study and Data

2.1..Study area

This study investigates the Karoon river watershed in south-west Iran with about 67000km^2 area (Figure1). According to Iran's hydrological divisions, this region is a part of the Persian Gulf basin. Based on the De Martonne classification of aridity index (de Martonne, 1926), the watershed climate has a great diversity. As the largest river by discharge, the Karoon river is separated into two main branches namely; Arvand and Bahmanshir rivers and continues to the Persian Gulf.

In recent years, extreme precipitation events have been observed in this watershed. One of these devastating precipitations occurred in 2019. A series of devastating floods and flash floods have deluged large parts of the watershed following the unprecedented rainfall events from March 17th to April 20th. During this incident, the amount of rainfall accumulation for Khorram Abad, Ahvaz, and Shahrekord located in the Karoon basin is 71%, 52%, and 49% of the average annual rainfall from 2003 to 2018 for each city, respectively. Therefore, accurate precipitation forecasts can be used as an effective management tools to avoid or reduce the damage of the mentioned natural disasters, prevent further degradation of natural resources and promote sustainable development.

Figure 1. *The location and topography of the study area.*

The observed long-term average monthly precipitation for this region is shown in Table 1.

Table 1. *Observed Long-term Average Monthly Precipitation*

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Prec. (mm)	66.11	46.74	52.4	31.3	16.13	9.62	9.44	9.71	9.48	14.77	39.07	59.75

2.2.. Data Sources

2.2.1. Observation data

Global Precipitation Climatology Centre (GPCC) data firstly has been established in 1989 by Germany's National Meteorological Service, the Deutscher Wetterdienst (DWD), on request of the World Meteorological Organization (WMO) (Yazdandoost et al., 2020). It is a precipitation dataset based on around 80000 observational stations from several different sources and provides different spatial resolution gridded data (2.5° x 2.5°, 1.0° x 1.0°, 0.5° x 0.5°, and 0.25° x 0.25° resolution). In this study, the monthly records of GPCC from 1982 to 2018 with the spatial resolution of a one-degree cell (according to the forecast's resolution) as the reliable surrogate reference gridded data for the observed precipitation (Azizi et al., 2015; Darand & Zand, 2016; Rezayi et al., 2011) was used.

2.2.2. Forecast data

Five NMME models have been utilized at 1° (one-degree) spatial resolution to provide monthly forecasts of precipitations over the study area. More information about the used NMME models is condensed in Table 2. The ensemble means of each model from 1982 to 2010 (hindcast or reforecast period) have been used to form non-parametric Copula and reforecast-based calibration. The presented post-processing process's validity has been assessed (directly to each model's ensemble means) for the data from 2011 to 2018 as the forecast period.

Table 2. *Summary of the Five NMME Models and their Characteristics, used in the study*

Model	Hindcast period	Forecast period	Ensemble size
NCEP-CFSv2	1982-2010	2012-present	24 (28)*
GFDL	1980-2010	2011-present	12
CMC1-CanCM3	1981-2010	2011-present	10
CMC2-CanCM4	1981-2010	2011-present	10
NCAR-CCSM4	1982-2010	2011-present	10

*Note. The value in the parenthesis presents the ensemble size for the forecast period.

3. Methodology

To improve the NMME precipitation forecast data as the main objective of this research, a three-step post-processing method based on the Copula-Bayesian approach is proposed (Figure 2).

As this framework benefited from copula analysis twice, it is so called the Double Copula in short, here. A detailed description of the steps is described in the following. In this approach, the existence of the correlation between the historical observations and estimated forecasts (hindcast period) is supposed, and it is expected that this assumed correlation would remain consistent in the future (forecast period) (Khajehei & Moradkhani, 2017).

