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Research Article

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Posted Date: June 9th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-216566/v1>

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Validation of the Global Environmental Multiscale Model (GEM) for Iran

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Abstract

The Global Environmental Multiscale Model (GEM) is an integrated forecasting and data assimilation system developed by Environment and Climate Change Canada. The model is currently in operational use for data assimilation and forecasting at global 25 km to 15 km scales; regional 10 km scales over North America; and 2.5 km scales over Canada. To demonstrate the performance of the GEM model for forecasting applications, global forecast outputs of GEM at the 25 km scale were compared to temperature and precipitation datasets collected over an area of 1,648,000 km² especially representative of the country of Iran on a daily temporal scale. Using the De Martonne method for climate classification and data from 177 meteorological stations, the country of Iran was classified into three zones: an arid zone with 87 stations; a semi-arid zone with 63 stations; and a humid zone with 27 stations. GEM model outputs were compared to observations in each of these demarcated zones. The results show good agreement between modelled and measured daily temperatures with Kling-Gupta efficiencies of 0.76, 0.71 and 0.78 in arid, semi-arid and humid regions respectively, and a moderate agreement between modelled and measured annual precipitation with 50.06%, 35.6% and 15.38% differences in arid, semi-arid and humid regions, respectively. The results also indicate that there is a significant systematic error between the elevation of the stations and the average elevation of corresponding GEM grid cells (13%). The results provide an evaluation of the model performance for Iran to be utilized for climate change applications in a regional context and can serve as a basis for the development of future high-resolution GEM model versions on a global scale.

Keywords: GEM model, Iran, gridded datasets, large-scale modelling, land surface schemes, uncertainty, verification, De Martonne climate classification.

1 Introduction

Climate change impacts on hydrology are significant, altering the hydrological cycle and water resources at local and regional scales (IPCC, 2018). Due to the global nature of the climate system and the complexity of climate physics, climate change impact assessments are often implemented at a continental and regional scale. However, regional extents are often not associated with commonly-utilized scales of hydrological analyses in the context of water resources management (Varis et al. 2004; Nohard et al. 2006; Hattermann et al. 2017a; Hattermann et al. 2018b), and general circulation models (GCMs) and numerical weather forecasting models are utilized for forecasting (Dankers et al. 2014; Her et

al. 2019). Despite having high uncertainty for some regions, large-scale models often provide accurate forecasts (Janssen, 1998) and therefore there is a need to evaluate the application of large-scale models in a regional context.

Rain and temperature measurements are often spatially interpolated, and the interpolation process may not capture the spatial variability of precipitation and temperature fields due to a sparse gauge network in some regions (Wong et al. 2017; Mohammadlou et al. 2019). Recognizing limitations related to climate parameter observation and interpolation methods, a number of attempts have been utilized to combine multiple datasets for a more accurate gridded estimate of hydro meteorological variables (Xie and Arkin 1996; Maggioni et al. 2014; Shen et al. 2010). In a similar context to application of large-scale models, these datasets have to be assessed for regional modelling applications.

Quantification of uncertainties in temperature and precipitation data inputs are essential prerequisites for hydrological modelling applications (Wong et al. 2017; Her et al. 2019). Gridded climate products incorporating multiple sources of data have recently been developed with the aim of providing better and more reliable measurements for use in climate, land surface, water and energy balance studies (Maurer et al. 2001; Roads et al. 2003).

The Global Environmental Multiscale Model (GEM) is an integrated forecasting and data assimilation system developed by the Canadian Centre for Meteorological and Environmental Prediction (CCMEP) of Environment and Climate Change Canada (ECCC) and is used operationally for numerical weather prediction applications. The GEM model is indicative of a long-term development of a comprehensive and fully-integrated global atmospheric environmental forecasting and simulation system (Desgagné et al. 2014).

Over the past few decades, researchers have coupled atmospheric and hydrological models to improve runoff simulations and predictions of climate and weather (Middelkoop et al. 2001; Fowler et al. 2007; Pietroniro et al. 2007; Corney et al. 2013; Tian et al. 2013; Taye et al. 2015). For example, Environment and Climate Change Canada's National Hydrological Research Centre have used the MEC model as the foundation for a coupled land surface and hydrological model known as MESH (Modélisation Environnementale communautaire - Surface Hydrology) that links the CLASS (Canadian LAND Surface Scheme) model with the WATFLOOD model for flood forecasting (Pietroniro et al. 2007). The model is usually driven using atmospheric forcing variables from numerical weather prediction systems.