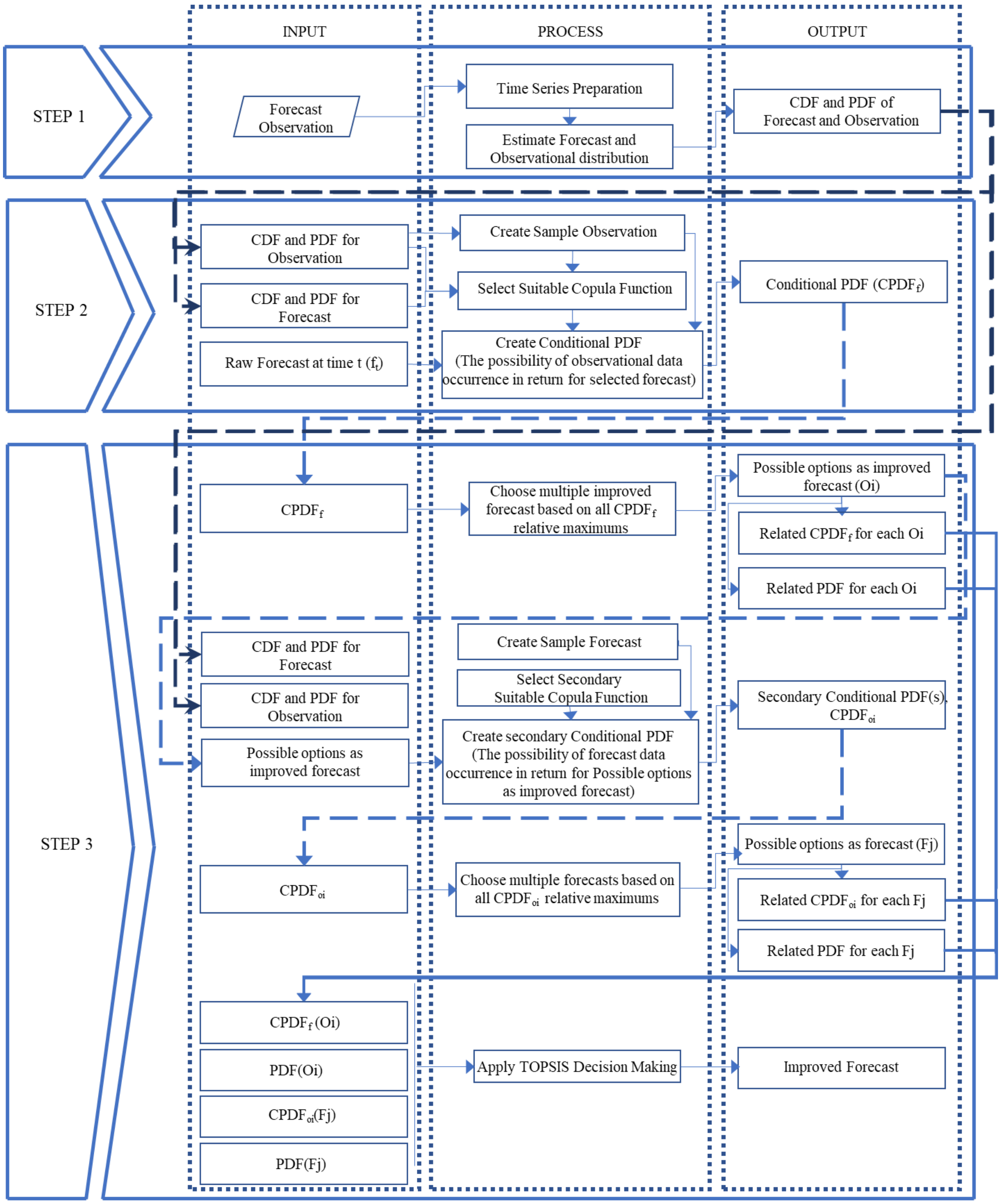

Figure 2. The dominant perspective of the Post-Processing.

3.1.. Input data preparation

First, the available data must be classified to the observational and the forecast time series for each month of the year. In this regard, the GPCC and the ensemble raw NMME data time-series are formed for each month separately. Then, the obtained time-series containing the monthly precipitation data (with the annual time steps for each 1-degree cell) will be used to prepare a marginal distribution. Later, the normal kernel density distributions as the marginal distributions are separately fitted to the historical observations and model in the analyses period (which its efficiency was approved in Yazdandoost et al. 2020 & Yazdandoost et al. 2021). The historical period from 1982 to 2010 is used to set the marginal distribution and kernel Copula function. Finally, as an input variable, the obtained fitted distributions will be evaluated for the forecast period (2011 to 2018).

3.2.. Estimation of Conditional Probability Density Function (CPDF)

A dependence among the observational and predicted precipitation data can be completely described by the Copula based methods. Let $F_{x_i}\left(F_{x_i} = u_i\right)$ be the marginal distribution of each ith variable (x_i). The Sklar's Theorem (Sklar, 1959) assures the existence of a unit cube functions, C, such that:

$$F(x_1, x_2, \dots, x_n) = C\left[F_{x_1}(x_1), F_{x_2}(x_2), \dots, F_{x_n}(x_n)\right] = C(u_1, u_2, \dots, u_n) \tag{1}$$

See (Nelsen, 2007) for a comprehensive overview of copulas and their mathematical properties.