Over the last decade, significant improvements have been made with respect to GEM hydrological process representation (Bélair et al., 2009). Also, many studies have been conducted with GEM and demonstrate the veracity of the model for regional forecasting applications. However, most studies are on the evolution of the

model structure; these studies include Yeh et al. (2002); Zadra et al. (2004); Qaddouri and Lee (2010); Desgagné et al. (2014); Xu et al. (2018); Husain et al. (2019); Bahremand et al. (2019a). Since this paper is intended to provide a foundation for the implementation of the MESH Land Surface Model (LSM) in Iran for potential use and research purposes, our focus is on the evaluation of GEM model performance accuracy with respect to atmospheric physics.

Since Iran is a country with arid and semi-arid regions, climate change has a large impact on infrastructure (Samadi et al. 2009; Gohari et al. 2013; Rahimi et al. 2013; Madani et al. 2016); agriculture (Ahmadaali et al. 2018; Karimi et al. 2018; Zarei and Moghimi 2019; Mokarram et al. 2020); environment (Abbaspour et al. 2012; Sharifika 2013; Madani 2014; Kazemi et al. 2019); and water resources (Abbaspour et al. 2009; Haghighi and Klove 2017; Afshar et al. 2019; Moshir et al. 2020) in this region. Due to the gridded structure of GEM, if the accuracy and performance of this model is confirmed, it can be used as a suitable spatial forecasting tool, especially in areas without gauging stations or with a sparse gauge network, where human access to many regions is limited by topographic or geographical elements.

Atmospheric and weather forecasting models are often coupled with land surface models and thereby provide initial boundary conditions. Assessing meteorological forcing can lead to a better understanding of hydrological simulation processes and can identify error in predictions. This study therefore evaluates the GEM model with temperature and precipitation data for Iran utilizing data from 177 meteorological stations in a regional context. Global 25 km gridded datasets providing temperature and precipitation data are used for verification of GEM performance. Investigating the uncertainty of model outputs provides an indication of regional model performance.

2 Materials and Methods

2.1 Study Area and Climate Classification

Iran is a country with an area of 1,648,000 km² geographically situated between 25° N to 40° N and 44° E to 63° E (Fig.1). Iran is a mostly mountainous country where two major mountain chains, the Alborz Range and the Zagros Range, divide the country into climactic zones. The topography of Iran ranges from -28 m to 5610 m elevation relative to sea level. Iran has an arid and semi-arid climate in the interior regions of the country (Sodoudi et al. 2010; Fallah et al. 2017). Rainfall is strongly dependent on latitude and elevation (Razmi et al. 2017; Piri et al. 2017). The mean annual rainfall over Iran is ~240 mm. The rainfall maximum is ~1,800 mm on the Caspian seashore and ~400 mm on the slopes of the Alborz and Zagros mountains

(Solati et al. 2012). Precipitation is influenced by the western Mediterranean oscillation (Ghasemi and Khalili 2008). Significant influences of the El Niño southern oscillation on the air temperature of Iran were also reported by Nazemosadat and Ghasemi (2004) and Choobari et al. (2017). In the context of the research reported in this paper, temperature and precipitation data was selected from 2012 to 2015 for 177 synoptic stations (cf. Appendix).

The De Martonne classification is widely utilized for quantification of regional climate (Coscarelli et al. 2004; Baltas 2008; Hrnjak et al. 2013; Pellicone et al. 2019). The associated classification equation is:

$$I = \frac{P}{T + 10} \quad (\text{Eq.1})$$

In the above Equation 1, P is the average annual rainfall (mm), T is the average annual temperature (Celsius), and I is the De Martonne aridity index (dimensionless). The equation provides a convenient method for climate classification related to the ranges identified in Table 1.

Table1. Climate classification of De Martonne aridity index (Alizadeh 2013; Hrnjak et al. 2013).