The probability distribution function $c(u_1, \dots, u_n)$ is calculated according to equation (2).

$$c(u_1, \dots, u_n) = \frac{\partial^2 C(u_1, \dots, u_n)}{\partial u_1 \dots \partial u_n} \tag{2}$$

Also, the joint distribution function (f), which will be used in predicted precipitation improvement, is as below:

$$f(x_1, \dots, x_n) = c(u_1, \dots, u_n) \prod_{i=1}^{n} f_{x_i}(x_i) \tag{3}$$

By placement the kernel copula function (non-parametric estimation of Copula) as a joint distribution function in the Bayesian equation (equation 4a), the CPDF will be created as the likelihood of observational data event, given each raw forecast data (equation 4b).

$$f(f, o) = f(f).f(o|f) \tag{4a}$$

$$f(o|f) = \frac{f(f, o)}{f(f)} \tag{4b}$$

For bivariate joint distribution function, CPDF in equation (4b) can be calculated as:

$$f(s_o|f_t) = \frac{c\left(U_s = u_s, U_f = u_f\right) f(f_t) f(s_o)}{f(f_t)} = c\left(U_s = u_s, U_f = u_f\right) f(s_o) \tag{5}$$

In the last equation $f(s_o|f_t)$ is the CPDF in time t, $f(s_o)$ and $f(f_t)$ are the marginal distributions of the samples from the observation and forecast at time t, respectively. The sample data has 500 random data with the same distribution of observations in the hindcast period (Khajehei & Moradkhani, 2017). For each specific raw forecast data, the process mentioned above for creating CPDF (as $CPDF_f$) will be carried out.

3.3.. Determination of improved forecast data

The $CPDF_f$ illustrates the likelihood of sample observation data to the particular raw forecast. As discussed before, the unresolved underlying question in using non-parametric or semi-parametric distribution is how the improved forecast of $CPDF_f$ should be selected. In this regard, this study has offered a novel method to identify the best improvement for the predicted data between relative maximums of calculated $CPDF_f$ in the semi-parametric or non-parametric approaches. In order to do this, for each pair of correlated events, equation 6 is established as the same as the equation 4b.

$$f(f|o) = \frac{f(o,f)}{f(o)} \tag{6}$$

So, for each sample observation (O_i) which is the relative maximum of CPDF$_f$, we have:

$$CPDF_{O_i} = f(s_f|O_{i,t}) = \frac{c(U_f = u_f, U_s = u_s)f(s_f)f(O_{i,t})}{f(O_{i,t})} = c(U_f = u_f, U_s = u_s)f(s_f) \tag{7}$$

In which, s_f is 500 random sample data with the forecast time series' distribution. $CPDF_{O_i}$ refers to the CPDF of each ith relative maximum (O_i) of $CPDF_f$.

Next, the relative maximums of $CPDF_{O_i}(F_j)$, which are closer to the raw forecast (f_t) are chosen. Each of O_i and F_j has a unique conditional likelihood of occurrence based on $CPDF_f$ and $CPDF_{O_i}$. In this study, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method as a decision-making tool, which developed by (Hwang & Yoon, 1981), is used to prioritize the $O_i s$. In this multi-criteria decision-making method, the selection alternatives (maximum relative points) are ranked based on the degree of similarity to the desired values (observation) and the one with the first rank is introduced as the best potential for selection. See (Garg, 2019) for the related equations and method properties. The likelihood of an occurrence forecast given the observation and vice versa besides the PDF of each sample observation and forecast are the four input criteria of TOPSIS to introduce the sample observation by taking the relative closeness to the ideal solution.

3.4.. Assessment of the method validation

The reliability of raw NMME data is evaluated by the KGE criterion (equation 8). According to Khajehei and Moradkhani (2017), the acceptable amount of the KGE value was considered more than 0.6. For the fewer values, the importance of the post-processing appears. Next, Validation and quantification of the raw or improved NMME models' uncertainties are fundamental issues to evaluate their performance. Four volumetric indices developed by A AghaKouchak and Mehran (2013) is used to assess the skill of forecast NMME models (raw and improved values), especially to detect extreme forecast of precipitation values (equation 9-12). The first one, the Volumetric Hit Index (VHI), calculates the volume of correctly detected improved precipitation volume and missing observation values. The Volumetric False Alarm Ratio (VFAR) calculates the volume of false simulation (here the inaccurate improved data) to the volume of simulations. The Volumetric Miss Index (VMI) describes the missing observation's volume to the correctly detected simulation volume and missing observations. At last, the Volumetric Critical Success Index (VCSI) which indicates an overall measure of volumetric performance such as volumetric hit, false alarm and misses (A AghaKouchak & Mehran, 2013). One of the benefits of volumetric indexes is their ability to decompose biases of improved data by evaluating different thresholds. According to main purpose of this study, these indexes are a suitable tool to evaluate the efficient performance of NMME data post-processing and extreme precipitation values' detection. In this study, the thresholds value applied to volumetric indices calculations is selected based on extreme value detection. Extreme precipitation should be rarer than the tenth or ninetieth percentile of the observed density probable precipitation function (Shaffie et al., 2019). For the areas with a high risk of flooding, the threshold value can be considered 0.9, as Shaffie et al. (2019) suggested.