CLIMATIC CONDITION	I VALUE
ARID	$I < 10$
SEMI-ARID	$10 < I < 19.9$
MEDITERRANEAN	$20 < I < 23.9$
SUB-HUMID	$24 < I < 27.9$
HUMID	$28 < I < 34.9$
VERY HUMID	$I > 35$

Using the De Martonne classification, the country of Iran was divided into an arid region with 87 stations; a semi-arid region with 63 stations; and a humid region with 27 stations (Fig. 1). The Global Environmental Multiscale Model (GEM) with 25 km × 25 km resolution (from 2012 to 2015) was applied to each of these regions. Kriging as a form of spatial interpolation was applied for generating the De Martonne zones used in the context of this study. Climate data over a 50-year period (Iran Meteorological Organization 2020) was used for calculating the De Martonne index using Eq. 1 and the intervals of Table 1 applied to the outputs of the kriging interpolation. The Mediterranean, Sub-Humid, Humid and Very Humid climatic conditions are all considered as humid climates within the context of the analysis presented by this paper that evaluates the GEM model with temperature and precipitation at a global 25 km scale for Iran.

Fig. 1 Study area (Iran) and De Martonne zones shown with the synoptic stations.

2.2 Background

The initial hydrostatic formulation of the GEM model as utilized in an operational context is described by Côté et al. (1998). The GEM model is nominally operated at a global 25 km to 15 km scale for medium-range forecasting; a regional 10 km scale for continental forecasting over North America; and a high-resolution 2.5 km scale for short-range forecasting over Canada. The GEM model formulation is Euler-based (Phillips 1966) and the model time step is nominally 30 minutes for variable-resolution simulations.

The gridded dataset of temperature and precipitation forcing data has a 30-minute time step for variable-resolution simulations (Côté et al, 1998). The forcing inputs were obtained from Environment and Climate Change Canada. For a daily scale, we aggregated 30-minute time step precipitation forcing data and averaged the 30-minute time step temperature forcing data. Synoptic station data

was obtained from the Meteorological Organization of Iran (Iran Meteorological Organization 2020).

2.3 Quantification of Error and Uncertainty

Criteria used to quantify error and uncertainty within the context of this paper are Relative Error Percentage (Eq. 2) (Brown et al. 2004), the Variance Ratio method (Eq. 3) (Mesplé et al. 1996), the Kling-Gupta efficiency (Eq. 4) (Gupta et al. 2009) and the coefficient of determination (R^2) (Eq. 5) (Rodgers and Nicewander 1988).

$$RE = \left(\frac{mod_{val} - obs_{val}}{obs_{val}} \right) \times 100 \quad (Eq.2)$$

$$R_{var} = \beta = \frac{\partial^2_{model}}{\partial^2_{observation}} = \frac{\frac{1}{N} \sum_{i=1}^N (mod_{val} - \mu_{mod})^2}{\frac{1}{N} \sum_{i=1}^N (obs_{val} - \mu_{obs})^2} \quad (Eq.3)$$

$$(Eq.4)$$

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

$$R^2 = \left[\frac{\sum_{i=1}^n (obs_{val} - \mu_{obs})(mod_{val} - \mu_{mod})}{\sqrt{\sum_{i=1}^n (obs_{val} - \mu_{obs})^2} \sqrt{\sum_{i=1}^n (mod_{val} - \mu_{mod})^2}} \right]^2 \quad 0 \leq R^2 \leq 1 \quad (Eq.5)$$

In the above equations, RE is the relative error (%), R_{var} is the variance ratio, obs_{val} is an observation value, mod_{val} is a model value, N is the number of comparisons, μ_{mod} is average of model data, μ_{obs} is average of observation data, r is the linear correlation between observations and simulations, R^2 is the coefficient of correlation between simulated and observed data (dimensionless), α is the bias ratio (dimensionless) and β is the variability ratio (dimensionless) as defined by Gupta et al. (2009) Mesplé et al. (1996) and Brown et al. (2004). As defined, β is the same as R_{var} in Eq 3.

3 Results

The GEM temperature and precipitation model outputs were compared with observations from 177 synoptic stations in the study region. The results show that the model has better performance for simulation of temperature than precipitation. At daily and monthly time scales, model performance in the semi-arid and arid regions is better than the humid regions, although the Kling-Gupta efficiency shows that the model gives better performance for humid regions at a monthly time scale. The geographical area of the arid and semi-arid regions is significantly higher than the area of humid regions. Consequently, the number of stations in the semi-arid and arid regions is higher than the number of stations in the humid region (cf. Appendix, Table A). The better model performance at a monthly time scale is nominally expected due to the aggregation of station data in a region.