Table 3. *Equations used for Validation and Quantification*

$$KGE = 1 - \sqrt{(r-1)^2 - (\alpha-1)^2 - (\beta-1)^2} \tag{8}$$

$$VHI = \frac{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \,\&\, OBS_i > t))}{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \,\&\, OBS_i > t)) + \sum_{i=1}^{n}(OBS_i|(SIM_i \le t \,\&\, OBS_i > t))} \tag{9}$$

$$VFAR = \frac{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \,\&\, OBS_i \le t))}{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \,\&\, OBS_i > t)) + \sum_{i=1}^{n}(SIM_i|(SIM_i > t \,\&\, OBS_i \le t))} \tag{10}$$

$$VMI = \frac{\sum_{i=1}^{n}(OBS_i|(SIM_i \le t \;\&\; OBS_i > t))}{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \;\&\; OBS_i > t)) + \sum_{i=1}^{n}(OBS_i|(SIM_i \le t \;\&\; OBS_i > t))} \tag{11}$$

$$VCSI = \frac{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \;\&\; OBS_i > t))}{\sum_{i=1}^{n}(SIM_i|(SIM_i > t \;\&\; OBS_i > t)) + \left(OBS_i\middle|(SIM_i \le t \;\&\; OBS_i > t)\right) + \left(SIM_i\middle|(SIM_i > t \;\&\; OBS_i \le t)\right)} \tag{12}$$

Parameters

r	correlation
α	the ratio of the variance of the forecast to the variance of the observation
β	the ratio bias
SIM_i	The NMME model value
OBS_i	The observation
n	Total number of observation (or NMME) data in the desired time-series
t	threshold

4. Post-processing results

In order to evaluate the accuracy of the raw precipitation data of each individual model ensemble mean, the consistency of data with the GPCC data for the most precipitated months was determined. Table 4 shows the evaluation of the KGE criterion for all the extent of study area during 1982-2018 and six rainiest months:

Table 4. *The KGE Values for the Six Rainiest Months*

Model	January	February	march	April	November	December
NCEP-CFSv2	0.35	0.21	0.27	-0.07	0.25	0.13
GFDL	-0.33	-0.25	-0.14	-0.44	-0.53	-0.08
CMC1-CanCM3	-0.27	-0.24	-0.08	-0.85	-0.48	-0.2
CMC2-CanCM4	-0.32	-0.12	0.005	-0.53	-0.4	-0.19
NCAR-CCSM4	0.25	0.31	0.31	-0.08	0.2	0.22

As seen, in all studied months, the amount of KGE of the study area is lower than 0.6; hence, it is essential to do the post-processing cell by cell.

As there is no intent to limit this study, the proposed post-processing procedure is applied for raw forecasts with 1 to 6-month length. However, in the first step, detailed information of the analysis for the 1-month length is described. Figure 3 shows the raw and improved monthly precipitation for January as the rainiest month in the forecast period compared to the GPCC data (for the 1-month length). According to the figure, the raw data predicted by CanCM4 is much less than the GPCC data, while the raw predicted values of GFDL model has been shown better performances. Post-processing has brought all the model's raw data values closer to the GPCC data and even the spatial patterns of post-processed precipitations are approximately similar to the GPCC value's pattern, confirming that most of the rainfall is along with the mountainous parts (in the eastern part) of the region.