As exhibited by Figure 2 and Figure 6, the variance ratio and relative error percentage show that variability of the modelled precipitation is higher than the observed precipitation ($R_{var} > 1$ and $RE > 0$). This is related to spatial differences between the gridded model and the point observation network of stations. Variability of precipitation in the humid region is less than variability of precipitation in the arid and semi-arid regions (Figure 2). Modelled temperatures at a daily and monthly time scale in the arid, semi-arid and humid regions exhibit appreciably high accuracy (Fig. 3) compared to measured temperatures. The associated Kling-Gupta index in the semi-arid region shows more variability compared with other regions. A for different zones is given in the Appendix as Table B and Table C. decomposition of the KGE criterion for daily temperature to components α , β , r As exhibited by Table 4 and the associated boxplot (Fig. 2) as well as the relative error map (Fig. 7), the model accurately represented temperatures in all regions. However, there is significant model error exhibited by measurements made at the elevation of the stations compared with model outputs at the average elevation of corresponding GEM grid cells (13%) (Fig.8). Figure 8 (B to D) also indicates this error in arid, semi-arid and humid regions.

Table 2. Annual error (%) for precipitation

Year		2012	2013	2014	2015
Arid	Observation average (mm)	130.98	137	126.71	117.49
	Model average (mm)	173.84	159.47	169.53	211.4

	Model error (%)	32.71	53.78	33.8	79.94	Average=50.06
	Observation average (mm)	288.24	256.41	257.14	271.17	
Semi-arid	Model average (mm)	364.66	332	340.8	417.32	
	Model error (%)	26.51	29.48	32.53	53.9	Average=35.61
	Observation average (mm)	719.55	643.37	621.70	707.5	
Humid	Model average (mm)	666.89	757.41	675.78	904.02	
	Model error (%)	7.31	17.73	8.7	27.78	Average=15.38

At an annual scale (Table 2), modelled precipitation error in the humid region is less than the modelled precipitation error in the arid and semi-arid regions. The modelled precipitation error in the humid region is 15.38%, in the semi-arid region 35.61%, and in the arid region 50.06%. As exhibited by Table 3, when analyzing the GEM model results at an annual scale, the arid region model temperature outputs have an average error of 19.64% and this error is slightly less than the humid region with average error of 20.18% and the semi-arid region with an average error of 27.57%. These results demonstrate that the GEM model temperature outputs are underestimated compared to observed data.

Table 3. Annual error (%) between measured and modelled temperatures.

	Year	2012	2013	2014	2015	
	Observation average (C°)	21.22	21.56	22.03	21.2	
Arid	Model average (C°)	16.78	17.09	18.16	17.09	
	Model error (%)	20.94	20.72	17.55	19.36	Average=19.64
	Observation average (C°)	14.78	14.74	14.81	14.51	
Semi-arid	Model average (C°)	10.57	10.54	10.98	10.54	
	Model error (%)	28.60	28.45	25.87	27.36	Average=27.57
	Observation average (C°)	15.25	15.17	15.46	15.31	
Humid	Model average (C°)	12.25	11.96	12.57	12.07	
	Model error (%)	19.69	21.14	18.68	21.19	Average=20.18

Table 4. The average and median of Kling-Gupta Efficiency (KGE) at daily and monthly scales of model application.

		Temperature			Precipitation		
		Arid	Semi- arid	Humid	Arid	Semi- arid	Humid
Daily	mean	0.76	0.71	0.78	0.22	0.24	0.15
	median	0.76	0.71	0.79	0.26	0.35	0.08
Monthly	mean	0.75	0.70	0.79	-0.14	0.05	0.14
	median	0.75	0.70	0.81	0.76	0.70	0.79

Fig. 2 GEM model simulation performance for precipitation at a daily (a) and monthly (b) time scales, including daily and monthly precipitation in arid, semi- arid and humid regions. In the above sub-plots, b is the slope of a linear regression equation, a is the abscissa of a linear regression equation, r^2 is the coefficient of determination, R_{var} is the variance ratio, and KGE is the Kling-Gupta Efficiency Results marked 1 to 6 indicate: 1 (daily scale for arid), 2 (daily scale for semi-

arid), 3 (daily scale for humid regions), 4 (monthly scale for arid), 5 (monthly scale for semi- arid) and 6 (humid regions for all data).