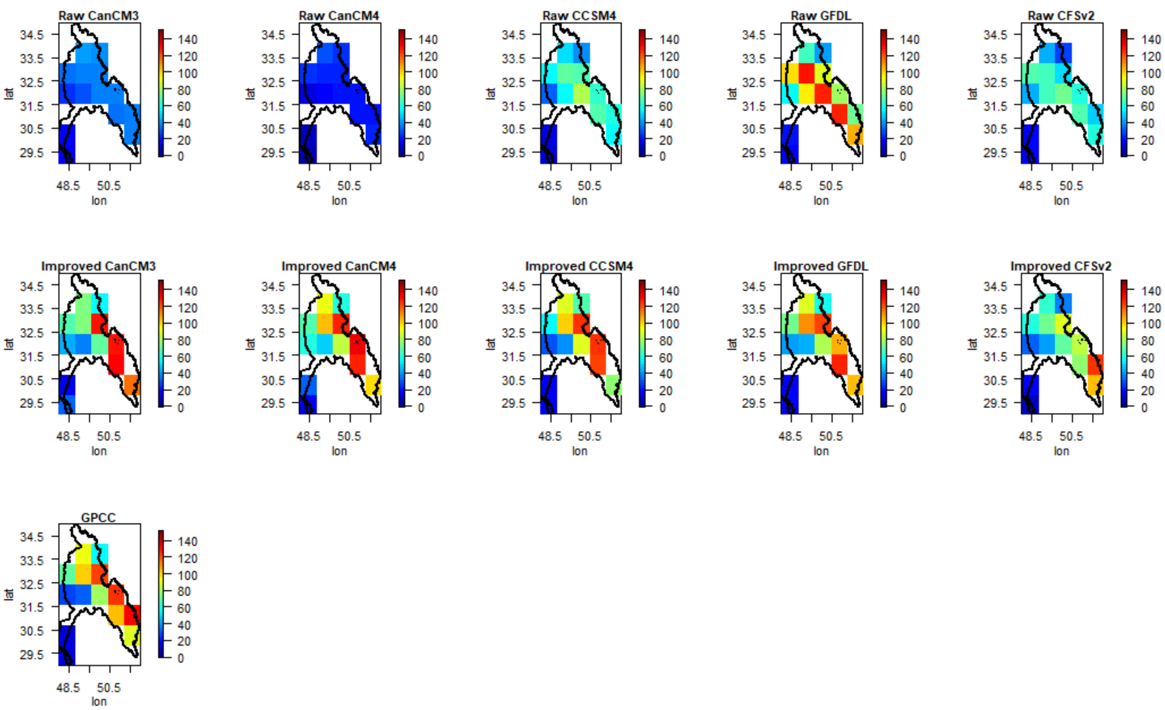

Figure 3. The Spatial distribution of Karoon basin precipitation for January in forecast period..

In order to assess the skill of post-processing method, Table 5 presents the comparison of each raw and improved NMME models forecasts against the GPCC calculated over the extent of study area. In this table, the columns refer to the results of one (January) to the six-month (January to June) length forecasts starting from January of years 2011 to 2018.

Table 5. *Comparison of the Raw and Improved NMME Models Against the GPCC data (% error)*

NMME model	Length (month)

		J	JF	JFM	JFMA	JFMAM	JFMAMJ
CanCM4	raw	-68	-71.4	-77	-72.2	-66.7	-66.1
	improved	29.5	23.2	-0.89	-6.9	0.2	3.4
CanCM3	raw	-40.7	-25	-22.9	-12.6	-4.5	-3.1
	improved	18.5	-3.7	1.7	17.7	14.88	17.55
CFS2	raw	-12.2	37.7	33.4	49.8	55.9	56.6
	improved	-11.8	10.2	-2.8	0.5	14.9	-5
CCSM4	raw	-20	-15.8	-26.1	-18.7	-11.77	-10.9
	improved	7.5	23.1	12.8	12	13.91	2.01
GFDL	raw	29.7	26.2	32.67	49.5	61.63	62.9
	improved	14.4	10.7	17.6	13.86	15.29	11.5

As seen in this table, the raw data of CanCM3, CanCM4 had the lowest estimates while CCSM4 is almost underestimated and the GFDL is almost overestimated. However, applying the Double Copula post-processing method has shown that none of the model always have the best performance for each length of forecasts consequently investigation of the skill of all models is a proper way for facing with involved uncertainties. As expected, in most models and different studied periods, the model error after post-processing has been significantly reduced.

In Figure 4, Taylor diagram as an efficient instrument is used to display the quality of model improvements against the GPCC values for 1 to 6-month length for various forecast models. According to the displayed results, the shorter the forecast length, the higher dispersion of the Taylor diagram’s estimated variables for raw data. In other words, in higher periods, almost all models (except CFSv2) have presented closer results. In terms of CC, in all different length analysis, most of the improved NMME models have been able to make significant positive correlation with observational data while among raw model data, the CCSM4 has the only positive correlation with GPCC data. In terms of RMSE, the estimated values of improved data have shown significant increase against the raw model data. Generally, it seems that CCSM4 had the best and CanCM3 had the worst performance among the raw data.

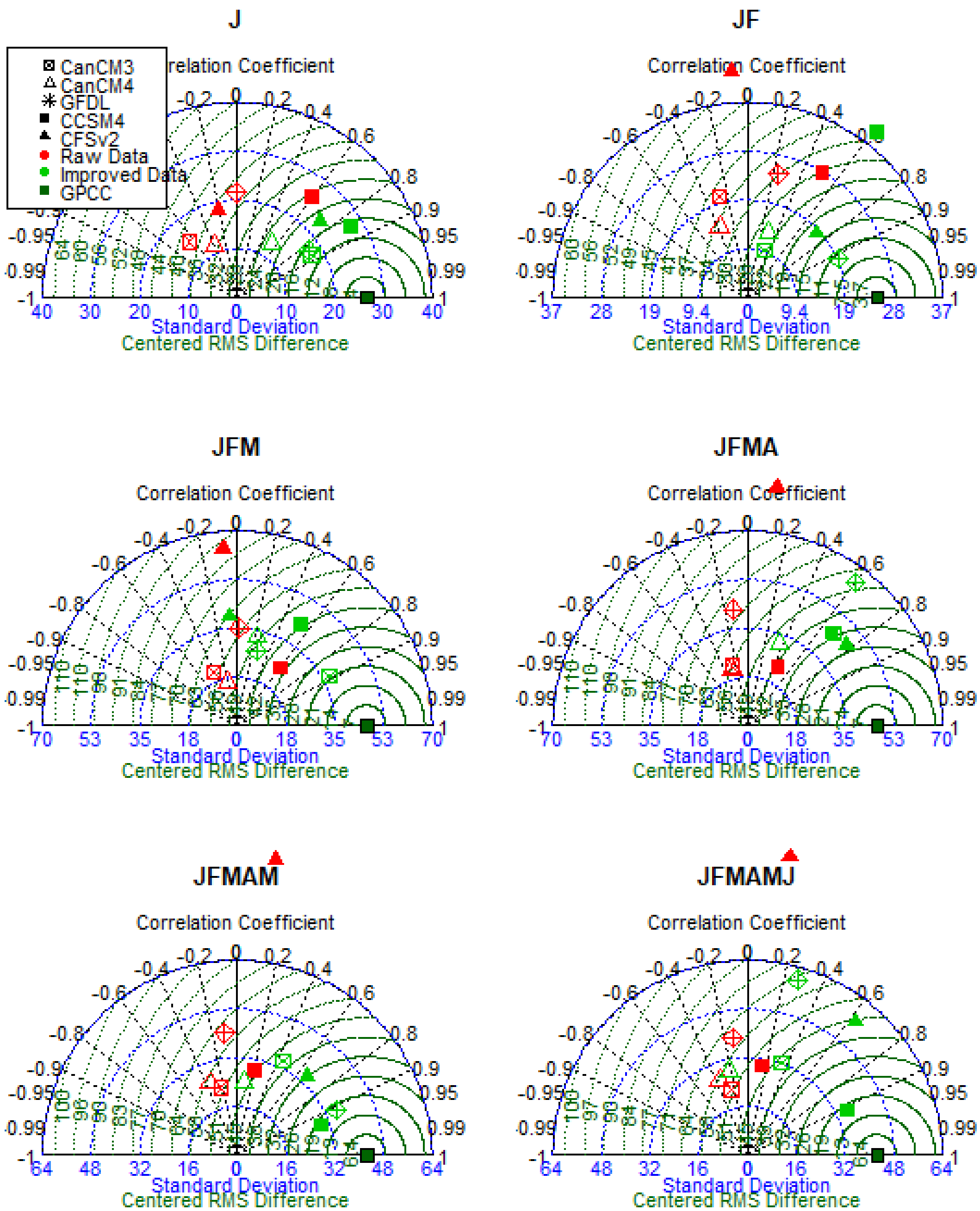

Figure 4. The Taylor diagram of raw and post-processed NMME models with 1 to 6-month period in Karoon basin.

To evaluate the performance of NMME models in terms of temporal conditions, each model's skill was evaluated against the observational data at each 1-degree pixel. As a non-limiting example, Figure 5 shows the temporal distributions of the five NMME model's precipitation with

1-month length at the region. In this figure, each subplot presents a comparison of observational precipitation data with each raw and improved NMME models forecasts. As seen, the number of months with heavy rainfall has not changed over the past years significantly, and most of these rainfalls had occurred from October to April. The results show that improved data are more consistent with observation data. Therefore, the efficiency of the Double Copula post-processing method has been proved.

Furthermore, the inter-comparison of models shows that the raw GFDL model often tends to overestimate precipitation. Besides, it has estimated the highest precipitation values compared to the observed values, and the CFSv2 model has the most similarity to the observation data. Based on the obtained results, it can be claimed that the proposed method is truly able to improve the overall results and identify the extreme precipitation values. Since the intensity or frequency of heavy rains in the region has not increased significantly, it can be considered that the cause of recent floods in the region is maybe due to increased urbanization and/or change in land use/cover, which subsequently causes a change in runoff.