Fig. 3 GEM model simulation performance for temperature at a daily (a) and monthly (b) scale. A full description of sub-plot labelling is given in the caption of Fig. 2.

Fig 4. Kling-Gupta efficiency map for precipitation on a daily timescale for Iran.

Fig 5. Kling-Gupta efficiency map for temperature on a daily timescale for Iran.

Fig. 6. Relative error percentage for precipitation on a monthly timescale for Iran.

Fig. 7. Relative error percentage for temperature on a monthly timescale for Iran.

Fig 8. Elevation of stations plotted with respect to the average elevation of corresponding GEM grids for the entire geographic region of Iran (A); only arid regions (B); semi-arid regions (C); and humid regions (D). A linear fit equation is shown on the graphs along with a R^2 value.

4 Discussion and Conclusions

The GEM model applied at a $25 \text{ km} \times 25 \text{ km}$ spatial resolution predicted temperature and precipitation for the region of Iran using data from 2012 to 2015. The resolution of datasets required for running the GEM model at a global scale only became available at a $15 \text{ km} \times 15 \text{ km}$ resolution in 2019, outside the temporal period

considered in this study. The performance of the model was compared with temperature and precipitation data from 177 synoptic stations in three demarcated regions (arid, semiarid and humid) at three temporal scales (daily, monthly and yearly).

The following conclusions can be obtained from this study:

- On a daily timescale, precipitation analyses indicate greater accuracy of the model in semi-arid regions with $KGE = 0.24$ and arid regions with $KGE = 0.22$ compared to the humid region with $KGE = 0.15$. The variation of measured precipitation in the humid region is less than the arid and semi-arid regions. The negative KGE values indicates that the model overestimates daily rainfall in most regions of Iran (Fig 4). The relative error of rainfall indicates overestimated precipitation on a monthly scale. In some areas of the Zagros Mountains, rainfall is overestimated, and the error associated with model application is therefore higher in desert and arid areas (Fig 6).
- Modelled temperature at daily and monthly time scales in the humid and semi-arid regions has less error than modelled temperature at the same time scale in the arid region. However, modelled temperature variability in the semi-arid region is higher than the modelled temperature variability in other regions. Daily modelled temperatures are also in good agreement with observed temperatures at all measurement stations (Fig 3). The positive KGE values indicates that the model underestimates daily temperature in most regions of Iran. Also, the KGE values to assess temperature represented better performance of the model in the north and northeast of Iran (Fig 5). The error associated with temperature is less than the error associated with precipitation and on a monthly scale, the southern regions of Iran have less error (Fig 7).
- At an annual scale, precipitation error in the humid region (15.38%) is less than precipitation error in the arid (50.06%) and semi-arid regions (35.6%); in addition, precipitation is overestimated by the model.
- For temperature, the modelled annual error in the arid region (19.64%) is less than the model error in the humid (20.18%) and semi-arid regions (27.57%); temperature is also underestimated by the model in all regions.
- The model bias at monthly and annual time scales is greater than the model bias at a daily time step. The model may therefore be more accurately applied in an operational context for calculating the water and energy balances at a daily time step for the region of Iran.

- Due to mass and energy fluxes between the earth surface and the atmosphere, applying an atmospheric model in combination with land surface and hydrological models can better simulate the hydrological cycle and enhance our understanding of physical processes, particularly for the region of Iran.

As Fig. 8 represents, there is a significant systematic error between the elevation of the stations and the average elevation of corresponding GEM grid cells (13%). This indicates that the average elevation of the grid cells is greater than the elevation of the measurement stations. Therefore, temperature underestimation and bias associated with the GEM model at daily, monthly and annual scales is related to the higher elevation of grid cells as described in this paper. It can be concluded that overestimation of precipitation is partly related to differences in elevation at an annual scale, although this difference in precipitation is less and more irregular due to its random nature and high fluctuations. Figure 8 shows that differences between the elevation of stations and the average elevation of corresponding GEM grid cells in the semi-arid region is greater due to the mountainous nature of the region. An investigation of future climate change impacts may require large scale modeling for the region of Iran. Consequently, the GEM model has the potential to be used for predictions and forecasts in Iran.