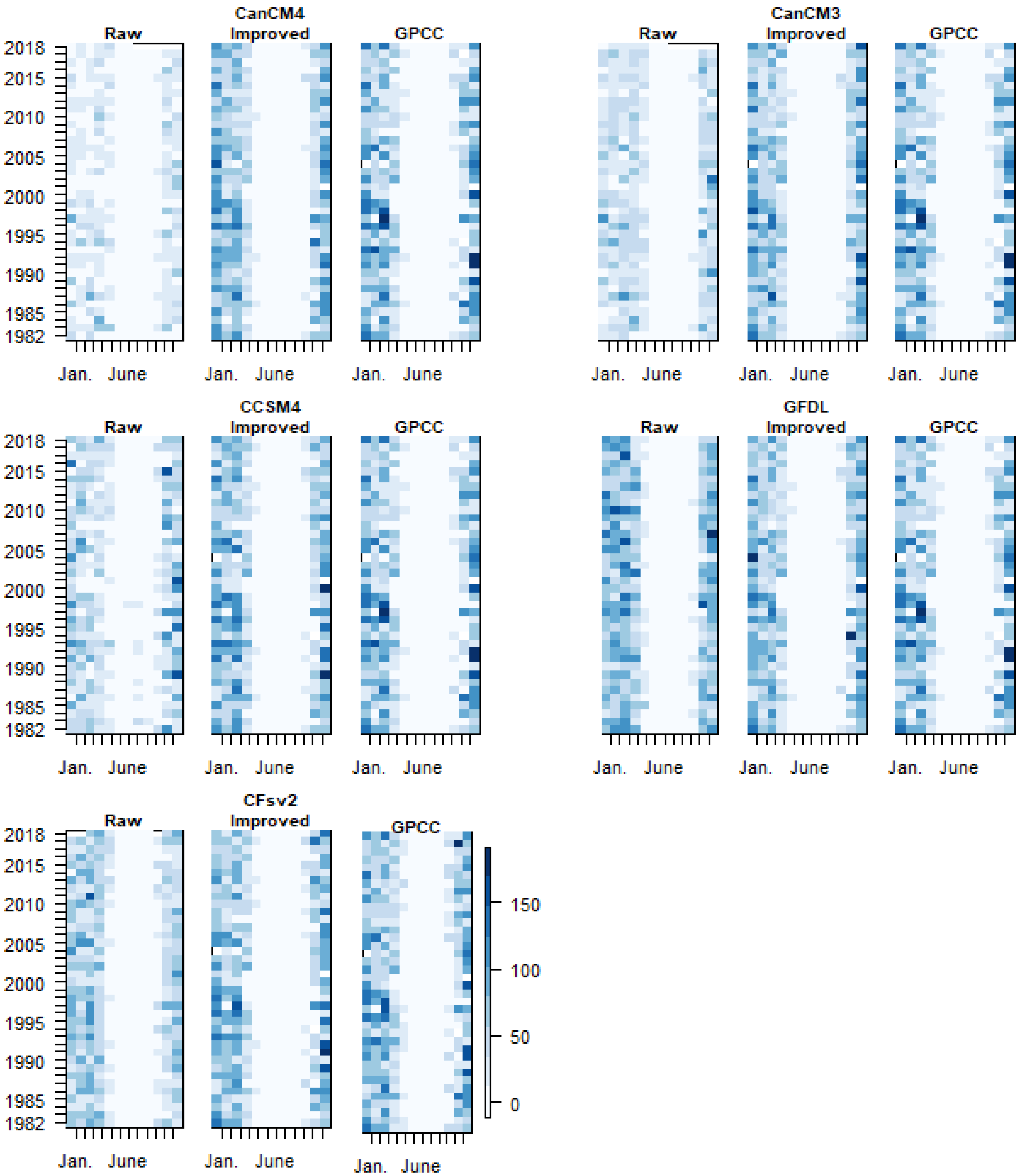

Figure 5. The temporal distribution of precipitation.

For precise investigation of post-processing ability to recognize extreme precipitations, the KGE and four mentioned volumetric indexes values for the January (1-month length) are investigated. Figure 6 (as a StarPie diagram) shows different models' performance over the hindcast and forecast periods. In this figure, each pie ranges from 0 to 1 (like volumetric indexes). The closer the index values to 1, the better the model performance. For the VMI and VFMR indexes, the values of 1-VMI and 1- VFMR are used as the substitutes. In the case of negative KGE values, they have been specified by a star sign (*). As shown, the Double Copula method has high ability to improve the raw NMME data and detect extreme values. As seen in Figure 6, amongst the raw data results, the estimated KGE values for the raw CFSv2 and CCSM4 models are higher than the others. Due to other models' negative KGE values, using them for other hydrological calculations will definitely lead to unreliable results.