There are often significant differences between modelled and observed environmental quantities for gridded data products (e.g. Stephens et al. 2010; Erler and Prltier. 2016; Wong et al. 2017; Xu et al. 2019; Ahmed et al. 2019). Biases are partially alleviated by application of a higher-resolution model with an explicit treatment of convection (Xu et al. 2019). Moreover, a higher-resolution model has a resolution that provides a closer match to geographic areas associated with the native resolution of observations. Therefore, agreement between modelled outputs and associated observations tends to be better in the tropics but significantly worse in the mid-latitudes when a model is applied at scales approaching a global domain of application.

A number of factors contribute to the better performance of gridded datasets such as the temporal model domain, spatial distribution of data sources, and the method of interpolation used to create a gridded data product (Ahmed et al. 2019). Moreover, the number, distribution, data quality of stations, and topography affects adequate representation of environmental conditions in a geographic area by gridded data products (Fu et al. 2014; Sun et al. 2014). However, in this study, systematic model error correction such as elevation error can greatly improve bias correction

and improve the model performance at different temporal scales over the three climatic zones.

The results from this study can provide important guidance for bias correction and selection of gridded precipitation products for driving hydrological models applied to a study domain coincident with the region of Iran. The GEM model thereby has the potential to be used in this region of West Asia for prediction and forecasting applications.

Acknowledgements

We thank Environment and Climate Change Canada, the University of Saskatchewan (Saskatoon, Saskatchewan, Canada), and the Global Institute of Water Security (GIWS) for providing data for this study. The Iranian weather organization provided synoptic station data. This research was performed in the context of a PhD by the first author at the Gorgan University of Agricultural Sciences and Natural Resources (Student Grant: 9619074140) and was initially started as the sabbatical research of the second author at the University of Saskatchewan.

Declarations

Ethics Approval: No ethics approval was required for this modelling study since the experimentation involved computer programs and no human subjects.

Consent to participate: Since no human subjects were required for participation, consent to participate was not required. All authors consent to the publication of the manuscript and participated fully in the publication process.

Consent for publication: All of the authors give consent for the publication of this article in Theoretical and Applied Climatology and all authors have read the final version of the manuscript submitted to the journal.

Funding: Student Grant: 9619074140 funded by Gorgan University of Agricultural Sciences and Natural Resources, Iran.

Conflicts of interest/Competing interests: We have no conflict of interest to declare.

Availability of data and material: Most part of the data utilized for this study is available as a download from Figshare (doi: 10.6084/m9.figshare.13370153). Any further information as required can be obtained from the corresponding author.

Code availability: Not applicable.

Authors' contributions: 1. Data preparation, analysis and manuscript preparation (MM), 2. Supervision, conceptualization, results interpretation (AB), 3. Data development (DP), 4. Review and edit (NK), 5. Advise, review and edit (SR).

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APPENDIX

Table A. a summary of the meteorological stations and study regions

Zones	Mean elevation of zones (m)	Mean elevation of stations (m)	Number of synoptic stations	Stations density (10000/km ²)	Date cooperated with GEM	Missing Data
Arid	1153	1075.7	87	0.78	4 years	NO
Semi-Arid	1377	1088.86	63	1.2	4 years	NO
Humid	1119	1122.53	27	2	4 years	NO
country	1305	1097.53	177	1.07	4 years	NO

Table B. The decomposition of daily temperature KGE criterion to components α , β , r for regions of Iran.

Zones	α	β	r	KGE
Arid	0.75	0.98	0.98	0.75
Semi-Arid	0.72	0.91	0.98	0.7
Humid	0.78	1.01	0.98	0.77

Table C. The decomposition of daily precipitation KGE criterion to components α , β , r for regions of Iran.

Zones	α	β	r	KGE
Arid	1.02	1.68	0.6	0.23
Semi-Arid	1.24	1.21	0.41	0.33
Humid	1.49	1.09	0.35	0.15

Supplementary Files

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