According to the volumetric indices shown in the figure, during the forecast period, the extreme precipitation values are better identified in the raw GFDL model. As seen in the second row of Figure 6, the post-processed precipitation values in both hindcast and forecast periods have been improved significantly. Among these modified precipitation values, the KGE index has the lowest value while the CFSv2 has the least value. In other words, modified forecasts can still be improved to gain sufficient certainty. However, in terms of other indices, the post-processing algorithm has been very successful.

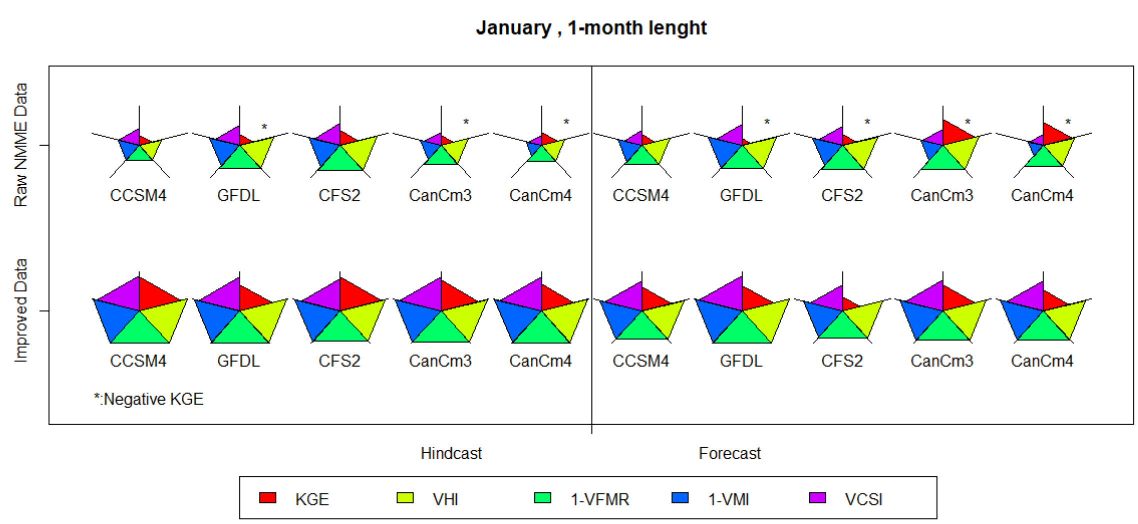

Figure 6. The KGE and volumetric indices results of NMME models for January

5. Conclusion

Seasonal precipitation forecast is one of the main inputs of hydrological forecasting models. If these forecasts have good reliability, they can provide useful information for decision-makers in water resources management.

In this paper, a novel Copula-based Bayesian approach named Double Copula is used as the post-processing method to value the use of non-parametric distribution for both of the marginal distributions and copula function in order to improve the NMME precipitation forecasts. Here, the normal kernel density distribution function as marginal distribution and kernel Copula function as bivariate function are employed to create Conditional Probability Distribution Function (CPDF). Introducing several relative maximum likelihoods in CPDF can make a challenge for choosing the best improved data. In order to address this issue, here, a novel method is suggested that chooses the relative maximum points and applies the Copula Bayesian approach for the second time on the selected values diversely to receive the initial forecast value for given sample observations. Finally, the TOPSIS decision-making method is applied to pick out the most likelihood sample observation. The proposed post-processing method is examined on Karoon Basin, one of the most experienced flood damage in Iran. Five NMME models for the hindcast (1982-2010) and forecast periods (2011-2018) are used. To evaluate the accuracy of the ensemble's mean, the GPCC observational database is used as the observation data. The KGE values reveal the requirement of model output improvement. By investigating the obtained results for forecasts with 1 to 6-month length, we show:

1- The spatial and temporal distributions of GFDL raw models is more similar to the observational data.

2- GFDL raw models' values are relatively performed better than other models. Conversely, CanCM3 and CanCM4 models miss the early months of each year.

3- According to the post-processed data, the spatial and temporal distributions are highly consistent with the observations. However, in creating time-series and subsequent processing methods, the spatial and temporal coherence of data with adjacent cells is ignored.

4- Based on the used volumetric indexes (VHI, VMI, VFMR, and VCSI) the raw forecast model values have low skill for estimating extreme values of precipitation while after the post-processing procedure, the strength of the Double Copula method in determining the extreme values were demonstrated.

5- The higher accuracy and correlation of different improved NMME data imply lower uncertainties than raw estimations.

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